Advances in Artificial Intelligence and Machine Learning; Research 5 (3) 4242-4259 Received 05-06-2025; Accepted 02-09-2025; Published 09-09-2025

Detecting Social Stock Pumping in the Russian Equity Market Using Machine Learning

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Abstract

This study investigates the phenomenon of social stock pumping in the Russian equity market and explores effective machine learning models for its detection. Social stock pumping is defined as a market anomaly in which coordinated publications on social media trigger abnormal increases in stock prices and trading volumes without fundamental justification. The paper proposes a methodology for identifying such events based on a combination of behavioral and market indicators. A dataset of 615 social pumping episodes across 104 Russian companies over the period 2019–2025 was constructed. To assess the impact of social media, two proprietary indices were developed: the Russian Social Media Intensive Index (RSMII) and the Russian Social Media Sentiment Index (RSMSI). Five classification models were trained to detect manipulation events: logistic regression, KNN, random forest, SVM and CatBoost. The CatBoost model showed the best performance (AUC-ROC = 0.97, F1 score = 0.91). A comparison with normal trading days confirmed the presence of statistically significant anomalies in prices, trading volumes, and social indicators on pump days. The results demonstrate that machine learning models (particularly CatBoost and KNN) substantially outperform logistic regression in terms of accuracy and recall when detecting social pumping cases. The proposed methodology can be applied by regulators and market participants to monitor informational influence and manage associated risks.

Keywords: Machine learning, Market manipulation, Sentiment analysis, Social pumping, Stock market.

1. INTRODUCTION

The stock market is one of the key components of the financial system. Its stable functioning and development are essential for stimulating economic growth and attracting investment [1]. However, the problem of stock market manipulation poses serious risks to all participants, as it undermines the trust of both retail and institutional investors [2].

Citation: Gleb Khaziev. Detecting Social Stock Pumping in the Russian Equity Market Using Machine Learning. **Advances in Artificial Intelligence and Machine Learning**. 2025;5(3):236.

In recent years, the emergence of social networks and online forums has introduced new formats of market manipulation, such as the implementation of pump-and-dump schemes through coordinated online activity. Well-known cases include the actions of Reddit forum users, who contributed to sharp price increases in the shares of companies such as GameStop, AMC Entertainment, BlackBerry, and others [3].

In the past five years, the issue of social stock pumping has gained particular relevance in the Russian market. Between 2021 and 2025, the number of retail investors grew from 10 million to 35 million, and their share in trading turnover increased from 40% to 75% [4]. Social networks have become the primary source of investment information for many of these investors [5], creating opportunities for coordinated price influence via Russian platforms and forums. The Bank of Russia has already confirmed several cases of stock price manipulation linked to the Telegram platform [6], and although legislative responses were considered, no regulatory changes have been adopted to date.

The emergence of new manipulation formats, the rapid influx of retail investors, and the growing role of social media as an information channel have led to a need for new detection methods. With the advancement of machine learning (ML) and artificial intelligence (AI), researchers have increasingly applied these technologies to the detection of stock market anomalies [7–9]. ML models have demonstrated improved performance over traditional econometric techniques due to their ability to capture nonlinear and complex manipulation patterns [10–12].

Recent studies have also emphasized the role of investor sentiment — derived from textual analysis of social media discussions — as a significant variable in detecting social stock pumping [13–15]. While the topic has been extensively explored in markets such as the US, India, China, and Turkey [12, 16], similar research in the Russian equity market remains virtually absent.

The objective of this study is to develop effective machine learning models for detecting social stock pumping in Russian equities and to address this research gap.

1.1 Related Work

The issue of market manipulation and the identification of manipulative trading activity has long been a topic of academic interest. Earlier studies prior to 2010 were primarily based on the foundational works of Allen and Gale [17] and Aggarwal and Wu [18], with differences in sample sizes, market coverage, and financial instruments, but largely unified in methodological approach [19, 20].

With the development of artificial intelligence and machine learning methods, a new research direction has emerged. Since the 2010s, various ML techniques have been actively applied to analyze market manipulation cases.

Uslu and Akal [9] examined confirmed manipulation episodes on the Borsa Istanbul (BIST) between 2010 and 2015. They constructed detection models based on 75 stocks, encompassing 256 identified manipulation cases with an average duration of 66 days. The authors tested several models, including Decision Trees (DT), Logistic Regression (LR), k-Nearest Neighbors (KNN), Random Forest (RF), Naive Bayes (NB), Support Vector Machines (SVM), and a custom stacking ensemble.

The ensemble model showed the highest performance with Accuracy = 0.93, Precision = 0.88, and F1 Score = 0.91.

Nam [16] studied social stock pumping events on Reddit using a dataset of 18,555 posts and 312,578 comments. The authors applied machine learning models such as XGBoost, Random Forest, SVM, MLP, CNN, and BiLSTM, finding that a Convolutional Neural Network (CNN) model performed best (Accuracy = 87%, Precision = 58%, Recall = 79%, F1-score = 62%). Despite its relative success, the moderate quality of predictions highlighted the need for carefully curated datasets and precise labeling to effectively train detection models.

Additional studies used as the theoretical foundation for this research are listed in **TABLE 1**, which summarizes recent machine learning–based approaches to detecting market manipulation and social stock pumping.

Table 1: Studies on stock market manipulation using machine learning methods

Authors	Market	Study Period	Sample Size (manipulation cases)	Methods Used	Best Performing Method
1. Li et al. (2017) [21]	China	2013-2016	4,593 (919)	KNN, DTC, LDA, QDA, LR, ANN, SVM	KNN, DT
2. Islam et al. (2018) [22]	USA	1996-2018	7,988 (1,198)	LSTM RNN	LSTM RNN
3. Liu et al. (2021) [23]	China	2014-2016	6,720 (249)	SVM, LR, Borderline SMOTE–SVM, Borderline SMOTE–LR	Borderline SMOTE–SVM
4. Youssef et al. (2021) [24]	USA	2012-2019	278,000 (909)	XGBoost, KNN & SVM	XGBoost
5. Herrera et al. (2022) [25]	Spain	2004-2018	151 (20)	Random Forest, GLM, Gradient Boosting Machine and Deep Neural Networks	All effective

1.2 Key Contributions of the Study

1. Development of a unique dataset on social stock pumping cases, comprising 615 identified episodes and 6,765 total observations: 615 days with confirmed social pumping and 6,150 normal trading days. This extensive dataset ensures greater reliability in evaluating model performance and allows for more robust conclusions regarding model validity in the Russian market. The dataset is notably larger than those used in comparable studies [12, 26].
2. Proposal of an original methodology for identifying social pumping events using five classification models: four machine learning algorithms (CatBoost, Random Forest, KNN, and SVM) and a traditional logistic regression model.
3. Integration into the classification models of two proprietary indices designed to capture behavioral market signals: the Russian Social Media Intensive Index (RSMII) and the Russian Social

Media Sentiment Index (RSMSI), which quantify the intensity of discussion and investor sentiment, respectively.

4. In contrast to prior studies [14, 27], which primarily rely on market indicators to detect anomalies, this research enhances model precision by incorporating a broad set of technical analysis features.

2. DATA AND METHODS

2.1 Data

The study uses data from 104 publicly traded Russian companies over the period 2019 to 2025. The dataset is complete and balanced across all companies. Information was collected using custom Python-based data parsers, along with market data sourced from finam.ru. The analysis was conducted on a daily frequency, resulting in a dataset of 6 765 observations.

To construct the sentiment index, the study collected investor posts from the Russian social media platforms Pulse and Telegram. The Pulse dataset includes 601,297 publications from 2019 to 2025, while the Telegram dataset contains 234,926 messages from 2015 to 2025.

In this study, we focus on two primary social platforms (Telegram and Pulse) as sources of social media signals. This selection is justified by their dominant role in the information environment of Russian retail investors. A comprehensive review of all major platforms used by individual investors in Russia (including VK, Smart-Lab, MFD, InvestFuture, FinTwit, and Reddit) indicates that Telegram and Pulse jointly cover the majority of investor communication channels in terms of audience reach, trading discussion volume, and real-time sentiment dynamics (**TABLE 2**).

Descriptive statistics for the dataset are presented in **TABLE 3**.

Explanations of individual variables from Table 2:

- *High-LowClose* - the daily price range (difference between the high and low prices), normalized by the closing price. It is calculated as follows:

$$\text{HighLowClose\_t} = \frac{High\_t - Low\_t}{Close\_t} \times 100\%, \tag{1}$$

- *PriceChangeDay* - the relative change in the closing price compared to the previous trading day. It is calculated as follows:

$$\text{PriceChangeDay\_t} = \frac{Close\_t - Close\_t - 1}{Close\_t - 1} \times 100\%, \tag{2}$$

- *PriceChangePreviousDay* - the relative change in the closing price of the previous day compared to the day before that. It is calculated as follows:

$$\text{PriceChangePreviousDay\_t} = \frac{Close\_t - 1 - Close\_t - 2}{Close\_t - 2} \times 100\%, \tag{3}$$

Table 2: Social media platforms used by Russian retail investors

Platform	Description	Main Content	Popularity & Activity
Telegram	A messenger application that enables the creation of public and private channels. Since the early 2020s, it has become the primary source of information for Russian retail investors.	Trading ideas, signals, market analysis, issuer news, and exclusive channel content.	Extremely high. Thousands of financial channels, with top audiences ranging from 50,000 to 700,000 subscribers.
Pulse	A built-in social platform for discussions within the T-Bank brokerage application, also accessible via web.	News commentary, trading ideas, and user discussions.	The most popular investment platform among Russian retail investors. Recognized as the top investment social platform in 2022 with over 4 million monthly active users.
VK (VKontakte)	Russia's largest social network by user base. Financial content is organized through public pages and groups.	Market reviews, educational posts, user discussions in comments.	Moderate. Primarily attracts younger investors and novice traders. Major groups have 50,000–200,000 followers.
Smart-Lab Forum	One of the oldest Russian investment forums, operating since 2008.	Discussions of stocks, strategies, trade blogs, and deal analysis.	High among active retail investors. ~50,000–70,000 unique daily visitors and over 1 million monthly.
MFD Forum	A long-standing Russian-language investment forum active since the early 2000s.	Issuer discussions, market news, strategy exchange.	Less popular than Smart-Lab, but remains active: ~5,000–10,000 unique daily visitors. Often used by experienced investors.
Investfuture	A popular educational platform and community for retail investors (website, Telegram, and YouTube presence).	News, analytics, educational materials, and community discussions.	Moderate. The combined audience exceeds 1 million users, though the core active discussion base is smaller.
FinTwit (Twitter/X)	Twitter was previously popular among professional investors until it was restricted in Russia after 2022.	Short-form commentary, article links, and trade discussions.	Low since 2022. Now has a niche audience using VPNs.
Reddit (r/ru_ investing, r/stocks)	International forum with Russian-language threads.	Strategy discussions, stock analysis, and experience sharing.	Low relevance for Russian investors. Limited niche audience with only several thousand members.

Table 3: Descriptive statistics for the period 2019–2025 (N = 6765)

Phase	Indicator	Observations	Mean	Min	Max	Standard deviation
5 days before pump	OPEN	3,075	1,235	0.105	20,300	2,108
	HIGH	3,075	1,255	0.106	20,650	2,136
	LOW	3,075	1,216	0.104	19,800	2,081
	CLOSE	3,075	1,238	0.105	20,150	2,112
	VOLUME	3,075	28,678,307	2	7,864,390,000	256,098,936
	High-LowClose (%)	3,075	3.3%	0.2%	31.2%	2.7%
	PriceChangeDay (%)	3,075	0.2%	–16.5%	21.5%	2.4%
	PriceChangePreviousDay (%)	3,075	0.4%	–17.3%	23.4%	2.5%
	VOLChange (%)	3,075	46.4%	–99.0%	8,972.1%	301.6%
	IndexIntensive	3,075	27	0	407	47
	IndexSentiment	3,075	1	–50	175	8
Pump day	OPEN	615	1,251	0.109	20,100	2,138
	HIGH	615	1,304	0.115	22,650	2,277
	LOW	615	1,230	0.106	19,800	2,107
	CLOSE	615	1,277	0.111	21,800	2,225
	VOLUME	615	72,071,813	154	12,443,370,000	675,525,520
	High-LowClose (%)	615	5.9%	0.7%	37.7%	5.3%
	PriceChangeDay (%)	615	2.2%	–9.5%	41.6%	4.7%
	PriceChangePreviousDay (%)	615	2.5%	–8.2%	40.4%	4.9%
	VOLChange (%)	615	546.3%	–74.9%	80,236.4%	3,618.8%
	IndexIntensive	615	50	0	709	75
	IndexSentiment	615	6	–68	99	15
5 days after pump	OPEN	3,070	1,274	0.102	24,500	2,234
	HIGH	3,070	1,297	0.104	25,850	2,300
	LOW	3,070	1,247	0.101	23,300	2,180
	CLOSE	3,070	1,271	0.102	24,600	2,236
	VOLUME	3,070	52,206,227	10	17,778,216,000	507,849,993
	High-LowClose (%)	3,070	4.0%	0.4%	44.5%	3.5%
	PriceChangeDay (%)	3,070	–0.1%	–20.9%	38.5%	3.2%
	PriceChangePreviousDay (%)	3,070	0.2%	–22.4%	39.9%	3.3%
	VOLChange (%)	3,070	2.8%	–97.3%	1,745.1%	94.3%
	IndexIntensive	3,070	35	0	1,238	88
	IndexSentiment	3,070	1	–95	335	12

- *VOLChange* - the relative change in trading volume compared to the previous day. It is calculated as follows:

$$\text{VOLChange\_t} = \frac{Volume\_t - Volume\_t - 1}{Volume\_t - 1} \times 100\%, \tag{4}$$

2.2 Methods

The methodology for hypothesis testing in this study consisted of the following stages (**FIGURE 1**):

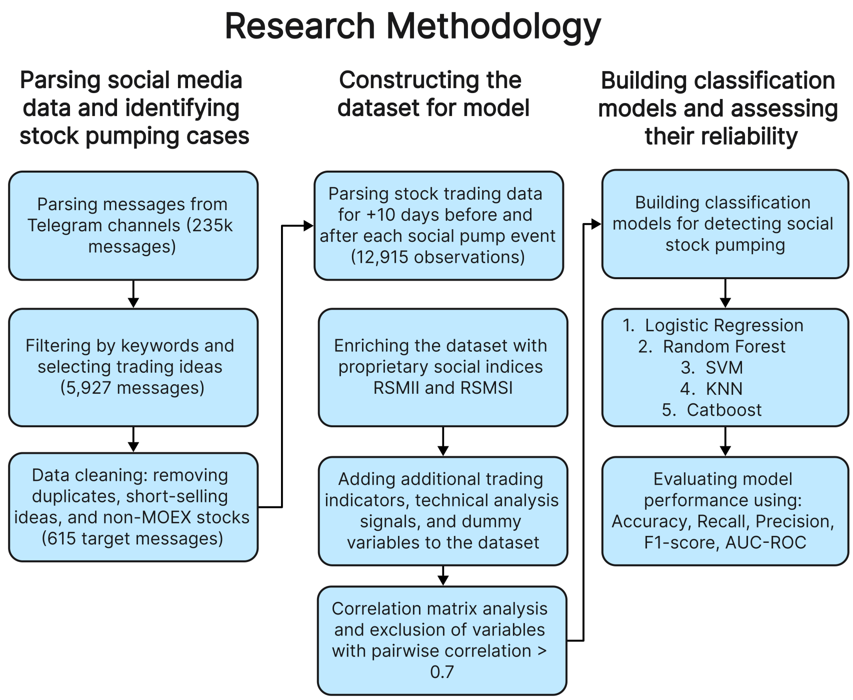

Figure 1: Research workflow diagram

1. **Data collection from Telegram**. Messages were parsed from financial and investment-related Telegram channels popular among Russian retail investors. Using Python and the Telegram API, a total of 234,926 posts were collected from November 2015 (the earliest available message) through March 2025.
2. **Filtering for trade recommendations**. Messages were filtered for potential trading ideas using keywords such as "idea," "trade idea," "valuation," as well as "recommendation," "we recommend," "buy," "purchase," "investment idea." Out of 83,079 messages analyzed from selected channels, 5,927 were identified as potentially promotional or containing buy recommendations for specific stocks.
3. **Data cleaning and inclusion criteria.** To ensure high-quality signals, the following filtering criteria were applied:
   - Only posts related to Russian companies listed on the Moscow Exchange (MOEX) were retained;
   - Short-selling ideas were excluded;
   - Duplicate or repeated recommendations within short timeframes were removed;
   - Posts mentioning more than one company were excluded.

To ensure the validity of the detected pump events and isolate the effect of social media signals, we manually verified each case to exclude confounding fundamental drivers such as earnings announcements, dividend declarations, insider transactions, and official corporate disclosures. Relevant events were identified using company filings on the official disclosure portal (e-disclosure.ru).

The final dataset includes 615 unique trade recommendation posts that could have influenced investor behavior and triggered social pumping effects.

4. **Market data aggregation.** Daily trading data for affected companies were collected for each pump day, as well as for 10 days before and after the event. Data included open, close, high, low prices, and trading volume. A total of 12,915 trading day records were collected using Python parsers from finam.ru.

5. **Integration of behavioral indices.** Two proprietary indices were introduced to quantify social media activity and sentiment: RSMII (Russian Social Media Intensive Index) — a measure of discussion intensity; RSMSI (Russian Social Media Sentiment Index) — a measure of investor sentiment.

RSMII is calculated as follows:

$$RSMII = TgIndex + PulseIndex \tag{5}$$

Telegram component:

$$TgIndex = \sum((NViews/10000) + NReposts/(Nviews * RepostFreq)) \tag{6}$$

where NViews = number of views, NReposts = number of reposts, RepostFreq = average repost rate (0.00194 for this dataset).

Pulse component:

$$PulseIndex = \sum(NComments) \tag{7}$$

where NComments = number of ñomments.

RSMSI is the sum of sentiment scores from both platforms: Telegram Sentiment Index and Pulse Sentiment Index.

$$\mathrm{TgSIndex} = \sum\left(\mathrm{Sentiment}\left(\frac{\mathrm{NViews}}{1000}\right)\left(1 + \frac{\mathrm{NLikes}}{\mathrm{NViews} \times \mathrm{EngageLevel}} + \frac{\mathrm{NReposts}}{\mathrm{Nviews} \times \mathrm{RepostFreq}}\right)\right), \tag{8}$$

where $\sum$ denotes the summation of sentiment values for each message related to a specific stock-issuing company over a given period (day), Sentiment represents the polarity of the message (taking the value 1 for positive sentiment and –1 for negative sentiment), NViews = number of views of the message, EngageLevel = average engagement rate (reactions-to-views ratio) on the corresponding social media platform, NLikes = difference between the number of positive and negative reactions, NReposts = number of reposts, RepostFreq = average repost-to-view ratio for the given platform.

$$PulseSIndex = \sum(Sentiment \times NLikes \times NComments)\,, \tag{9}$$

where Sentiment equals 1 for positive tone and –1 for negative tone, NLikes = difference between positive and negative reactions, NComments = number of comments.

6. **Calculation of additional trading indicators.** To enhance model performance, four groups of features were computed:
   - Price dynamics: daily price changes (open–close), high–low spread over close, changes relative to previous day (price and volume).
   - Technical indicators: percentage changes in exponential moving averages (12/26 days), fast and signal MACD, Stochastic Oscillator, Momentum, RSI.
   - Lagged and normalized features: normalized close price and volume, volume Z-score, rolling volume average, volume momentum, price-volume correlation, opening price gaps, intraday range, trend divergence, volatility, lagged returns and volumes (1–3 days).
   - Alternative volume metrics: normalized alternative volume, rolling volume average, and momentum-based features.

   Furthermore, to account for broader market dynamics and macroeconomic shocks, we included the daily return of the IMOEX index (Moscow Exchange index) as an explanatory variable in the model. This benchmark captures general market sentiment and allows us to differentiate between systemic price movements and idiosyncratic anomalies potentially driven by social media activity.
7. **Multicollinearity control.** A correlation matrix was computed for all independent variables. Variables with pairwise correlation above 0.7 were removed to avoid multicollinearity in the models.
8. **Model construction.** Five classification models were built to detect social pumping episodes:
   - Logistic Regression
   - Random Forest
   - Support Vector Machine (SVM)
   - k-Nearest Neighbors (KNN)
   - CatBoost (gradient boosting model developed by Yandex)
9. **Model evaluation metrics.** Model performance was assessed using the following metrics:
   - Accuracy – the proportion of correctly classified observations over the total sample;
   - Recall – the proportion of correctly identified positive cases (manipulations);
   - Precision – the proportion of true positives among all predicted positives;
   - F1-score – harmonic mean of Precision and Recall;
   - AUC-ROC – area under the ROC curve, indicating the model's ability to distinguish between classes at different thresholds.

3. RESULTS AND DISCUSSION

3.1 Results

Before building classification models for detecting social stock pumping, it is essential to assess whether social media publications can indeed cause abnormal price and volume surges in stocks.

To this end, we analyzed deviations in closing prices and trading volumes during days identified as social pump events (SOCIALPUMP = 1) and compared them with normal market behavior days (SOCIALPUMP = 0).

To estimate expected (normal) values of trading volume and return dynamics in the absence of social stock pumping events, we employed a simple linear regression model for each event individually. Specifically, for each selected event day (defined as the day with the highest impact score within a given period), a separate model was constructed based on the 10 trading days immediately preceding the event.

For each stock, we used a time-indexed linear regression of the target variable (either daily return percentage or volume change) against a simple time index. The regression equation is defined as:

$$Yt = \alpha + \beta \times t + \epsilon t, \tag{10}$$

where Yt is the observed value (return or volume change) on day t, and t ∈ [1,10] represents the sequence of the 10 prior days. The model parameters alpha and beta were estimated from this 10-day window, and then used to forecast the expected value on day t=11, corresponding to the event day.

The difference between the actual and forecasted value for the event day represents the anomaly or deviation from normal behavior:

$$\Delta Y = Yactual - Ypredicted, \tag{11}$$

The anomalies were calculated as the difference between actual values and forecasted values obtained from a baseline model of normal behavior constructed using a 10-day window prior to each event:

- **DELTA_CLOSE_PCT** – deviation of the closing price from its forecast, in percentage terms;
- **DELTA_VOL** – deviation of trading volume expressed as a multiple of its forecasted value.

As a control, we considered normal trading days to be the three days before and after each pump event. The descriptive statistics are presented in **TABLE 4**.

As shown in **TABLE 4**, the average price deviation (DELTA_CLOSE_PCT) on pump days is 0.019 — approximately 63 times higher than on normal days (0.0003), indicating abnormal price spikes. Trading volume deviations (DELTA_VOL) are also dramatically larger — 4.87 versus 0.10 — a 48-fold increase, signaling heightened market attention. The standard deviation of price increases 2.5 times, while the volume variability grows over 25 times, confirming elevated volatility during pump episodes.

Social indicators also differ significantly: the IndexIntensive (discussion intensity) averages 50.07 on pump days versus 34.05 on normal days. The IndexSentiment (investor sentiment) is 6.46 versus 1.99 — more than triple on average.

To assess the statistical significance of these differences, a t-test was conducted on four key variables. Results are shown in **TABLE 5**.

Table 4: Comparative statistics on pump vs. normal trading days

Indicator	Pump Days (n=615)	Normal Days (n=3690)
Mean DELTA_CLOSE_PCT	0.019	0.0003
Mean DELTA_VOL	4.87	0.10
Std. Dev. (Price)	0.05	0.02
Std. Dev. (Volume)	36.30	1.46
Min Price Deviation	–0.16	–0.19
Max Price Deviation	0.41	0.20
Mean IndexIntensive	50.07	34.05
Mean IndexSentiment	6.46	1.99
Std. Dev. IndexIntensive	75.07	73.51
Std. Dev. IndexSentiment	14.94	11.58

Table 5: T-test results for key indicators

Indicator	t-statistic	p-value	Conclusion
DELTA_CLOSE_PCT	9.03	< 0.000001	Statistically significant price surges on pump days
DELTA_VOL	3.33	< 0.001	Significant increase in trading volume on pump days
IndexIntensive	4.86	< 0.001	Discussions intensity significantly higher on pump days
IndexSentiment	7.29	< 0.001	Investor sentiment significantly higher on pump days

These results confirm the presence of statistically significant differences:

- The deviation in closing prices (**DELTA_CLOSE_PCT**) is highly significant ($t = 9.03$, $p < 0.000001$), indicating consistent abnormal returns on pump days.
- Trading volume (**DELTA_VOL**) also rises markedly ($t = 3.33$, $p < 0.001$), reflecting intensified market activity in response to social media content.
- **IndexIntensive**, capturing discussion intensity, is significantly higher ($t = 4.86$, $p < 0.001$), suggesting coordinated information influence.
- **IndexSentiment**, representing emotional tone, is likewise elevated ($t = 7.29$, $p < 0.001$), indicating a predominantly positive sentiment environment during pumps.

Thus, the t-test results validate that all key market and social indicators differ significantly on days with presumed social influence, supporting the existence of the social pumping effect.

Following this validation, five classification models were developed to detect social stock pumping. Their performance is shown in **FIGURE 2** and **TABLE 6**.

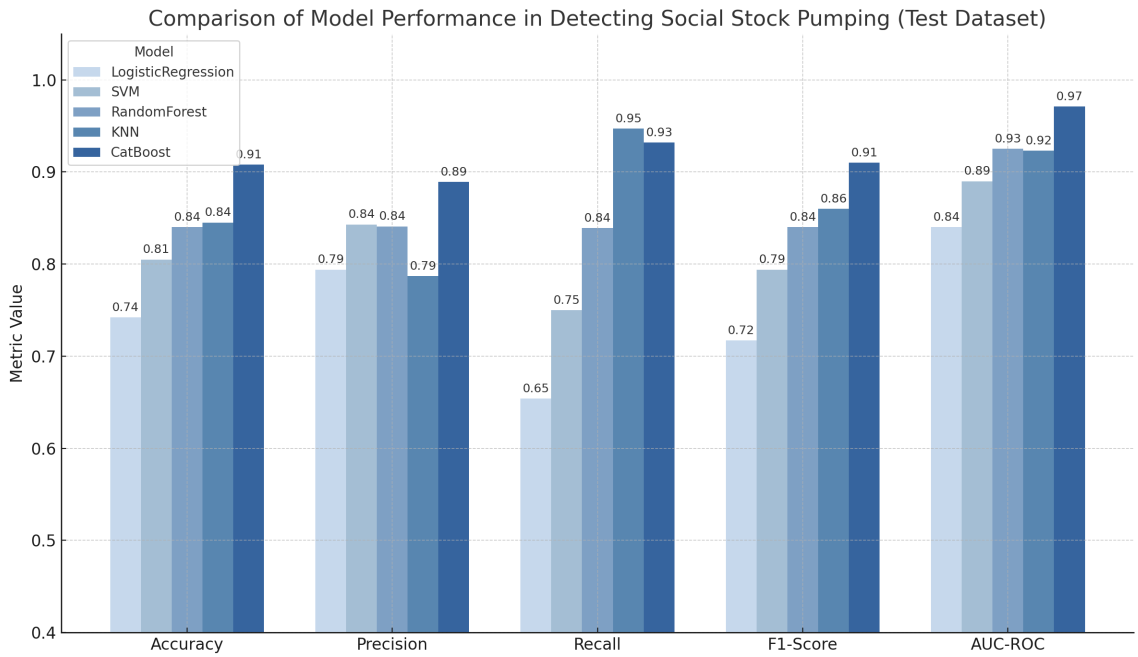

Figure 2: Model performance on the test dataset

Table 6: Performance of classification models with RSMII and RSMSI (training vs test datasets)

Model	Dataset	Accuracy	Precision	Recall	F1-score	AUC-ROC
CatBoost	Train	0.988	0.986	0.991	0.988	0.999
CatBoost	Test	0.908	0.889	0.932	0.910	0.971
Random Forest	Train	0.880	0.871	0.892	0.881	0.954
Random Forest	Test	0.840	0.841	0.839	0.840	0.925
Logistic Regression	Train	0.754	0.793	0.686	0.736	0.842
Logistic Regression	Test	0.742	0.794	0.654	0.717	0.840
KNN	Train	0.897	0.846	0.972	0.904	0.981
KNN	Test	0.845	0.787	0.947	0.860	0.923
SVM	Train	0.839	0.860	0.810	0.834	0.915
SVM	Test	0.805	0.843	0.750	0.794	0.890

CatBoost and **KNN** showed the best performance, correctly identifying over 90% of social pumping cases (Recall). Among all predicted positive cases, 79% (KNN) and 89% (CatBoost) were true pumps (Precision). Both models achieved AUC-ROC scores above 0.90, indicating excellent classification capability.

Random Forest and **SVM** delivered moderate results, identifying 75–84% of pump cases with slightly lower accuracy and precision compared to CatBoost.

Logistic Regression significantly underperformed, with a Recall of only 65% missing 35% of actual pump events. Although Precision reached 79%, the model's low sensitivity limits its practical usefulness.

Overall, machine learning models consistently outperformed logistic regression, particularly in terms of the composite ROC-AUC metric, which was 8–13% higher for ML models.

These findings confirm that machine learning algorithms are more effective than traditional econometric models in identifying social stock pumping events in the Russian equity market.

To assess the contribution of social features (intensity and sentiment indices), a comparative analysis was conducted using classification models trained both with and without these variables (**FIGURE 3** and **TABLE 7)**.

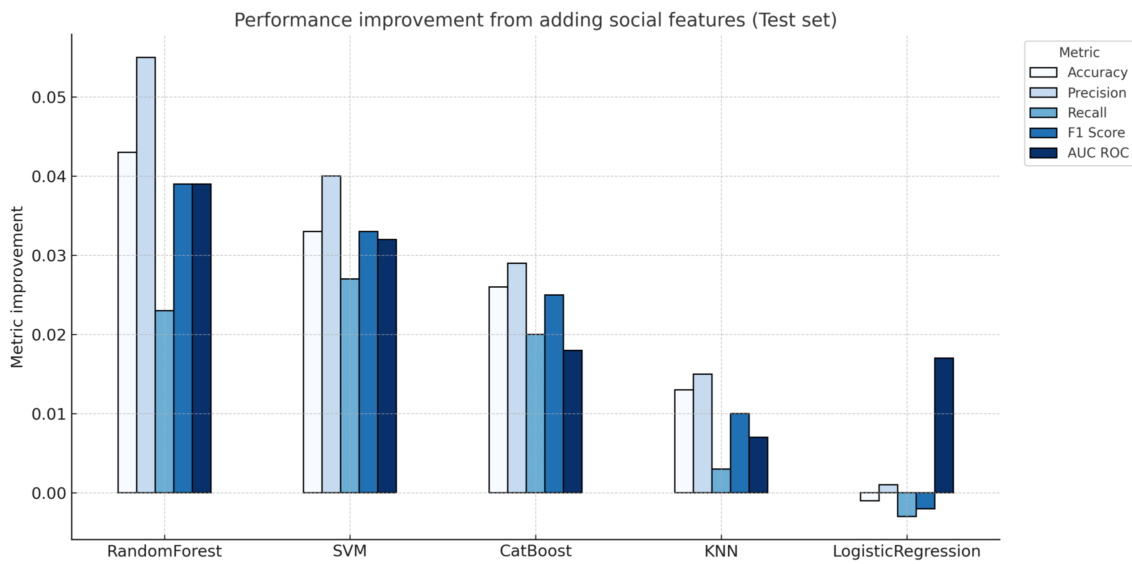

Figure 3: Effect of social features on model performance (test set)

The results demonstrate that the inclusion of social features leads to a notable improvement across all major performance metrics on the test set:

- For the CatBoost model, the AUC-ROC increased from 0.952 to 0.971 (+1.9 percentage points), and Recall improved from 0.912 to 0.932.
- For the Random Forest model, the AUC-ROC rose by 3.9 percentage points, while Precision increased by 5.5 percentage points.

All machine learning models, with the exception of logistic regression, exhibited consistent improvements in both ranking quality (e.g., AUC-ROC) and classification accuracy (e.g., Precision, Recall, F1-score).

Table 7: Performance of classification models without RSMII and RSMSI (training vs test datasets)

Model	Dataset	Accuracy	Precision	Recall	F1-score	AUC-ROC
CatBoost	Train	0.981	0.973	0.990	0.981	0.998
CatBoost	Test	0.882	0.860	0.912	0.885	0.952
Random Forest	Train	0.844	0.833	0.862	0.847	0.923
Random Forest	Test	0.797	0.787	0.815	0.801	0.886
Logistic Regression	Train	0.739	0.779	0.666	0.718	0.826
Logistic Regression	Test	0.743	0.793	0.657	0.719	0.822
KNN	Train	0.880	0.819	0.974	0.890	0.976
KNN	Test	0.833	0.772	0.943	0.849	0.916
SVM	Train	0.797	0.814	0.771	0.792	0.883
SVM	Test	0.773	0.803	0.724	0.761	0.858

These findings indicate that indicators of discussion intensity and sentiment in social media contain informative signals that enhance the ability to distinguish episodes of social stock pumping from normal trading behavior. Therefore, the hypothesis regarding the relevance of social features receives empirical support.

3.2 Discussion

The results obtained indicate that, on social pump days, stocks exhibit abnormally large increases in both price and trading volume. Specifically, the average price deviation was more than 60 times higher compared to normal days, and the volume deviation was nearly 48 times greater. Moreover, social activity indicators (RSMII and RSMSI) and investor were also significantly elevated on pump days.

To evaluate the causal relevance of these social signals, the study implements several safeguards. First, all analyzed pump cases were filtered to exclude periods with fundamental events such as earnings announcements, dividend distributions, or insider trades. Second, a baseline model of expected price and volume behavior was built using a 10-day pre-event window for each episode. Deviations were calculated relative to this baseline, allowing us to isolate anomalies not explained by natural market dynamics. Third, the event day was fixed based on the known occurrence of a social media burst (SOCIALPUMP = 1), providing a clear temporal anchor. In all observed cases, the abnormal market reaction either coincided with or followed the spike in social media indicators, satisfying the criterion of temporal precedence.

While a strict causal relationship cannot be formally proven within the observational framework, this analytical structure creates a quasi-experimental design that strongly suggests a triggering role of social media activity in short-term market distortions. Accordingly, the wording of this conclusion has been adjusted to better reflect the evidence.

A comparison with previous studies supports the validity of the results obtained. Semenova and Winkler [28] demonstrated that waves of positive discussions on Reddit can lead to sharp increases in stock prices. Ranco et al. [29] found that sudden spikes in mentions and discussions of individual Dow Jones companies on Twitter can statistically significantly induce abnormal price increases of 1–2%, even in the absence of fundamental events—thus providing evidence of a causal link between social media activity and market anomalies.

Our results show that machine learning models (especially CatBoost and SVM) achieve high accuracy in detecting social pump events, significantly outperforming the logistic regression benchmark. ROC-AUC scores exceeded 0.90, while F1-scores reached 0.91, reflecting a strong ability to detect subtle anomalies caused by informational influence.

Similar approaches have been applied in the international literature. Nam and Skillicorn [16] tested six models for detecting pump-and-dump manipulation schemes. The best performance was achieved by a Convolutional Neural Network (CNN), with an accuracy of 85% and an F1-score of 62%. Li et al. [21] evaluated seven classification models to identify stock manipulation cases in the Chinese market. The highest performance across all metrics was demonstrated by the K-Nearest Neighbors (KNN) and Decision Tree (DT) models, with overall accuracy and AUC-ROC values ranging from 89% to 99% across all models. These findings suggest that incorporating sentiment analysis, discussion intensity, and comprehensive market indicators—as implemented in the present study—can further improve the reliability of models for detecting socially driven stock surges.

Thus, in comparison to previous studies, the proposed machine learning models deliver superior accuracy and recall in identifying social pumping episodes.

3.3 Limitations

Despite promising results, the study has several limitations:

- Lack of participant-level trading data. Due to the unavailability of microstructure data in the Russian equity market, it is not possible to confirm whether specific investors or groups were directly responsible for social pumping episodes. This limits the ability to establish a definitive causal link between social media activity and the actions of particular market participants.
- Limited coverage of social media platforms. The study focuses on two major platforms widely used by Russian retail investors—Telegram and Pulse. While these sources cover the majority of investor discussions, the analysis does not incorporate other platforms such as Smartlab or VK, nor does it distinguish between different content types or user engagement levels. Future work may expand platform coverage and explore the differential influence of each communication channel.
- Macroeconomic factors and baseline modeling. Although the predictive models include a variable reflecting the dynamics of the IMOEX index to partially control for market-wide effects, the baseline model of normal behavior is based on a 10-day rolling window and may not fully capture broader macroeconomic shocks or long-term seasonal patterns. Future research could refine this modeling by incorporating macroeconomic indicators explicitly or applying more adaptive temporal structures.

4. CONCLUSION

The objective of this study was to develop effective methods for detecting social stock pumping in the Russian equity market—instances where social media publications cause abnormal increases in stock prices and trading volumes. The proposed methodology combines market-based and behavioral features to identify such episodes.

The main findings of the study are as follows:

1. On social pump days, stocks exhibit statistically significant increases in both price and trading volume. These anomalies are associated with social media publications and are accompanied by spikes in discussion intensity and positive investor sentiment.
2. Machine learning models (CatBoost, SVM) demonstrated high performance, with ROC-AUC values exceeding 0.90 and strong F1-scores, allowing for accurate differentiation between genuine market activity and socially induced anomalies.

Theoretical Contribution. This work contributes to behavioral and institutional finance theory by highlighting non-traditional sources of market information such as social media and investor sentiment. It empirically confirms the impact of social media publications on abnormal price and volume changes in Russian equities, thereby advancing theoretical understanding of short-term anomalies in emerging markets.

Practical Implications. The proposed models and methods may be applied by:

- **Financial regulators** for monitoring abnormal social media activity and detecting not only socially-driven stock pumps but also potentially illegal market manipulation;
- **Investment firms and traders** for assessing risks related to short-term price surges and incorporating social influence factors into trading strategies.

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