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The Development of a Method for Forecasting the Business Valuation of Public Companies Within the Framework of the Comparative Approach Using Artificial Intelligence

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ABSTRACT

The article focuses on the study of issues related to assessing the business value of publicly traded companies using artificial intelligence. **The purpose of the study** is to develop a model for predicting the business value of publicly traded companies within the framework of a comparative approach. The relevance of this work is that in times of uncertainty, it can be difficult to justify the market value of the business of public companies due to the fact that historical transaction prices, which are used as the basic information for calculating market value in the framework of the capital market method, may not reflect the company's future prospects. **The scientific novelty** of the research consists in developing a method for predicting the business value of publicly traded companies using the main section of artificial intelligence — machine learning. The authors used the following **methods** in their scientific research, including logical and statistical methods (correlation analysis) and machine learning techniques such as linear regression, decision tree, tree ensembles, and recurrent neural network. The developed method consists of six stages which integrate the main steps of machine learning with the classical stages of data cost estimation. Based on the results of testing the method, eleven models of extra-random decision trees have been developed. These Trees allow us to predict the direction of movement of industry indexes Moscow Exchange depending on exogenous and technical indicators. It can be **concluded** that the developed models have a high level of accuracy (based on the test data R2 of 0.99 and MAPE below 1%) of forecasting industry indices and the suitability of the method for solving the problem of predicting the share price of a single public company within the context of the capital market method. **The prospect of further research** relates to the development of predictive models for all public companies, taking into account their financial characteristics and behavioral factors. This article will be beneficial for practicing appraisers in their evaluation of businesses in this field and for investors.

Keywords: methods of value assessment; comparative approach; industry indices; valuation factors; machine learning models

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INTRODUCTION

Forecasting the business value of public companies is an essential part of investment decision-making, risk assessment, and strategic planning. For a long time, traditional valuation methods such as revenue, cost, and comparison with similar companies have been the basis for analysts and investors in determining the value of a company.

The comparative approach is based on the principle that the value of a company can be determined by comparing it with similar companies whose market value is known. This method is widely used because of its simplicity and interpretability.

However, a significant disadvantage of the comparative approach is the retrospective nature of transaction prices with analog companies, which are the basis for calculating multipliers. It turns out that the calculated multiplier value does not reflect the prospects of a similar business in any way, which makes this approach indicative and not applicable in conditions of external uncertainty.

With the development of artificial intelligence (AI) and big data technologies, it has become possible to improve the comparative approach (the capital market method, since sufficient data is available for modeling), increasing its accuracy by predicting the share prices of analog companies.

The purpose of the study is to develop a method for predicting the business value of public companies within the framework of a comparative approach based on AI algorithms. Taking into account the objectives of the study, the tasks are defined:

1. To study key areas of artificial intelligence and their practical application in the financial sector and business valuation.

2. Identify the factors and available cost indicators that affect stock prices and the market value of the business of public companies.

3. To determine the main stages of the method of forecasting the business value of public companies within the framework of the market-capital method of a comparative approach using AI algorithms.

4. To test the proposed method using the example of industry indices of the Moscow Stock Exchange.

METHODS

In the study by K.-Y. Leong et al. [1], "which is devoted to the valuation of business shares in developed countries, it is noted that the best result in valuation is provided by a comparative approach (capital market method, P/E multiplier). However, the capital market method is not applicable in conditions of high volatility of stock prices" [2]. It seems that AI technology will eliminate this disadvantage of the comparative approach.

AI is an end-to-end technology capable of implementing functionality previously available only to humans. As an end-to-end technology, AI combines classical programming, data and feature engineering, and mathematical algorithms. These directions allow you to solve problems of different classes and with different types of data. The task of teaching a machine to work with numerical, textual, graphical and other information is solved using the main section of AI — machine learning. Machine learning is divided into surface learning (based on a certain class of models based on well-known mathematics: linear and logical regression, nuclear methods — the method of support vectors, decision trees, ensembles of trees — random and extra-random forests, gradient boosting on trees) and deep learning (neural networks: fully connected, recurrent, transformers, pre-trained tracers and generative neural networks).

The AI industry is actively developing all over the world. Over the past 10 years, global private investment in this area has increased 30-fold and reached $ 154 billion in 2023.[1]

[1] Artificial intelligence statistics. INKLIENT. 2024. URL: https://inclient.ru/ai-stats/ (accessed on 05.10.2024).

The technology is becoming widespread in "transport and logistics, retail, mining, IT, and consumer goods production." [2] AI is also actively used in the financial and banking industries. Its main section, machine learning, has been used since the 2010s. with the democratization of technologies, Python libraries, and the emergence of new algorithms based on decision trees, which surpassed kernel methods (the most famous SVM method is the support vector method proposed by Vladimir Vapnik and Corinna Cortez in 1995 [3]) and neural networks in the architecture of those years. However, the emergence of new neural network architectures in 2021 brought them back to the attention of the scientific community.

In the financial sector, work on the application of individual AI algorithms did not appear synchronously with the advent of new algorithms. In order to study the degree of elaboration of the topic to the database of scientific publications dimensions.ai[3] a request was made: "artificial intelligence in business value assessment." As a result, 104 publications were received. Using the Bert Topic[4] toolkit, the statistics of keywords in the annotation of the found articles were calculated. Among the most frequently mentioned words are the following: prediction, forecasting, stocks, machine learning, market and models. Based on the text analysis, the publications that are most suitable for the research topic have been selected. The publications are structured into four thematic areas:

1. Using social media and news to forecast the stock market. Studies by M. Choi et al. [4], V.K. Abinanda, F.N. Sabiyath [5], L.T. Vu et al. [6], C. Huang et al. [7], R. Kaur, A. Sharma [8, 9] show that signals from social media and analysis of news tonality can be used to predict stock market movements. L.T. Vu et al. [6] conclude that the impact of news on stock price changes is negligible. The use of machine learning methods such as neural networks improves the accuracy of predictions.

2. Machine learning models for stock forecasting in stock market trading (technical approach).

The works of P.R. Low, E. Sakk [10], B. Gülmez [11], Q. Li et al. [12], L. Hang, et al. [13], C. Chen et al. [14], A. Shet et al. [15], [16], [17] are devoted to the use of neural networks with memory effect (LSTM) and recurrent neural networks (RNN) for predicting stock prices of foreign companies. Some works (M. Sarkar, et al. [18], A.I. Ali et al. [19], C. Karthikeyan et al. [20]) use time series models and moving averages. Some domestic publications devoted to forecasting stock prices of Russian companies also use autoregressive models such as ARIMA and SARIMA [21]. However, this approach may not always be suitable, as it does not allow for the establishment of causal relationships between indicators. A separate area of research involves the creation of neural network-based trading agents for algorithmic trading over short periods of time [22].

According to the author of this study, the use of neural networks does not allow for interpretability of forecasts. Historical stock prices do not reflect all the influencing factors and are not sufficient to predict future trends.

3. The impact of the company's financial performance on the price and profitability of shares.

In the works of J. Prastika et al. [23], E. Hendawy et al. [24], V. Jeevan et al. [25] it was noted that financial indicators significantly affect the profitability of stocks. The research concluded that long-term predictability of profitability can be achieved using accounting, technical and macroeconomic factors. Memory-enabled neural networks also help analyze historical data to predict future prices.

4. Machine learning for predicting financial performance and estimating business value.

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[2] Artificial intelligence in Russia — 2023: trends and prospects. Yakov and Partners. Yandex. 2023. URL: https://yakovpartners.ru/upload/iblock/c5e/c8t1wrkdne5y9a4nqlicderalwny7xh4/20231218_AI_future.pdf (accessed on 05.10.2024).

[3] An open platform for scientific and technological information. URL: https://app.dimensions.ai/ (accessed on 14.11.2024).

[4] The repository of the BERTopic library. GITHUB. URL: https://github.com/MaartenGr/BERTopic?ysclid=m3is73ssu7397642569 (accessed on 14.11.2024).

In the studies of P.S. Koklev [26], X. Chen et al. [27], U.G. Pinar, N.U. Seyma [28], P. Geertsema, H. Lu [29], R. Zhang et al. [30], B.V. Sonja, J. Katunar [31], S. Budennyy et al. [32, 33] machine learning methods are used (neural networks, trees solutions, gradient boosting, and others) to assess the financial performance of companies and determine the value of the business. The team of authors [34] uses regression to forecast the value of shares of PJSC Transcontainer depending on the dollar exchange rate and oil prices, which is clearly insufficient in the context of modern economic conditions in Russia. Sopelnik and L.V. Fedoseeva [35] compare the technical and fundamental indicators of American companies and conclude that it is advisable to combine them to improve the accuracy of the forecast.

The models presented in scientific publications are applicable to foreign companies (since they were developed on samples from other countries that are characterized by different market specifics) and are not widely available. Only the work of I.N. Galkin [36] includes Russian companies in its sample for the development of the model. However, the cost calculation is based on retrospective reporting, which does not reflect future prospects and does not take into account exogenous factors.

As a result of the analysis of scientific papers, it is advisable to conclude that the issues of the influence of exogenous factors on stock prices and the value of Russian business have not been sufficiently studied. Problems remain related to the volatile nature of the Russian stock market, the macroeconomic situation, and the influence of various behavioral factors on price movements. These aspects must be taken into account when forming a motivated judgment about the value of a business within the framework of a comparative approach.

It is also worth noting that out of all the variety of machine learning models, it is difficult to make a choice to achieve the research objectives. Decision trees are characterized by their relative simplicity, interpretability, and computational savings compared to neural networks. To make a final decision in favor of any model, it is necessary to conduct an experiment on a specific data set.

RESULTS AND PROSPECTS

The concepts of price and value are clearly distinguished in the valuation process. Prices reflect historical market transactions and serve as the basis for determining value, considering goals, objectives, and prerequisites. Value, on the other hand, is believed to have a probabilistic nature, due to the various effects of factors that are characterized by their fundamental essence, based on a company's long-term ability to generate cash flows in the future. These factors take into account both the inherent risks and the impact of the external environment. The stock price can be influenced by supply, demand, behavioral and exogenous factors. Accordingly, prices may fluctuate significantly in the short term.

When using the capital market approach to the comparative method, appraisers rely on historical stock transaction prices, which is both an advantage and a disadvantage of this method. However, this disadvantage is offset by calculating the average stock price over a specific observation period (typically a month). Nevertheless, the multipliers obtained in this way may lose their relevance the very next day after the calculations are performed. Therefore, methods are required to estimate the projected stock prices of companies.

The main stages of the business value forecasting method using AI algorithms are shown in *Fig. 1*.

- In the first stage, it is essential to analyze the various factors and identify the indicators that influence the final outcome.
- In the second stage, the data is cleaned (removal of omissions and outliers, checking for anomalies and correcting them), and the formation of a feature space. Another important step is to study the relationship

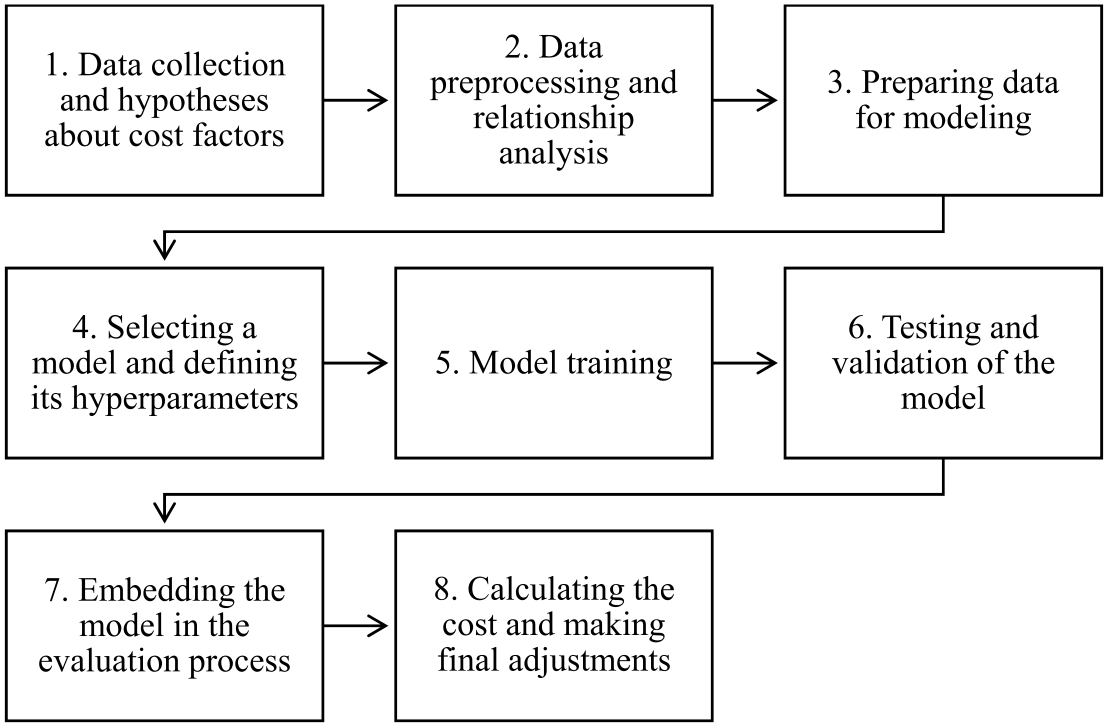

Fig. 1. **The Main Stages of the Business Value Forecasting Method Using AI Algorithms**

Source: Developed by the author.

of variables with the resulting indicator and select the most significant ones.

- In the third stage, the data is split into training and testing sets. This is usually done in a 70/30 or 80/20 ratio. They are then normalized and scaled to bring the data to a single scale for correct model training.
- In the fourth stage, a machine learning algorithm is chosen.
- In the fifth stage, different models are trained on training data (setting up hyperparameters, using cross-validation methods to prevent overfitting). The performance of the model is evaluated. Based on the results of the stage implementation, it is necessary to choose the best model.
- In the sixth stage, the best model is tested on data that is not available to it during training.
- In the seventh stage, solutions are being developed to automate the process of data collection and updating. The model is being integrated into existing tools and processes.
- In the eighth stage, the model is applied as part of an appropriate cost estimation approach.

Approbation of the method using the example of forecasting industry indices (the steps of developing the model using the example of IMOEX are described below)

Stock prices are more susceptible to the ratio of supply and demand for securities in the market, the situation in macroeconomics, debt and money markets. The value of a business is less volatile and depends on cash flows, current and future growth rates, and the risks associated with obtaining them. However, a significant part of the external factors also affect the expected cash flows of the business. According to T. Copeland [37], the cost of a business' equity, determined by the results of a profitable approach, should be close to the cost determined based on the share price. Copeland [37] calls this a "cost perception gap" and makes recommendations for minimizing it through a set of measures to improve the operational efficiency of the business and the strategy of management interaction with the market.

Thus, it can be argued about a single basic set of indicators that must be considered when assessing the value of the underlying asset — the company's business, which is capable of creating cash flows. The difference between the cost of a business's equity and the share price lies in the composition of rights (ordinary and preferred shares that grant different sets of rights to their owner), the degree of control, the terms of the transaction, objectives, assumptions, and limitations of the valuation process.

Within the framework of the target system of indicators for forecasting the value of a business, the following should be highlighted:

1. Financial information according to official reports (frequency: quarterly, semiannual, annual).

2. Fundamental macroeconomic and sectoral indicators (frequency: daily, monthly, quarterly, annually).

3. Non-financial reporting — ESG (annual basis).

4. News background (the frequency is daily, but there is no sufficient archive of news in the public domain).

However, not all indicators of the target system are suitable for practical testing of the business value forecasting method due to the difference in the frequency of their updates.

Of course, the operational, financial and non-financial indicators of the company are important. However, they are not comparable in terms of step with the available indicators and stock prices, which makes their use impossible at this stage and must be addressed in future studies.

It is important to keep in mind some of the features of behavioral valuation. They consist in analyzing the emotional background of events and its impact on the cost [38]. The basic prototype of the model for assessing the general news background in Russia was developed by the author, but a sufficient array of news on companies has not yet been collected to mark them up [39].

Among a fairly large set of macroeconomic and industry indicators, predictors comparable in daily increments have been selected, for which there are forecasts of contributors (*Table 1*). Technical indicators are characteristic only of the stock market and do not reflect causal relationships, but they are an important indicator of the market and indicate the direction of price movement [40].

Each of the indicators presented in *Table 1* reflects important aspects of the economic environment and financial conditions that directly affect the operating activities of companies, their profitability and valuation.

The Moscow Exchange Composite Index (IMOEX) and 10 industry variables were selected as target variables: "oil and gas (MOEXOG), electric power (MOEXEU), telecommunications (MOEXTL), metals and mining (MOEXMM), finance (MOEXFN), consumer sector (MOEXCN), chemistry and petrochemistry (MOEXCH), information technology (MOEXIT), construction companies (MOEXRE), transport (MOEXTN)".[5]

The whole process is implemented in the Python software environment and using its main libraries: pandas, numpy, matplotlib, sklearn, phik, tensorflow, keras.

The statistics on the presented indicators were uploaded from the sources cbonds.ru and finam.ru for 10 years (2014–2024), a longer period includes information about events that are no longer relevant to the current market situation, which may mislead the model.

The total size of the combined data array for all indicators and target variables was 2,372 rows. No missing values or duplicates were found in the data array.

In order to study the quantitative characteristics of the relationship between variables, the Pearson correlation coefficient and the Phik method were used. The Pearson coefficient measures only a linear relationship. If the relationship between the variables is non-linear, the Pearson coefficient may be close to zero even with a strong dependence. Also, significant emissions can significantly

[5] Moscow Stock Exchange industry indexes: what they are, what they are, and how to use them. URL: https://journal.tinkoff.ru/news/industry-index/ (accessed on 05.10.2024).

Table 1

Indicators Affecting Industry Indices and Stock Prices

No.	Name of the indicator	Unit of measure	Rationale
External fundamental			
1	Gold exchange rate	rub/gram	– Rising gold prices indicate instability in the global economy, which can lead to lower investments in risky assets, including stocks. – For companies engaged in gold mining and processing, changes in prices for this metal directly affect their income and profitability. An increase in the gold exchange rate increases the revenue of such companies, which can have a positive impact on the value of their shares. – Rising gold prices may indicate expectations of higher inflation, which affects the value of companies' cash flows and, consequently, the valuation of their shares by investors
2	The exchange rate of a foreign currency is the US dollar against the ruble	rub.	– A weak ruble (high dollar exchange rate) makes Russian exports more competitive on world markets, increasing the profits of export-oriented companies, which can lead to an increase in their shares. However, importers face increased costs for the purchase of foreign goods and raw materials, which can reduce their profitability and negatively affect share prices. – Companies with debt in foreign currency, with a weakening ruble, face an increase in debt in ruble terms, which can reduce their financial stability and negatively affect the value of shares. – Exchange rate fluctuations can influence the inflow or outflow of foreign capital from friendly countries, which directly impacts the demand for shares in Russian companies
3	The price of Brent crude oil is	dollars per barrel	– Many Russian companies are involved in oil production and export. Rising oil prices increase their revenue and profits, which contributes to higher prices for their shares. – Oil revenues make up a significant part of the state budget. High oil prices improve the economic situation in the country, increase confidence and can lead to an overall increase in the stock market. – Oil prices affect the foreign exchange market. Rising oil prices may strengthen the ruble, which in turn affects other sectors of the economy and companies
4	The yield on Russian government bonds in rubles for a period of 10 years (the value of the point on the G-Curve)	%	– Government bonds are considered low-risk instruments. An increase in their yield makes bonds more attractive compared to stocks, which can lead to a redistribution of capital from the stock market to the debt market, reducing demand for stocks and their prices. – Rising bond yields may signal future interest rate increases or inflation expectations, which negatively affects the assessment of future earnings of companies and their shares. – Higher yields on debt instruments can increase the cost of borrowing for companies, especially if they attract financing through bond issuance, which reduces their profits and may negatively affect stock prices

Table 1 (continued)

No.	Name of the indicator	Unit of measure	Rationale
5	RUONIA 1M (the average rate at which banks lend to each other for a period of one day)	%	– The change in RUONIA reflects the cost of short-term borrowings for banks and, indirectly, for companies. An increase in the rate increases the cost of companies servicing short–term loans, which can reduce their profitability and negatively affect stock prices. – This is an indicator of liquidity in the banking system and may signal the actions of the Central Bank to change monetary policy. Tightening policy (rising interest rates) may lead to a decrease in economic activity and negatively affect the stock market. – Investors can switch between money market instruments and stocks depending on the rate level. The rise of RUONIA makes money market instruments more attractive, which may reduce demand for stocks
Technical			
6	Moving averages of the industry index over 50 and 200 days	rub.	– The intersection of moving averages can serve as a signal to open or close positions. For example, when the 50-day moving average crosses the 200-day moving average from the bottom up (the "golden cross"), this may indicate the beginning of an uptrend. A reverse intersection ("dead cross") may signal a downtrend

Source: Developed by the author.

Table 2

Correlation of Indicators with the Moscow Exchange Index Based on Pearson's Coefficient and Phik

No.	Indicator	Designation	Pearson's coefficient	Phik
1	200-day moving average	SMA_200	0.96	0.92
2	50-day moving average	SMA_50	0.82	0.97
3	Gold exchange rate	Gold	0.68	0.86
4	The exchange rate of the foreign currency — the dollar against the ruble	USD/RUB	0.55	0.80
5	RUONIA 1M (the average rate at which banks lend to each other for a period of one day)	RUONIA 1M	–0.47	0.83
6	The yield on Russian government bonds in rubles for a period of 10 years (the value of the point on the G-Curve)	Yield Curve 10Y	–0.31	0.80
7	The price of Brent crude oil	Brent	0.29	0.71

Source: Calculated by the author using Python.

Table 3

The Quality Metrics of Models (on a Validation Sample) for Forecasting the Moscow Stock Exchange Index Created Using Machine Learning

Model	MAE, in units of the target attribute	MSE	RMSE	MAPE, %
Linear regression	86.60	15103.17	122.89	3.58
ElasticNet	193.35	64 567.72	254.10	7.69
Random Forest	26.61	1930.49	43.94	1.11
Extra Trees	20.31	1173.32	34.25	0.86
CatBoost	28.36	1820.58	42.67	1.20
Lightgbm	31.64	4119.49	64.18	1.32
LSTM	534.08	421 646.38	649.34	22.38

Source: Calculated by the author using Python.

affect the value of this coefficient. Phik is a correlation metric designed to identify more complex and non-linear relationships between variables.

The calculation results are presented in *Table 2*. After analyzing them, we can conclude that moving averages (especially over 200 days) are the most significant indicators demonstrating a strong relationship, both linear and general. The gold exchange rate and the exchange rate also play a significant role.

The Phik method confirms the presence of significant nonlinear dependencies.

Next, the sample was divided into a training sample (1,412 observational objects), a validation sample (456 observational objects), and a test sample (305). After calculating the technical indicators, the sample size changed slightly from the gaps that had to be deleted.

The next step was to scale or normalize the indicators. Normalization of indicators [27] is aimed at bringing various features to a single scale or distribution, which can significantly increase the efficiency and accuracy of machine learning models. Due to the fact that the distribution of the studied features cannot be considered normal, we will use the RobustScaler method based on median and quartile range (IQR). The formula underlying RobustScaler is presented below [41]:

$$X_{scaled} = \frac{X - X_{median}}{IQR}, \tag{1}$$

where X_{scaled} — the normalized value of the feature; X— the initial value of the feature; X_{median} — median of the attribute value; IQR — the quartile range. Represents the difference between the third and first quartiles. $Q3 - Q1$.

The method centers the data by subtracting the median and scales the data by dividing by the quartile range. This method is more resistant to outliers in the data, as it uses the median and IQR.

After scaling, the following models were trained: linear regression, ElasticNet, Random Forest, Extra Trees, CatBoost (a framework for gradient boosting on trees from Yandex). Lightgbm (Light Gradient Boosting Machine, a framework for implementing gradient boosting from Microsoft), LSTM (Long Short-Term Memory) neural network. The metrics known for regression tasks were used as “indicators of model quality in the validation sample”:

- MAE (Mean absolute error — the average of the absolute differences between the predicted and actual values);

```
# ExtraTreesRegressor model training

model_et_3 = ExtraTreesRegressor(n_estimators=100,
random_state=42)

model_et_3.fit(features_train, target_train)

# Evaluating the accuracy of the model based on the validation sample

predictions = model_et_3.predict(features_valid)

# Calculation of quality metrics on a validation sample

mae = mean_absolute_error(target_valid, predictions)

mse = mean_squared_error(target_valid, predictions)

rmse = np.sqrt(mse)

mape = np.mean(np.abs((target_valid - predictions) / target_valid)) * 100
# As a percentage

# Output of results

print('MAE models "Extra Trees": {:.2f}'.format(mae))

print('MSE of the "Extra Trees" model: {:.2f}'.format(mse))

print('RMSE of the "Extra Trees" model: {:.2f}'.format(rmse))

print('MAPE models "Extra Trees": {:.2f%'.format(mape))

        MAE of the "Extra Trees" model: 20.31

        MSE of the "Extra Trees" model: 1173.32

        RMSE of the "Extra Trees" model: 34.25

        BRAND of the "Extra Trees" model: 0.86%

## Testing the model

predictions_test_ = model_et_3.predict(features_test)

mae_et = mean_absolute_error(target_test,
model_et_3.predict(features_test))

mape = np.mean(np.abs((target_test - predictions_test_) /
target_test)) * 100

print("MAE of the 'ET' model in the test sample:", mae_et)

print("MAPE models 'ET' in the test sample:", mape)

        USING the 'ET' model in the test sample: 19.426519344262346

        The BRAND of the 'ET' model in the test sample:
        0.7981173886945636

# Calculation of R2 for predicted values and true values

r2_predictions = r2_score(target_test, predictions_test_)

print("R2 for predicted values: ", r2_predictions)

        R2 for predicted values: 0.9979873225849911
```

Fig. 2. **Code in Python Extra Trees Model**
Source: Compiled by the author using the Python library.

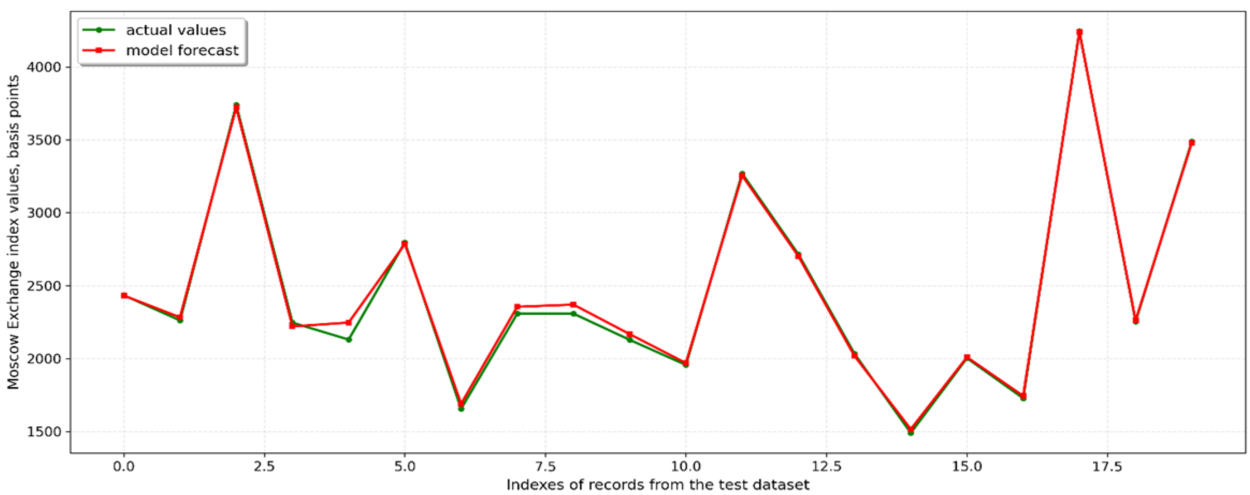

Fig. 3. **Chart of Actual Values and Predictions by the Moscow Stock Exchange Index Model**
Source: Calculated by the author using Python.

- MSE (Mean square error — the average of the squared differences between the predicted and actual values);
- RMSE (Root mean square error — the square root of the RMS error);
- MAPE (Mean absolute percentage error — the average of absolute percentage errors between predicted and actual values)" [42].

The quality metrics obtained from the results of training models where the Moscow Stock Exchange index was used as the target metric are presented in *Table 3*.

Based on the results of training and validation, it is advisable to conclude that ensemble models on trees (Extra Trees, Random Forest, Catboost, Lightgbm)

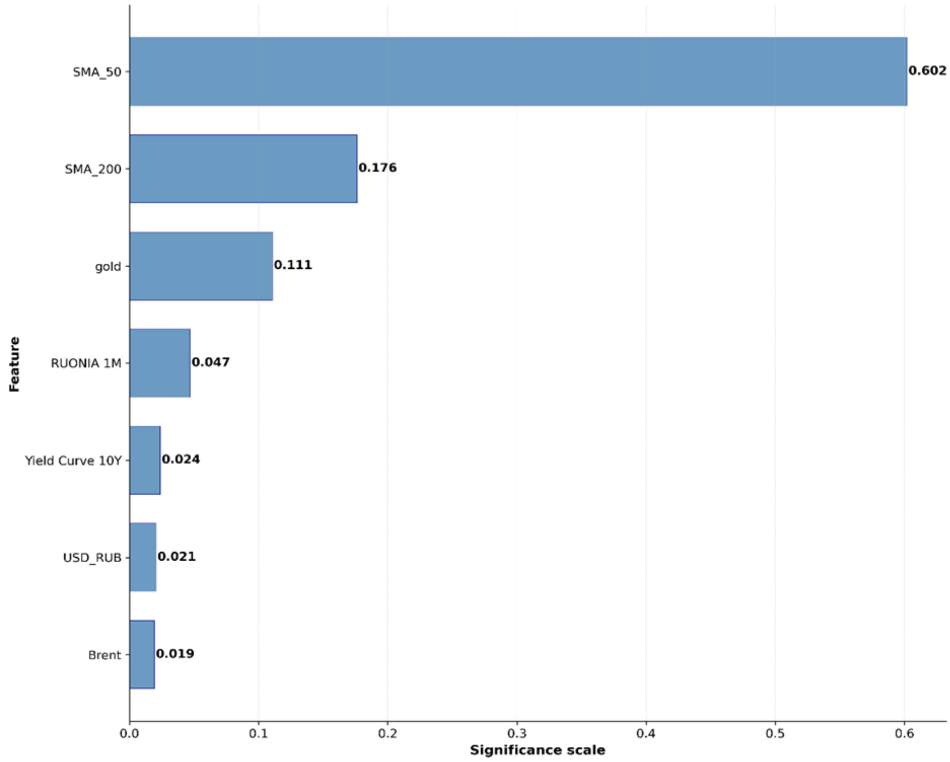

Fig. 4. **Feature significance scale in the Extra Trees Model**
Source: Calculated by the author using Python.

```
def get_prediction(USD_RUB, Brent, gold, Yield_Curve_10Y, RUONIA_1M, SMA_50, SM_200):
    # Creating an array with input data
    features = np.array([[USD_RUB, Brent, gold, Yield_Curve_10Y, RUONIA_1M, SMA_50, SM_200]])

    # Scaling 6 input data
    scaled_features = robust_scaler.transform(features)

    # Getting the prediction of the model
    prediction = model_et_3.predict(scaled_features)
    return prediction

# Example of using a function to get a prediction
USD_RUB = float(input("Enter the value of USD/RUB: "))
Brent = float(input("Enter the Brent value: "))
gold = float(input("Enter the value of gold: "))
Yield_Curve_10Y = float(input("Enter the value of Yield Curve 10Y: "))
RUONIA_1M = float(input("Enter the value of RUONIA 1M: "))
SMA_50 = float(input("Enter the SMA value 50: "))
SMA_200 = float(input("Enter the SMA 200 value: "))

prediction_result = get_prediction(USD_RUB, Brent, gold, Yield_Curve_10Y, RUONIA_1M, SMA_50, SMA_200)
print("Predicted value:", prediction_result)

Enter the value of USD/RUB: 90.4
Enter the Brent value: 82
Enter the gold value: 7790
Enter the Yield Curve value 10Y: 16.5
Enter the value of RUONIA 1M: 18.8
Enter the SMA value 50: 2796.0134
Enter the SMA 200 value: 3136.39810
Predicted value: [2507.5184]
```

Fig. 5. **Python Function for Applying Extra Trees Models**
Source: Compiled by the author using Python.

Table 4

Forecast Values of Indicators and Industry Indices According to the Developed Models (Compiled by the Author Based on Data as of the End of September 2024)

Ticker	Branch	Index value on 27.09.2024	Industry Index Forecast for the End of 2024	Change, %	SMA200	SMA50	Gold Price	Dollar to ruble exchange rate	RUONIA 1M	Yield Curve 10Y	Brent
IMOEX	Moscow Exchange Index	2858	2 507	–14	3 136	2 796					
MOEXOG	Oil and gas	7904	6 336	–25	8 591	7 586					
MOEXEU	Electric power industry	1 645	1 439	–14	1 899	1 658					
MOEXTL	Telecommunications	1 669	1 553	–7.5	1 993	1 702					
MOEXMM	Metals and mining	6 627	6 268	–5.7	7 839	6 633					
MOEXFN	Finance	9 424	7376	–27.7	10 335	9 566	7790	90.4	18.8	16.5	82
MOEXCN	Consumer sector	7648	6 114	–25	8 539	7 600					
MOEXCH	Chemistry and petrochemistry	29 371	32 788	+11.6	33 459	29 076					
MOEXIT	Information technology	3 155	2 000	–57	–	3 243					
MOEXRE	Construction	7356	7315	–0.56	–	7985					
MOEXTN	Transport	1 594	1 509	–5.6	1 831	1 599					

Source: Calculated by the author based on Finam data.

demonstrate the best results in terms of quality metrics. The best result was demonstrated by the Extra Trees model.

The program code of the Extra Trees model is shown in *Fig. 2*.

The model creates a set of decision trees on random subsets of data and features, which makes it resistant to noise and outliers, and can effectively use the interaction between features. For the recurrent neural network LSTM, which has a rather complex architecture, there may not be enough data for training.

The best Extra Trees model was tested on test data (to assess the model's ability to generalize new, previously unseen data) using the R2 metric, which takes values from 0 to 1, where 1 indicates that the model perfectly matches the data, and 0 means that the model does not explain the variation better than a simple average value. As a result, the R2 for the predicted values was 0.997.

The graph of predictions and actual values of the Moscow Exchange index, shown in *Fig. 3*, also indicates the high quality of the model obtained.

The significance of the features of the Extra Trees model is shown in *Fig. 4*. The most significant signs were technical indicators and fundamental ones — the gold exchange rate and the RUOINA-1M rate.

The forecast of the Moscow Stock Exchange index in accordance with the developed model seems to be the most effective over a time horizon of up to 1 year in accordance with those forecast indicators that are available at the valuation date. An important aspect of the application of the model is the availability of reasonable forecasts for the indicators that are used in the model.

The results of a macroeconomic survey conducted by the Bank of Russia[6] are used as the source of the forecast for the ruble-dollar exchange rate and Brent crude oil. The projected values for the ruble-dollar exchange rate at the end of 2024 amounted to 90.4 rubles, and Brent crude oil — 82. The gold exchange rate in the base scenario until the end of 2024 in the amount of 7790 rubles was taken according to forecasts of the analytical department of SberCI B.[7]

BKS-express[8] data of 16.5% and 18.8%, respectively, were used as the source of the forecast of the yield curve of 10-year OFZ and RUONIA 1M for the end of 2024. Technical indicators are calculated for the end of September (27.09.2024): SMA50–2796.01 bp, SMA200–3136.39. With the specified parameters, the Moscow Stock Exchange index will reach a level of 2507 bp. The forecast is probabilistic, and the aggravation of the geopolitical situation may lead to significant deviations from the expected results.

To apply the model, a function has been developed in Python, shown in *Fig. 5*. Using the function, you can enter parameter values and get a forecast of the model.

Based on the calculations performed, it can be concluded that the proposed method is effective and gives reliable results.

In the course of further work, 10 Extra Trees models were created to predict the industry indices of the Moscow Stock Exchange based on data from the last ten years. A total of 23,710 observations were analyzed for all indexes from 2014 to 2024. The developed models showed excellent results on test data: the coefficient of determination (R2) is at least 0.9, the average absolute percentage error (MAPE) is less than 1%. Based on the created models, a forecast of the values of industry indices is made, which is presented in *Table 4*.

In the current macroeconomic situation, according to the basic forecast indicators,

[6] The macroeconomic survey of the Bank of Russia. URL: https://cbr.ru/statistics/ddkp/mo_br/ (accessed on 05.10.2024).

[7] The forecast of gold prices until the end of 2024 and in the long term. SberCI B. URL: https://sbercib.ru/publication/prognoz-tsen-na-zoloto-do-kontsa-2024-goda-i-v-dolgosrochnoi-perspektive (accessed on 05.10.2024).

[8] The OFZ and foreign currency bond market. Forecast for the fourth quarter of 2024. BKS Express. URL: https://bcs-express.ru/novosti-i-analitika/rynok-ofz-i-valiutnykh-obligatsii-prognoz-na-iv-kvartal?ysclid=m1tgl8noqj200285787 (accessed on 05.10.2024).

most industries expect a correction by the end of 2024 compared to September.

The largest decrease is expected in IT (MOEXIT) — 57%, finance (MOEXFN) — 27.7%, oil and gas (MOEXOG) and consumer sector (MOEXCN) — 25%. The IT sector is limited in the ability to scale the demand for its products only by the domestic market. In the financial sector, high interest rates in the economy will negatively affect lending activity and borrowing costs, which will slow down the growth of the banking business. In the oil and gas sector, despite the growth of oil and gas revenues, there are price uncertainties, large capital expenditures for the reorientation of exports (especially for gas), rising costs due to an increase in the share of hard-to-recover oil, and a significant tax burden. In the consumer segment, rising prices can reduce consumers' purchasing power.

Chemistry and petrochemistry (MOEXCH) is the only industry expected to grow by 11.6% due to stable demand for chemical products.

The indicators taken into account in the model make it possible to explain the projected changes in the Russian stock market indices and correlate with the general situation in the industry.

CONCLUSIONS

The integration of modern machine learning techniques and big data analysis provides a deeper understanding of market trends and factors affecting business value. The practical testing of the method of forecasting the business value of public companies based on exogenous and technical indicators using machine learning gives grounds to conclude that it is sound.

The proposed method allows us to quickly substantiate the prospects of the industry in the context of expected macroeconomic parameters and build a motivated judgment about the expected share price of analogues of the evaluated company using the market-capital method of the comparative approach, within the framework of the cash flow discounting method of the revenue approach when calculating the terminal value through a multiplier or forecasting the expected market profitability within the framework of calculating the discount rate according to the U. Sharpe's [43].

The use of AI algorithms has the potential to significantly improve the accuracy and efficiency of stock price forecasting for public companies. This method can significantly reduce the labor costs associated with external appraisals and contribute to more informed investment decisions, leading to increased competitiveness in the financial market.

Further research plans include developing a model to forecast the share price of each public company listed on the Moscow Stock Exchange, taking into account a broader range of financial and behavioural factors.

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