Software Solution for the Implementation of a Predictive Analytics System for Investment Instruments

NATALIA MAMEDOVA[1], OLGA STAROVEROVA[1], ALEXEY EPIFANOV[1], HUAMING ZHANG[2], ARKADIY URINTSOV[1]
[1]Basic Department of digital economy, Higher School of Cyber Technologies, Mathematics and Statistics, Plekhanov Russian University of Economics, RUSSIA
[2]Deputy Dean, School of Economics, Shanxi University of Finance and Economics, CHINA

Abstract: This article raises the issues of research investment support tools and the study of existing IT solutions in the field of predictive analytics investment solutions. The research request is based on the lack of accuracy, and objectivity of existing methods of investment analysis and means of its automation. A review of existing technical solutions and technologies is carried out. The process of analyzing investment instruments has been studied, and bottlenecks in existing approaches to analysis have been identified. A solution for implementing a system of predictive analytics of investment instruments has been developed. The solution is based on the business requirements and functional requirements of the software development company.

Key-Words: predictive analytics, investment tool, investment analytics, information system, toolkit.

Received: September 23, 2022. Revised: December 4, 2022. Accepted: January 7, 2023. Published: February 14, 2023.

1 Introduction

It is believed that predictive analytics, as an end-to-end technology, has great potential, including in the financial and credit sphere, [1], [2]. There are two approaches in the field of financial market analysis - technical analysis and fundamental analysis. Each of them has its limitations. Fundamental analysis, due to the expert assessment used in its basis, is subjective and limited due to the presence of a human factor. Technical analysis has a high level of accuracy, but it becomes hostage to the prediction algorithms embedded in it and the ratio of key indicators. The ideal solution seems to be the implementation of predictive analytics solutions that will eliminate the bottlenecks of existing approaches. That is, they will increase the objectivity and accuracy of forecasts by using internal and external historical data, as well as real-time data. For such a segment of the financial market as investing, both the above approaches and their limitations are fair.

The development of a predictive analytics system for investment instruments is a complex process. The most responsible and difficult stage of the process is the selection of the source data and working with the data, that is, the scope of the Data Scientist technology.

The purpose of the research was to develop a tool for implementing a system of predictive analytics of investment instruments. The study was conducted in many areas. Firstly, the results of research on the topic of predictive analytics were summarized. Secondly, to identify the technological basis of the subject area, existing IT solutions supporting predictive analytics and specializing in the investment segment were studied. Based on this information, data on the bottlenecks of such IT solutions were summarized. The development of a tool for implementing a predictive analytics system was also preceded by an analysis of the mechanism implemented by analysts to predict changes in the investment market. The research process described in the article and its results have an implementation potential since the processes of implementing the predictive analytics information system are of commercial interest to information system developers.

The following parameters became the functional boundaries of the development toolkit:

- The user should be able to view the forecast at the current time, without being able to view the forecast history;
- There are no notifications about forecast changes (to reduce the volatility of decisions made based on the forecast);
- Historical data is provided by information resources located on the territory of the Russian Federation;
- The activities of the organization of the investor company and the consultant company are carried out on the territory of the Russian Federation.

2 Problem Formulation

Predictive analytics (other names – advanced analytics, advanced qualitative analysis, intelligent analysis) combines a variety of forecasting methods. It is aimed at preventing economic losses and finding the optimal logic of actions when making decisions, [3]. The analyst, using the methods of predictive analytics, looks for patterns in historical and transactional data and forms an educational program on potential risks and opportunities. A forecast is made based on several predictor variables in a given data set. Then the aggregated data is received by the decision-maker.

Predictive analytics is perfectly consistent with the SMART concept of goal setting and with the concept of Data-Driven Decision, [4]. And the benefits of using predictive analytics for business are considered obvious. Advanced quantitative analysis has demonstrated advantages in various sectors of the economy, [1], [5]. Solutions based on it allow you to find opportunities, and reduce uncertainty in risk management – all these are effects that reduce the impact of negative business factors. The results of predictive analytics improve the quality of business planning. As a final result, the detection of significant patterns, forecasting, and timely response to changes increase the competitiveness of an economic agent.

Traditionally, the following stages of predictive analytics implementation are distinguished: data connection; data preparation, analysis, and visualization; development of alternatives and testing of data models; application of predictive models; evaluation and/or forecasts of future results, [6].

Working out alternatives and testing data models is one of the most time-consuming stages. Its results can either determine the quality of the next stage (meaning the use of predictive models) or "reset" the stages already passed and return the analysis to its original position, starting the data connection stage again.

The development of alternatives and testing of data models is carried out in two directions – supervised learning and unsupervised learning. A detailed description of the order and features of the course of learning processes is not mandatory for the topic of our study, so we will limit ourselves to a summary of the essence based on the results of summarizing data from thematic sources, [7], [8].

Supervised learning is divided into two large categories: regression for quantitative responses (numerical value) and classification, which uses categorical variables of the response. Unsupervised learning is used to derive conclusions from datasets consisting of input data without specifying responses. The most common method of unsupervised learning is cluster analysis, which is used to investigate and search for hidden patterns in data.

Today you can find three of the most popular variations of the implementation of predictive analytics of investment instruments: technical analysis; trading advisor; predictive analytics systems.

The basic principle of technical analysis is to analyze the indicators of indicators. As a result, advice is taken to buy, sell or wait for investment actions. The scope of application of this type of predictive analytics implementation is mainly specialized sites dedicated to financial trading tools. If we talk about the specifics of the forecast, then it is completely determined by the price movement in the investment asset market. And in case of a strong price shift, the forecast itself may change to the opposite.

The implementation of predictive analytics by the type of trading adviser includes technical analysis itself but works with combinations of indicators and with their specific settings. The result of the work is a signal for the investor, who advises on buying or selling an investment asset. The Trading Advisor has a greater forecasting accuracy compared to technical analysis, as they are subjected to more fine-tuning in the investment strategy testing mode.

The latter type of implementation uses more complex predictive analytics algorithms. Such systems use machine learning models to train the system and build a forecast based on the results of collecting and analyzing data on changes in the price of an asset and based on studying the indicators of technical analysis indicators. The result of the predictive analytics system is a forecast for a given time period, for example, whether the price will continue to move in the current direction. Experts estimate the accuracy of the forecast of this type of predictive analytics as the highest – about 70% with an error of 2-3%. At the same time, it should be noted that the system does not offer a forecast of price changes in percentage or quantitative value.

Let's present the algorithm of the predictive analysis system using the example of SAP Predictive Analytics:

1. Selection of the data source(s).
2. Uploading quotes for a given time interval of trading platforms and a given calendar period.

3. Formation of data tables with information on each trading candle: the opening price, closing price, maximum value, minimum value, and trading volume.
4. Data preparation in two stages (from the point of view of the CRISP-DM methodology, these stages are similar to Data Understanding and Data Preparation):
   - Data Engineering, which includes data collection, understanding, as well as cleaning, and initial data processing;
   - Feature Engineering, which includes the formation of descriptive features to data on aspects of the behavior of the object whose model is being built.
5. Training the model using the ZigZag indicator, which shows how it was necessary to trade to get maximum profit. Other technical analysis indicators are also used at this stage. The libraries of the R language are used to calculate them.
6. Selection of features (feature selection), in other words - variables based on which the model is trained. The selection is carried out using various tools. In addition, the dependence of factors such as the correlation of features with the target variable or the quality of data is considered.
7. Creating new features based on existing ones (feature engineering). This stage allows you to improve the quality of the future model, while at the same time getting a more complete explanation of the data (for the interpreted model). In our case, the first stage of building a model in SAP Predictive Analytics was the creation of new features using the built-in Data Management solution.
8. Building a model in SAP Predictive Analytics (automatic selection of variables should be enabled).
9. Selection of variables with the smallest error in the final equation. Calculation of the final predictive strength of the model, robustness (stability of the result to new data sets). These values determine the quality and stability of the model.

After passing the specified actions according to the algorithm, the predictive analytics system generates a forecast about further price movement in a given period of time.

Our example demonstrates the capabilities of one of the predictive analytics systems. Open sources, [2], [9], [10] describe other systems of predictive analytics of investment instruments that form a forecast of price changes based on a particular set of technical analysis indicators. The picture of the results in the subject area under study is complemented by several practical works, [11], [12], [13], [14] describing the means of collecting and analyzing investment market data and technical analysis indicators using the libraries of the R and Python languages.

Based on the generalization of information from the above sources, it is concluded that price movement forecasts and predictive analytics of investment instruments are based on technical analysis and analysis of historical data. It assumes that external factors are embedded in the history of price changes.

However, it should be noted that predictive analytics systems do not consider the primary source of changes. Also, they do not evaluate external factors and events, the occurrence of which is known, but which has not yet occurred. Of course, after the fact, the price change in a certain period will reflect the influence of an external factor. But such a change is not tied to the cause (primary source) of this factor. As a result, the predictive analytics system can take a sharp price change for an anomaly and throw it out of the training sample.

For example, such an external factor as a change in the key refinancing rate dramatically affects the price of an investment instrument both at a certain point in time and in the long term. And this is only one of the factors, their list and assessment of significance are a separate topic for discussion, [15]. In practical terms, a predictive analytics system should be able to predict a fall in the value of an investment instrument in the short term due to the influence of an external factor, but at the same time predict a further upward trend in the long term. Thus, the investor will be able to wait for the asset price to fall, buy it at a more favorable price, and in the long term receive a greater profit from dividends or the sale of an investment instrument. In the future, considering the predictive analytics system of external factors will be able to minimize risks and maximize profits for the investor.

The disadvantages of predictive analytics systems include the fact that their forecast does not evaluate price changes in a given period of time. As a result, the analyst misses such important points as the best price to buy an investment instrument and the forecasted sale price of a trading asset. There is a significant limitation - the system can help an investor or trader to increase the number of successful transactions, but not improve his trading operations at a qualitative level.

A typical methodology for implementing and implementing a predictive analytics system consists of three stages:

1. Preparatory work:
- Evaluation of available data;
- Definition of requirements, quality metrics, and success criteria;
- Data transmission and dataset preparation;
- Forecast of economic effect.
2. Pilot project:
- Model development and training;
- Development of a system with an embedded model;
- Model and system testing;
- Checking the success criteria, and evaluating the effectiveness of the model.
3. Industrial operation of the system:
- Putting the system with an integrated model into commercial operation;
- Validation of the service (A/B testing metrics), including validation of the economic effect;
- Service support, including regular training.

The criterion of success is the achievement of the system's performance targets. In the case of a predictive analytics system, the key criteria for success are the percentage accuracy of the forecast and the percentage of correct forecasts.

At the same time, one should not lose sight of the calculation that the predictive analytics system saves time in searching for information, analyzing it, and making decisions based on analysis.

3 Problem Solution

The initiator of the business requirements is the customer of the predictive analytics system. As a result of communication and requirements collection, key business requirements for the product were identified:

1. Implement a system of predictive analytics of investment instruments to solve the problem of inaccurate forecasts for investment instruments.
2. Reduce the staff involved in the analysis of investment assets in the stock market.

Based on technical and fundamental analysis, a financial analyst forms a forecast (investment strategy), which describes the best entry and exit points, and various scenarios for the development of events.

We have identified the main bottlenecks in the implementation of the business process. The first is that the forecasts are subjective, despite the availability of solutions and methods of working with them. In open sources for one investment asset, you can find dozens of different forecasts and trading strategies from financial analysts, [16], [17]. Also, the bottleneck is the variability of price change scenarios, which also brings a subjective nature to analytics. And the last bottleneck is the time error, because of which a financial analyst can analyze a limited number of assets.

The implemented system using the developed solution should produce a full technical analysis and partially fundamental analysis of all assets, as well as give an objective forecast of the price movement of the selected asset. Thus, the user of the system will receive an objective forecast with one scenario and the probability of its execution. The number of analyzed assets is unlimited. Such a system will replace some of the employees involved in the analysis of trading assets, as well as improve the quality of forecasts, expressed in the number and accuracy of forecasts.

Among the general requirements for a predictive analytics system based on the developer solution, we have identified the following. The system of predictive analytics of investment instruments is designed to predict the movement of the asset price in a specified period of time. The user should be able to view this information, as well as the ability to configure the prediction time interval. It is necessary to achieve accessibility and ease of obtaining information on the movement of the price of an investment asset.

All forecasts must be displayed correctly and without errors on the on-screen forms of the application. It is necessary to ensure the operation of the system and update its data, including forecasts, in real-time.

The system should allow the user to create folders of selected trading instruments, and search the system by keywords, and attributes. The attributes that are searched for include: the name of the investment instrument; the name of the investment asset or its abbreviation.

The developed toolkit answers the following questions:

1. What data needs to be collected.
2. How the data should be analyzed.
3. How the predictive model is built and trained.
4. What functionality is needed.
5. How the price movement is predicted.

To determine the required data set, it is necessary to understand what relates to internal data and what relates to external data. The internal data will include all the data presented on the chart of the movement of the trading instrument•

- Date;
- Time;
- Time period;
- Opening price;
- Closing price;
- Maximum price value;
- Minimum price value;
- Trading volume.

The above list of recommended data can be requested from official trading exchanges via API requests. The implementation of the API is necessary in order for the predictive analytics system to work with historical data (Table 1).

Table 1. Set of API methods of the predictive analytics system.

Method	URL	Type	Description
GET	/predict-analyz/initialize	Privat	Data Storage Settings
GET	/predict-analyz/content	Privat	Get data from the selected directory
GET	/predict-analyz /select-disk	Privat	Checking for disk readability
POST	/predict-analyz /upload	Privat	Loading data
DELETE	/predict-analyz /delete	Privat	Deleting data
GET	/predict-analyz /preview	Privat	Detailed Data view
POST	/predict-analyz /create-directory	Privat	Create a folder
POST	/predict-analyz /create-data	Privat	Add new data
POST	/predict-analyz /update-data	Privat	Update data
GET	/predict-analyz /stream-data	Privat	Read data
GET	/predict-analyz /indicators	Public	Getting a list of data by IDs

With the selection of external data, the situation is more complicated, since for different types of trading instruments, there will be a different type of external data. Let's give, for example, a list of data for stock analytics:

- The exchange rate of the stock;
- Economic calendar based on the stock exchange rate;
- Economic reports of the company;
- Availability of dividends on the stock;
- Supply and demand (glass of prices).

This dataset can also be extracted from various sources that provide information in the form of tables with data.

The difficulties that arise at this stage are the need for text recognition to determine the type of news in the economic calendar, as well as the need to monitor market fluctuations in real-time. This indicator changes together with the price change, [18].

The next stage - exploratory data analysis (data mining) involves the discovery of information in the data. To do this, a sequence of operations should be performed:

- Select the data (tables, records, and attributes);
- Clear the data, including performing their conversion and preparation for modelling;
- Make derived data;
- Combine data;
- Bring the data into the desired format.

The essence of this stage is to sift through the data, clearing them of anomalies. Additionally, in the price series information, it is necessary to analyse information on technical analysis indicators.

Of all the available indicators, one of the most useful indicators for the model that will be trained in the Zig Zag indicator (SAP Predictive Analytics). In practical trading, it is not used to predict price movements, but it shows how it was necessary to trade to maximize profits. It is also used to generate a price series. If the price was rising, then the objective function in this period of time takes the value 1, if it was falling, then 0. Thus, a mark-up for a time series of prices is obtained (Figure 1).

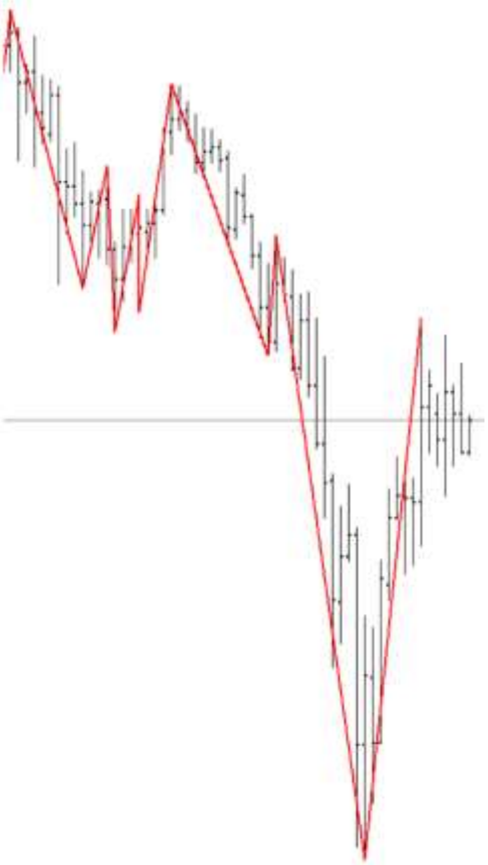

Fig. 1: The "Zig Zag" indicator is shown as a red stripe on the price chart.

The ZigZag indicator is designed to analyze price movements with a given or greater amplitude and is usually used by traders to visualize the trend - it helps to highlight significant changes in the quotation chart and ignore small fluctuations (noises). This tool is used by many trading platforms and is integrated as a function of software from different vendors. In our model, the ZigZag indicator is used to generate a price series to avoid noise and, as a result, prevent retraining of the model.

In addition to the price series, it is necessary to calculate a set of values of technical analysis indicators (Table 2).

Table 2. Set of values of technical analysis indicators.

Input	Technical name	Technical Analysis Indicator
I01	EMA5Cross	The intersection of EMA 5 and opening prices
I02	EMA17Cross	The intersection of EMA17 and the opening price
I03	EMA5_17Cross	Intersection of EMA17 and EMA5
I04	VolumeROC1	Rate of Change / Momentum
I05	CCI12	Commodity Channel Index 12
I06	MFI14	Money Flow Index 14
I07	MOM	Momentum 3 / Rate of Change
I08	Lag1	Price movement at the current bar (1)
I09	Lag2	Price movement at the current bar (2)
I10	Lag3	Price movement at the current bar (3)
I11	Lag4	Price movement at the current bar (4)
I12	Lag5	Price movement at the current bar (5)
I13	fastK	Stochastic Fast %K
I14	fastD	Stochastic Fast %D
I15	slowD	Stochastic Slow %D
I16	stochWPR	William's %R
I17	RSI14	Relative Strength Index (open) 14
I18	williamsAD	Williams Accumulation / Distribution
I19	WPR	William's %R 14
I20	AO	(Awesome Oscillator, AO) SMA5 — SMA34
I21	AC	AO smoothed 5-period average AO —SMA(AO, 5)
I22	MACD	EMA12 – EMA26
I23	MACD_SMA9	MACD smoothed by a 9-period moving average MACD-SMA(MACD, 9)
I24	DIp	The positive Direction Index
I25	DIn	The negative Direction Index.
I26	DX	The Direction Index
I27	ADX	The Average Direction Index (trend strength)
I28	Ar	aroon(HL, n) – 1 out (oscillator)
I29	chv16	Chaikin Volatility – chaikinVolatility (HLC,n) -1 out
I30	cmo16	Chande Momentum Oscillator – CMO(Med, n) -1 out
I31	macd12_26	MACD Oscillator 12, 26, 9
I32	Osma	Moving Average of Oscillator
I33	rsi16	Relative Strength Index med 16
I34	fastK14_3_3	Stochastic Oscillator 14 3 3 fastK
I35	fastD14_3_3	Stochastic Oscillator 14 3 3 fastD
I36	slowD14_3_3	Stochastic Oscillator 14 3 3 slowD
I37	smi13_2SMI	Stochastic Momentum Index SMI 13 2
I38	smi13_2signal	Stochastic Momentum Index signal 13 2
I39	vol16	Volatility 16
I40	SMA24Cross	Logarithm of the ratio of the opening price and SMA24
I41	SMA60Cross	Logarithm of the ratio of the opening price and SMA60
I42	SMA24_60Cross	The logarithm of the SMA24 and SMA60 relationship

The choice of indicators of technical analysis indicators is determined by the level of risk - the riskier the operation is, the more indicators are analysed. The result of the forecast is to buy, sell, or wait for advice. Sets of indicators are used mainly on thematic sites dedicated to trading instruments. The accuracy of the forecast is fixed at the moment for certain time periods. The time factor is of decisive importance in this case, since in the case of a strong price movement, the forecast may change to the opposite.

As additional indicators (correcting own calculations), it is recommended to supplement the technical analysis with the following indicators:

- I43 (SMA24Trand) The logarithm of the SMA24 ratio compared to the previous value;
- I44 (SMA60Trand) The logarithm of the SMA24 ratio compared to the previous value;
- I45 (MOM24) Momentum 24 / Rate of Change;
- I46 (MOM60) Momentum 60 / Rate of Change;
- PC (PC 1-PC16) Compression of features I01-I46 by the method of principal components in 16 values.

It is also necessary to collect and compare the values of economic indicators used in fundamental analysis (Table 3).

Table 3. Values of economic indicators used in fundamental analysis.

Input	Technical name	The name of the indicator
F01	T	Total revenue for the period
F02	P	Net profit for the period
F03	EBITDA	Profit before deduction of interest, taxes, depreciation and amortization expenses
F04	act	Assets
F05	obl	Obligations
F06	Y	Market capitalization
F07	P/E	Price/earnings per share ratio

The use of economic indicators for fundamental analysis has one single purpose — to identify securities that are currently very cheap or expensive, both relative to competitor securities and relative to their estimated fair value. Fundamental analysis based on the comparison of the values of economic indicators helps to adjust the strategy of selecting technical indicators when building a predictive analytics model. Fundamental analysis is a tool for "long" investments, as it is based on the following provisions:

• The current price of the investment object cannot objectively reflect the real value of the company;

• In the long term, the stock market tends to bring the market value closer to the true value.

To build a future predictive model, it is required to select features. In the prepared dataset, there are indicators of indicators that affect the target variable at the current time. However, you can get additional information if you determine the impact of these indicators for a certain period up to the current moment. According to our toolkit, time intervals were selected: 1 hour and 1 day before the current moment in time and new variables were created considering this "time lag".

Even more, information may be the degree of change in indicators from the moment in the past to the current moment. The natural logarithm of the quotient of the current indicators and indicators with a time lag of 1 hour and 2 days can be chosen as a method. Thus, it will be possible to obtain the degree of change of the indicator from the moment in the past (it increased or decreased), and if so, how much.

Accordingly, these steps will allow us to establish not only the relationship between the current values of the indicators and the target variable but also to consider the state of these indicators in the past, as well as the degree of their change.

As a basic model for the implementation of the system, it is proposed to use a linear regression model or a polynomial regression model, which will reveal the overfitting of the model.

As an implementation solution according to the toolkit, it is proposed to use Python programming languages using libraries: model-catwalk, sklearn, and the like. As an alternative, it is possible to use the R programming language with packages: AppliedPredictiveModeling, LiblineaR, astsa, and data.table, timeSeries, eclust.

The training of the model should be carried out on the prepared data. At the same time, the percentage of correct predictions during testing and training is accepted at least 70%.

The practice of using a trained predictive model is not presented in this study, since these results are a trade secret. However, the algorithm itself for data analysis and model construction is an open-to-use solution, that can be repeated and scaled.

4 Conclusion

This study describes the process of developing a solution that considers the main shortcomings of approaches to implementing IT solutions in the field of predictive analytics investment processes. The toolkit is based on the main components and principles of the standard methodology, supplemented and reworked for the object of research.

The developed solution does not consider many issues related to system testing and metrics evaluation, since the main task was to develop a solution for the implementation of the system. This solution will make it possible to make a qualitative selection of data for the analysis and training of the predictive analytics model of investment instruments.

The proposed solution will: improve the quality of forecasts (increase the accuracy of the forecast); minimize the costs of an investor or consultant company for the analysis of investment instruments (reduction of analysis time and optimization of labour resources); increase the objectivity of forecasts (rational choice of qualitative and quantitative indicators); simplify the process of analysing investment instruments for users of the information system (interpretation of results analytical evaluation).

The theoretical significance of this study lies in the fact that the fulfilment of the tasks set made it possible to generalize and structure information about the technologies used in the implementation of information systems using predictive analytics.

The conclusions made may be useful to future researchers as the initial data of independent scientific research.

If the research process itself is more focused on achieving theoretical significance and allows you to demonstrate the depth and scale of the work carried out, then the developer solution for implementing the predictive analytics information system is of applied importance. The practical significance of the results obtained lies in the fact that they can be used by financial organizations engaged in investment activities, such as banks, investment funds, private investment companies, as well as individuals engaged in investing funds through brokers.

References:

[1] Letourneau-Guillon L, Camirand D, Guilbert F and Forghani R, Artificial Intelligence Applications for Workflow, Process Optimization and Predictive Analytics, *Neuroimaging Clin. N. Am*. 30, 2020, e1–15

[2] Sezer O B, Gudelek M U and Ozbayoglu A M, Financial time series forecasting with deep learning: A systematic literature review: 2005–2019, *Appl. Soft Comput*. 90, 2020, 106181

[3] Gupta S, Drave V A, Dwivedi Y K, Baabdullah A M and Ismagilova E, Achieving superior organizational performance via big data predictive analytics: A dynamic capability view, Ind. *Mark. Manag*. 90, 2020, 581–92

[4] Sadeghi Eshkevari S, Cronin L, Sadeghi Eshkevari S and Pakzad S N, Input estimation of nonlinear systems using probabilistic neural network, *Mech. Syst. Signal Process*. 166, 2022, 108368

[5] Oo M C M and Thein T, An efficient predictive analytics system for high dimensional big data, *J. King Saud Univ. Comput. Inf. Sci*., 2019

[6] Markitanov D V, *Integration of predictive analytics system with industrial network*, Novosibirsk State Technical University, 2019

[7] Kashyap S, Corey K M, Kansal A and Sendak M, Machine learning for predictive analytics, *Mach. Learn. Cardiovasc. Med*., 2021, 45–69

[8] Nisbet R, Miner G and Yale K, The Data Mining and Predictive Analytic Process, *Handb. Stat. Anal. Data Min. Appl.*, 2018, 39–54

[9] Dinis D, Teixeira P and Barbosa-Póvoa A, ForeSim-BI: A predictive analytics decision support tool for capacity planning, *Decis. Support Syst*. 131, 113266, 2020

[10] Gulay E and Duru O, Hybrid modeling in the predictive analytics of energy systems and prices, *Appl. Energy* 268, 114985, 2020

[11] Weng B, Lu L, Wang X, Megahed F M and Martinez W, Predicting short-term stock prices using ensemble methods and online data sources, *Expert Syst. Appl*. 112, 2018, 258–73

[12] Ozbayoglu A M, Gudelek M U and Sezer O B, Deep learning for financial applications: A survey, *Appl. Soft Comput*. 93, 2020, 106384

[13] Zhou M, Financial auditing big data platform based on FPGA and convolutional neural network, *Microprocess. Microsyst*., 2020, 103461

[14] de Oliveira Carosia A E, Coelho G P and da Silva A E A, Investment strategies applied to the Brazilian stock market: A methodology based on Sentiment Analysis with deep learning, *Expert Syst. Appl*. 184, 2021, 115470

[15] Prince J T, A paradigm for assessing the scope and performance of predictive analytics, *Inf. Econ. Policy* 47, 2019, 7–13

[16] Wang C, Zhang X, Wang M, Lim M K and Ghadimi P, Predictive analytics of the copper spot price by utilizing complex network and artificial neural network techniques, *Resour. Policy* 63, 2019, 101414

[17] Gu X, Mamon R, Duprey T and Xiong H, Online estimation for a predictive analytics platform with a financial-stability-analysis application, *Eur. J. Control* 57, 2021, 205–21

[18] Loshin D, Knowledge Discovery and Data Mining for Predictive Analytics, *Bus. Intell*., 2013, 271–86.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.