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FORECASTING CORPORATE FINANCIAL PERFORMANCE USING MACHINE LEARNING METHODS AND TIME SERIES ANALYSIS

Abstract. The article discusses the problem of forecasting financial performance of companies using machine learning methods and time series analysis. The relevance of the research is due to the need to improve the accuracy of financial forecasting in conditions of high market uncertainty and digitalization of the economy.

The purpose of the study is a comparative analysis of forecasting models of quarterly revenue of companies based on financial and macroeconomic data. The study is based on quarterly data from 21 public companies for the period 2008-2025 using macroeconomic indicators, including the consumer price index, U.S. government bond yields, the price of Brent crude oil, and the NASDAQ Composite and S&P 500 stock indexes.

ARIMA, SARIMA, Prophet, linear regression, Support Vector Regression, Random Forest, XGBoost, and Long Short-Term Memory models were used for forecasting. Preliminary data processing, formation of lag signs and integration of macroeconomic factors are performed. The quality of the models was assessed using RMSE, MAE, MAPE and sMAPE metrics.

The results showed that ensemble machine learning algorithms provide higher prediction accuracy compared to classical time series models. Random Forest has shown the most consistent results. It is established that the choice of the optimal model depends on the industry specifics and the specifics of the company's time series. The developed approach can be used for financial planning, investment analysis and management decision support.

Keywords: machine learning, time series analysis, financial forecasting, company revenue, Random Forest, XGBoost, ARIMA, LSTM, macroeconomic indicators.

Introduction.

The development of the modern digital economy is accompanied by a rapid growth in the volume of financial data, which has created the prerequisites for the use of intelligent analysis methods in financial forecasting. For companies from all walks of life, forecasting key financial indicators is an important part of strategic management, which helps make informed decisions in budgeting, investment planning, company valuation, and financial risk management.

Traditional forecasting methods based on statistical time series models, such as self-regression models and exponential smoothing methods, are highly interpretable. However, in the presence of nonlinear relationships, structural changes and the influence of many external factors, the use of these methods is limited. After the global financial crisis and the outbreak of the "new corona" epidemic, financial time series began to experience increased volatility, and the original model underwent changes. These limitations are particularly noticeable [1].

In recent years, machine learning methods have been actively used in the field of financial analysis due to their ability to automatically identify complex relationships between objects without using explicit mathematical models. Random forest, XGBoost neural networks, regression with support vectors, and neural networks with short-term and long-term memory have proven themselves well in predicting companies' financial performance and are better than traditional models in conditions of nonlinear data dynamics.

Although the results of research in this area are very fruitful, most of the existing research focuses on stock price forecasts, while corporate revenue forecasts are relatively low. In addition, many studies consider only the use of one algorithm, without a comprehensive comparison of various machine learning methods and time series models.

Materials and Methods.

The research database contains quarterly financial reports of 21 American companies listed on the stock exchange from seven sectors of the economy, namely: information technology, energy, banking, manufacturing, hospitality, aviation industry and retail [2]. Figure 1 shows the structure of the analyzed period, which covers the period from 2008 to 2025, and most companies have data for a total of 68 quarters.

In addition to corporate financial statements, five macroeconomic indicators were included in the study:

– Consumer Price Index;
– the yield of ten-year US government bonds;
– the cost of Brent crude oil;
– NASDAQ Composite Index;
– the S&P 500 index.

The data sources were the databases of Refinitiv, Yahoo Finance and the Federal Reserve Bank of the United States (FRED).

Before building the models, a comprehensive preprocessing was performed as shown in Figure 2. At the first stage, the missing values and duplicate observations were checked. Next, a logarithmic transformation of the time series was performed to stabilize the variance. The stationarity of the series was evaluated using the extended Dickey–Fuller test (ADF). The STL decomposition of time series was used to identify seasonal patterns.

Figure 1 - Substantiation of the relevance of financial forecasting

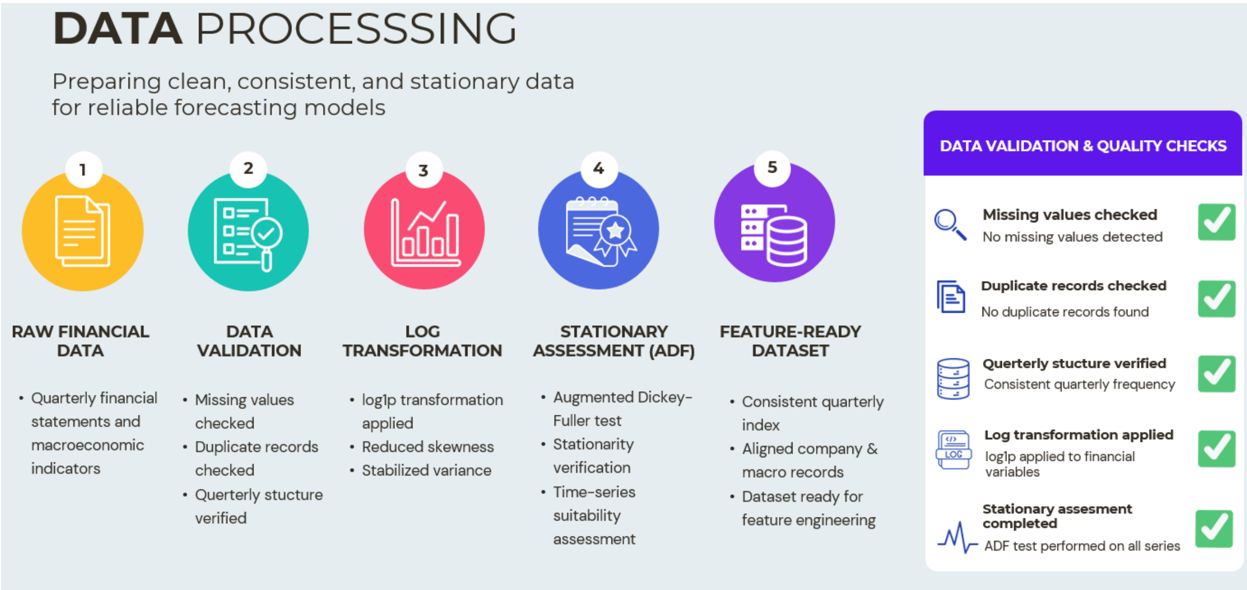

Figure 2 – Preliminary data processing

Special attention was paid to the formation of the feature space. According to Figure 3, the following groups of features were formed:

– lag variables (lag1, lag2, lag4, lag8);
– moving averages;
– sliding standard deviations;
– quarterly growth rates;
– seasonal signs;
– macroeconomic indicators;

– microeconomic financial indicators of the company.

Eight algorithms were used for forecasting:

– linear regression;
– Random Forest;
– XGBoost;
– Support Vector Regression;
– ARIMA;
– SARIMA;
– Prophet;
– Long Short-Term Memory.

The quality of the models was assessed using four of the most common metrics. The quality of the models was assessed using the following metrics formulas (1-4):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{3}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{(|y_i| + |\hat{y}_i|)/2} \tag{4}$$

where y_i is the actual value of the indicator, $\hat{y}_i$ is the predicted value, and n is the number of observations.

	date	fiscal_year	fiscal_year_raw	revenue	revenue_unit	fiscal_quarter	fiscal_period	company	is_outlier_iqr	lag_1	log_lag_1	lag_2	log_lag_2	lag_4	lc
0	2010-03-27	2010	2010	1.57	USD billions	1	2010Q1	AMD	False	1.65	0.974560	1.40	0.875469	1.18	
1	2010-06-26	2010	2010	1.65	USD billions	2	2010Q2	AMD	False	1.57	0.943906	1.65	0.974560	1.18	
2	2010-09-25	2010	2010	1.62	USD billions	3	2010Q3	AMD	False	1.65	0.974560	1.57	0.943906	1.40	
3	2010-12-25	2010	2010	1.65	USD billions	4	2010Q4	AMD	False	1.62	0.963174	1.65	0.974560	1.65	
4	2011-04-02	2011	2011	1.61	USD billions	1	2011Q1	AMD	False	1.65	0.974560	1.62	0.963174	1.57	

Figure 3 – Formation of features for machine learning models

To increase the reliability of the results, Rolling Origin Cross Validation was used, and the statistical significance of the differences between the models was determined using the paired Student's t-test and the Wilcoxon test [4].

Results.

The study was conducted on the basis of quarterly financial data from twenty-one public companies representing seven sectors of the economy. The sample includes enterprises from the technological, financial, energy, industrial, hotel, and retail sectors. The use of an industry-diversified sample made it possible to assess the stability of forecasting models for various types of time series behavior.

A preliminary analysis of the time series showed, according to Figure 4, that most of the studied sequences are characterized by a pronounced long-term trend and seasonality**.**

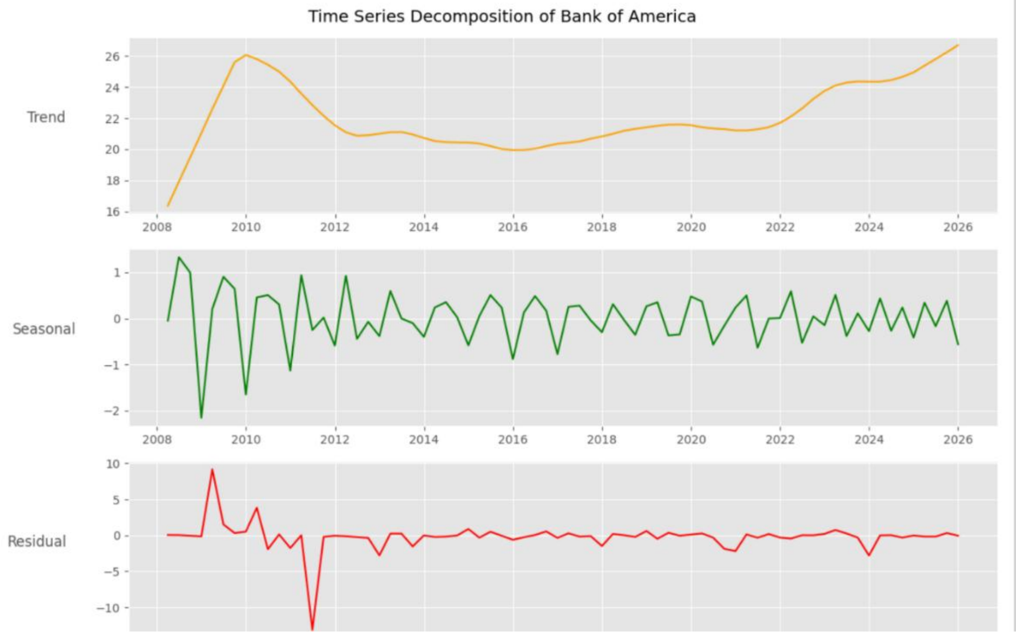

Figure 4 - Decomposition of the time series of the company's quarterly revenue

Structural changes related to the consequences of the COVID-19 pandemic and the subsequent recovery of the global economy have been identified for a number of companies. After performing the logarithmic transformation and the first differentiation, all time series satisfied the criterion of stationarity according to the results of the extended Dickey–Fuller test, which confirmed the possibility of using ARIMA family models and other forecasting methods.

The analysis of the autocorrelation function allowed us to establish the existence of a stable relationship between the current and previous values of quarterly revenue. The lag signs lag1, lag2, lag4 and lag8 turned out to be the most informative, reflecting the short-term and seasonal dependencies of financial indicators. The use of these features has significantly improved the accuracy of most machine learning models.\

To assess the influence of various groups of factors, four experimental forecasting scenarios were formed:

S1 — using only engineering features of the time series;

S2 — engineering attributes together with microeconomic indicators of companies;

S3 — engineering features in conjunction with macroeconomic indicators;

S4 is a complete set of features, including engineering, micro- and macroeconomic indicators.

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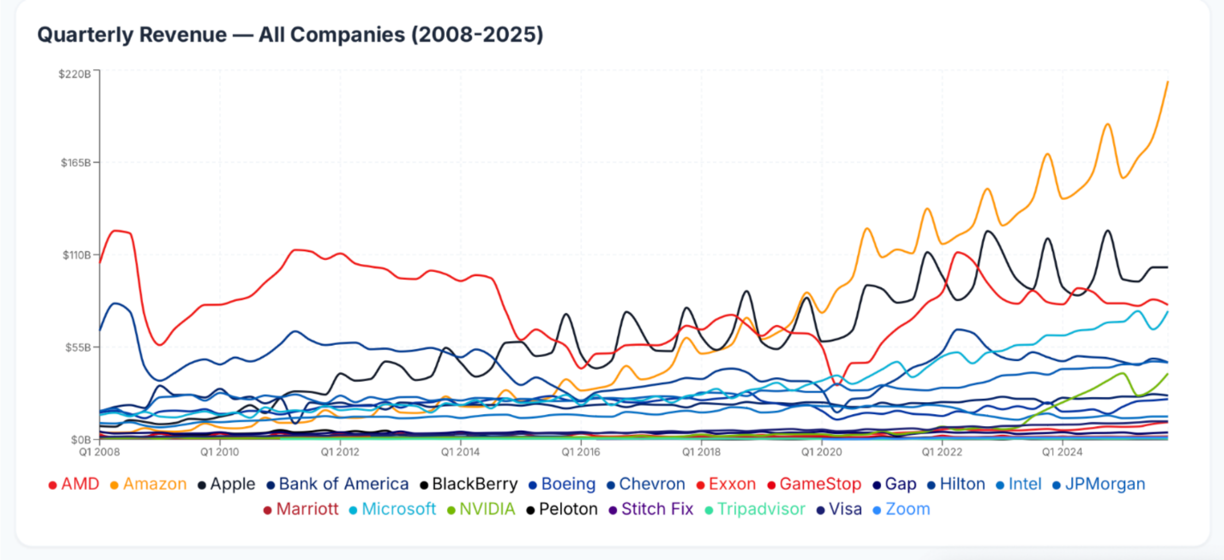

Figure 5 – The significance of lag signs in forecasting

Each scenario was evaluated using eight forecasting algorithms. The quality of forecasts was calculated using RMSE, MAE, MAPE, and sMAPE metrics.

The results showed significant differences in the effectiveness of the algorithms studied, as shown in Figure 7. Linear regression provided satisfactory accuracy only for companies with stable revenue dynamics and an almost linear pattern of financial performance changes. As the nonlinearity of the time series increased, the prediction errors increased.

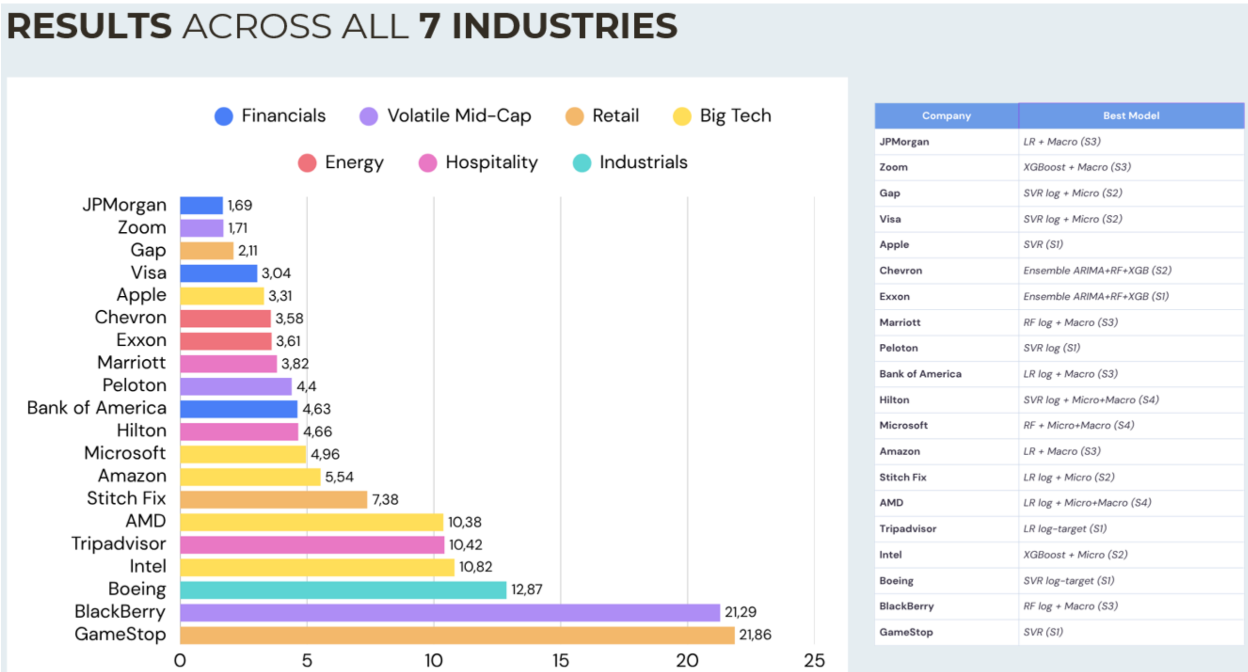

Figure 7 –Choosing the optimal forecasting model

Classical time series analysis models (ARIMA, SARIMA, and Prophet) effectively described pronounced seasonality and long-term trends, but their quality declined significantly when structural changes, sharp market fluctuations, and external economic shocks occurred.

The highest results among machine learning algorithms were demonstrated by the Random Forest and XGBoost models. Thanks to the ensemble construction of decision trees, these methods successfully modeled complex nonlinear dependencies between lag features, financial coefficients, and macroeconomic indicators. A particularly noticeable advantage was observed for companies with high financial volatility [5].

The Long Short-Term Memory model also provided high prediction accuracy in the presence of long-term time dependencies. However, the effectiveness of LSTM significantly depended on the size of the training sample and required significantly more computing resources compared to tree ensembles.

A comparison of the results for all the companies studied showed the absence of a universal forecasting model that works equally effectively for all sectors of the economy. For financial institutions, the use of macroeconomic factors led to a marked reduction in forecasting errors due to the high dependence of the banking sector on interest rates and the general state of the economy. A similar trend was observed for energy companies, whose financial performance is significantly determined by the dynamics of world oil prices [6].

In the technology sector, the impact of macroeconomic variables was less pronounced. For individual companies, the inclusion of additional macroeconomic indicators led to an increase in forecasting errors, which indicates the predominance of internal business development factors over the external economic environment.

The statistical analysis of the differences between the forecasting scenarios was performed using the paired Student's t-test and the Wilcoxon landmark rank criterion. The results obtained confirmed the statistically significant superiority of ensemble machine learning methods over most individual models. At the same time, the differences between the scenarios of using macroeconomic indicators turned out to be industry-dependent, which confirms the need for an individual selection of a set of indicators for each company [7].

The most stable results were obtained using the Random Forest algorithm, which provided the minimum sMAPE values for most of the studied companies, and a comparison of forecasting methods is shown in Table 1. The high efficiency of the model is explained by its ability to take into account complex nonlinear interactions between financial indicators, automatically identify the most significant features, and maintain resilience to outliers caused by the crisis events of recent years.

Table 1 – Comparison of forecasting methods

Метод	**Advantages**	**Limitations**
Линейная регрессия	Ease of implementation and interpretation	It does not take into account nonlinear dependencies
ARIMA	It describes stationary time series well	It is sensitive to structural changes

SARIMA	Takes into account seasonality	Limited by linear dependencies
Prophet	Automatically highlights the trend and seasonality	Less effective for complex dynamics
SVR	High accuracy with small samples	Requires hyperparameter settings
XGBoost	High precision and stability	Higher computational complexity
LSTM	It models long-term dependencies well	It requires a large amount of data
Random	High stability, automatic feature selection, high accuracy	large size of the ensemble increases the training time
Forest	Ease of implementation and interpretation	It does not take into account nonlinear dependencies

Discussion.

The results obtained confirm the high efficiency of modern machine learning methods in predicting the financial performance of companies. A comparison of the models shows that integrated algorithms, especially random forest and XGBoost, in most cases have higher prediction accuracy than traditional time series models. Their advantage lies in their ability to explain the complex non-linear relationships between financial, macroeconomic, and lagging variables.

However, the research results show that currently there is no universal model applicable to all sectors of the economy.

It is worth noting that the traditional ARIMA, SARIMA, and Prophet models still have practical value in analyzing stable time series with significant seasonality. However, when structural changes are caused by causes such as the global economic crisis or the COVID-19 epidemic, their forecasting accuracy is significantly reduced. Despite the positive results, this study still has some limitations. First of all, the macroeconomic factors used in the study are limited, and the analysis is based only on data from companies listed on the stock exchange in the United States. Secondly, to assess the quality of the forecast, the study mainly uses a point forecast, but does not analyze confidence intervals. Therefore, future research should expand the scope of macroeconomic indicators and use long-term memory models (ARFIMA), angle-of-view forecasting methods, and probabilistic methods to assess forecast uncertainty [8].

Conclusion.

The study conducted a comprehensive comparison of time series analysis models and machine learning algorithms for predicting quarterly revenue of companies in various sectors of the economy.

The constructed model, based on financial and macroeconomic data, is evaluated using RMSE, MAE, MAPE and sMAPE indicators. The results of the study show that a combination of technical characteristics and macroeconomic indicators can improve the forecasting accuracy of most companies.The random forest and XGBoost models demonstrate the best results and provide the lowest margin of error due to their ability to identify complex nonlinear dependencies and efficiently use a large number of functions.

The classical ARIMA, SARIMA, and Prophet models showed satisfactory accuracy in the presence of stable trends and seasonality, but the results were less resistant to changes in the structure of the time series. It was determined that the choice of the best model depends on the industry specifics of the company, the structure of the source data and the composition of the functions used.The results obtained confirm the expediency of using machine learning methods to solve financial forecasting problems and support managerial decision-making [9].

The practical significance of this research lies in the fact that the proposed methods can be used for financial planning, investment analysis, corporate risk assessment and the development of intelligent decision support systems.Promising areas for further research are the expansion of the scope of macroeconomic factors, the use of hybrid and probabilistic forecasting models, as well as the use of deep learning methods for long-term forecasting of financial indicators.

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КОМПАНИЯЛАРДЫҢ ҚАРЖЫЛЫҚ КӨРСЕТКІШТЕРІН МАШИНАЛЫҚ ОҚЫТУ ЖӘНЕ УАҚЫТ ҚАТАРЛАРЫН ТАЛДАУ ӘДІСТЕРІ НЕГІЗІНДЕ БОЛЖАУ

Аңдатпа. Мақалада Машиналық оқыту әдістерін және уақыт серияларын талдауды қолдана отырып, компаниялардың қаржылық көрсеткіштерін болжау міндеті қарастырылады. Зерттеудің өзектілігі жоғары нарықтық белгісіздік пен экономиканы цифрландыру жағдайында қаржылық болжаудың дәлдігін арттыру қажеттілігімен байланысты.

Зерттеудің мақсаты қаржылық және макроэкономикалық мәліметтер негізінде компаниялардың тоқсандық кірісін болжау модельдерін салыстырмалы талдау болып табылады. Зерттеу макроэкономикалық көрсеткіштерді, соның ішінде тұтыну бағаларының индексін, АҚШ мемлекеттік облигацияларының кірістілігін, Brent мұнай бағасын және Nasdaq Composite және S&P 500 қор индекстерін пайдалана отырып, 2008-2025 жылдар аралығындағы 21 ашық компанияның тоқсандық деректерінде орындалды.

Болжау үшін Arima, SARIMA, Prophet, сызықтық регрессия, Support Vector Regression, Random Forest, XGBoost және Long Short-Term Memory модельдері қолданылады. Деректерді алдын ала өңдеу, кідіріс белгілерін қалыптастыру және макроэкономикалық факторларды біріктіру орындалды. Модельдердің сапасы RMSE, MAE, MAPE және sMAPE көрсеткіштерімен бағаланды.

Нәтижелер ансамбльдік Машиналық оқыту алгоритмдері классикалық уақыт қатарының үлгілерімен салыстырғанда жоғары болжау дәлдігін қамтамасыз ететінін көрсетті. Ең тұрақты нәтижелерді Random Forest көрсетті. Оңтайлы модельді таңдау салалық ерекшелікке және компанияның уақыт сериясының ерекшеліктеріне байланысты екендігі анықталды. Әзірленген тәсілді қаржылық жоспарлау, инвестициялық талдау және басқару шешімдерін қолдау үшін пайдалануға болады.

Түйінді сөздер: машиналық оқыту, уақыт сериясын талдау, қаржылық болжау, компанияның кірісі, Random Forest, XGBoost, ARIMA, LSTM, макроэкономикалық көрсеткіштер.

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ПРОГНОЗИРОВАНИЕ ФИНАНСОВЫХ ПОКАЗАТЕЛЕЙ КОМПАНИЙ С ИСПОЛЬЗОВАНИЕМ МОДЕЛЕЙ ВРЕМЕННЫХ РЯДОВ И МАШИННОГО ОБУЧЕНИЯ

Аннотация. В статье рассматривается задача прогнозирования финансовых показателей компаний с использованием методов машинного обучения и анализа временных рядов. Актуальность исследования обусловлена необходимостью повышения точности финансового прогнозирования в условиях высокой рыночной неопределенности и цифровизации экономики.

Цель исследования заключается в сравнительном анализе моделей прогнозирования квартальной выручки компаний на основе финансовых и макроэкономических данных. Исследование выполнено на квартальных данных 21 публичной компании за период 2008–2025 гг. с использованием макроэкономических показателей, включая индекс потребительских цен, доходность государственных облигаций США, цену нефти Brent и фондовые индексы NASDAQ Composite и S&P 500.

Для прогнозирования применены модели ARIMA, SARIMA, Prophet, линейная регрессия, Support Vector Regression, Random Forest, XGBoost и Long Short-Term Memory. Выполнены предварительная обработка данных, формирование лаговых признаков и интеграция макроэкономических факторов. Качество моделей оценивалось по метрикам RMSE, MAE, MAPE и sMAPE.

Результаты показали, что ансамблевые алгоритмы машинного обучения обеспечивают более высокую точность прогнозирования по сравнению с классическими моделями временных рядов. Наиболее устойчивые результаты продемонстрировал Random Forest. Установлено, что выбор оптимальной модели зависит от отраслевой специфики и особенностей временного ряда компании. Разработанный подход может быть использован для финансового планирования, инвестиционного анализа и поддержки принятия управленческих решений.

Ключевые слова: машинное обучение, анализ временных рядов, финансовое прогнозирование, выручка компании, Random Forest, XGBoost, ARIMA, LSTM, макроэкономические показатели.

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Авторларға нұсқаулық

Сағадат Нұрмағамбетов атындағы Құрлық әскерлері Әскери институтының Хабаршы ғылыми-ақпараттық журналында материалдарды жариялау онлайн-беру және сараптамалық бағалау жүйесі Open Journal System пайдалану арқылы жүзеге асырылады. Тіркелу, қол жеткізу, материалды жіберу бөлімі арқылы жүзеге асады. Автор корреспонденция үшін қолжазбаны беру кезінде ілеспе хат ұсынуы тиіс.

Қолжазба төменде сипатталған талаптарға сәйкес рәсімделуі тиіс.

Мақаланың атауы – мақала мазмұны тақырыбына сәйкес болуы қажет. *Мақаланың шрифты (14 кегль).*

Аңдатпа – мақаланың қысқаша мазмұнын сипаттайды. Аңдатпа 300 сөзден аспай құралып қазақ, орыс, ағылшын тілдерінде рәсімделуі тиіс. *(14 кегль).*

Түйінді сөздер – мәтіндік белгі сөздерінің саны бестен кем болмауы керек. Үш тілде жазылады (қазақ, орыс, ағылшын).

Кіріспе – мақаланың өзектілігіне тоқталып, үлес қосқан отандық және шетелдік ғалымдардың жұмыстарын қарастыра отырып ашады.

Материалдар мен тәсілдер – зерттеу жүргізу барысында қолданған әдістерін көрсетеді.

Нәтижелері – теориялық және эксперименттік нәтижелер, жаңа деректер, ғылыми жаңалықтар, ұсыныстар келтіріледі.

Талқылау - Алдыңғы зерттеулерге сәйкес алынған нәтижелердің маңыздылығын талдау, ұқсастықтар мен айырмашылықтарды анықтау, жұмыстың ғылыми құндылығын негіздеу және одан әрі зерттеу бағыттарын ұсыну.

Қортындылау – зерттеу барысында мақаланың қортындысын шығару, алынған нәтиженің практикалық маңызын көрсету, өз тарапынан ұсыныс жасау керек.

Әдебиеттер тізімі – мәтіндегі сілтемелер олардың аталу ретімен өсуі бойынша нөмірленеді. Жарияланым туралы библиографиялық мәліметтер МЕМСТ 7.1. – 2003 «Библиографиялық жазба. Құрастырудың жалпы талаптары мен ережелері».

Мақалада электрондық ресурстарды пайдаланса интернеттегі мекен-жайы бар желілік ресурсқа сілтеме келтіріледі. Ресурсқа жүгінсе авторын,тақырыбын, қараған күнін көрсеткені дұрыс. Мақалада транслитирленген дереккөздердің болуы **міндетті** шарт болып табылады.

Әдебиеттер тізімі орыс тілінде және жалпы қабылданған ағылшын транслитерациясында ұсынылуы тиіс. Мұны http: //translit. ru/ немесе https:// transliteration. pro/ bsi сайтында көрсетілген бағдарламаның көмегімен жасауға болады.

Төменгі жағында авторлар туралы мәлімет үш тілде беріледі. Аты – жөні, лауазымы, ғылыми атағы, ғылыми дәрежесі жұмыс жасайтын мекемесі, қаласын, мемлекетін және электронды почтасын жазу керек. Көп автор болса мақалаға жауапты бір ғана автордың электронды почтасын көрсетеді.

Техникалық талаптар:

Мәтіндік файлдар Word форматында ұсынылуы керек.

- Шрифты - Times New Roman – 14 кегль.
- Жоларалық интервал – 1,0.
- Шеті: - жоғарғы және төменгі – 2 см, сол жағы – 3 см, оң жағы – 2 см.
- Абзацтық алу – 1 см.
- Мақаланың көлемі 10 беттен аспау қажет.

Руководство для авторов

Публикация материалов в научно-информационном журнале Вестник Военного института Сухопутных войск имени Сагадата Нурмагамбетова осуществляется с использованием Open Journal System, системы онлайн-подачи и экспертной оценки. Регистрация и доступ в разделе отправка материалов. Автор для корреспонденции обязан предоставить сопроводительное письмо при подаче рукописи.

Рукопись должна быть оформлена в соответствии с требованиями, описанными ниже.

Название статьи – должно соответствовать содержанию статьи, теме исследования. Шрифт статьи *(14 кегль).*

Аннотация – краткое изложение содержания научной статьи. Объем аннотации составляет не более 300 слов, оформляется на 3-х языках. *(14 кегль).*

Ключевые слова – текстовые метки, количество ключевых слов от 5, оформляется на 3-х языках (казахском, русском, английском).

Введение – изложение актуальности темы исследования с обязательным рассмотрением отечественных и зарубежных работ.

Материалы и методы – описываются методы, использованные в ходе исследования.

Результаты – приводятся основные теоретические и экспериментальные результаты, фактические данные, обнаруженные взаимосвязи и закономерности.

Обсуждение - анализировать значение полученных результатов в свете предыдущих исследований, выявляя как сходства, так и отличия, обосновывая научную ценность работы и предлагая направления для дальнейших исследований.

Заключение – подведение итогов работы, обоснование новизны и актуальности исследования.

Список литературы – ссылка в тексте нумеруются по возрастанию в порядке их упоминания. Список литературы оформляется строго по ГОСТ 7.1. – 2003 «Библиографическая запись. Библиографическое описание. Общие требования и правила составления».

При использовании в статье источников из электронных ресурсов в списке литературы необходимо указать на сетевой ресурс с полным адресом в интернете. Желательно указывать дату обращения к ресурсу.

Список литературы должен быть представлен на русском языке и в общепринятой английской транслитерации. Это можно сделать с помощью программы, указанной на сайте http://translit.ru/, либо https://transliteration.pro/bsi

Ниже даются **сведения об авторах на** трех **язык**ах**.** ФИО автора(-ов), данные авторов: должность, ученое звание, ученая степень наименование учреждения, города, государства. При наличии нескольких соавторов, рекомендуется указать адрес электронной почты всех авторов.

Технические требования

Текстовые файлы следует представлять в формате Word.

- Шрифт – Times New Roman, размер – 14pt.
- Междустрочный интервал – 1.0.
- Поля:- Края-верхняя и нижняя – 2 см, левая – 3 см, правая – 2 см.
- Абзац – 1 см.
- Объем статьи – не должен превышать 10 страниц.

Guidelines for Authors

The publication of materials in the scientific journal Bulletin of the Sagadat Nurmagambetov Military Institute of Land Forces is carried out using the Open Journal System, an online submission system and peer review. Registration and access are in the section submission of materials. The corresponding author shall be obliged to provide a cover letter when submitting a manuscript.

The manuscript must be formatted in accordance with the requirements described below.

The research paper title should correspond to its content and research topic. It is indicated in capital letters in the center of the page *(MS Word in size 14 Times New Roman).*

Abstract is a summary of the research paper content. The abstract should be written in no more than 300 words in Kazakh, Russian, and English *(MS Word in size 14 Times New Roman).*

Keywords. The number of key words must be at least 5, and be written in 3 languages (kazakh, russian, english).

Introduction should include consideration of domestic and foreign research and actuality of research topic.

Materials and Methods are the research methods used during the subject consideration.

Results reveals main theoretical and experimental results, new facts, suggestions and recommendations.

Discussion - The purpose of the discussion is to analyze the significance of the results obtained in the light of previous research, identifying both similarities and differences, substantiating the scientific value of the work and suggesting directions for further research.

Conclusions are the summing up study results, presenting practical recommendations, as well as own proposals.

Bibliography and Transliteration. The list of references in the text is numbered in ascending order in the order of their mention. The list of references is drawn up strictly according to GOST 7.1. – 2003. “Bibliographic record. Bibliographic description. General requirements and rules of compilation”.

When using sources from electronic resources in the article in the list of references, it is necessary to indicate a network resource with a full Internet address. It is advisable to specify the date of access to the resource.

The list of references should be presented in Russian and in the generally accepted English transliteration. This can be done using the program listed on the website. http://translit.ru/, or https://transliteration.pro/bsi

The research paper design requirements: The ICSTI code, the research paper title, the full name of the author(s), the authors data: position, academic title, academic degree, name of institution, city, state, e-mail.

Technical requirements

Text files should be submitted in Word format.

- Font-Times New Roman, size – 14pt.
- Line spacing – 1.0.
- Fields: Edges-top and bottom – 2 cm, left – 3 cm, Right – 2 cm.
- Paragraph – 1 cm.
- The volume of the article should not exceed 10 pages.