FORECASTING OF FINANCIAL MARKET INDICATORS USING ARTIFICIAL INTELLIGENCE SYSTEMS

Abstract. Financial markets are the foundation of the modern economy, facilitating the movement of capital between its owners and borrowers, thereby enabling businesses to develop and innovate. These markets provide a platform for price discovery and risk management. At their core, they act as intermediaries between those who have surplus funds and those who need financing. The functioning of financial markets provides borrowers with a mechanism for accessing capital and capital owners with an opportunity to earn a return on their investments. This interaction between capital owners and borrowers is essential for economic growth and development. Rapid changes in the global economy and the impact of information technology have brought significant changes to the way financial markets function, simplifying communication between market participants and increasing efficiency. However, these changes have also created a number of risks caused by uncertainty. The use of artificial intelligence systems in building a model for forecasting financial indicators based on processing a large data set can significantly improve the accuracy and quality of forecast data. The authors have conducted a comparative analysis of forecasting methods, identifying their respective strengths and weaknesses, and the potential for their application to forecasting indicators. Based on the findings of this study, the authors propose a model for forecasting financial market indicators using artificial intelligence systems. The model comprises two components: 1) a time series LSTM, a network with a long short-term memory, designed to analyse and forecast financial time series data by capturing time dependencies and patterns inherent in market indicators; and 2) an NLP-Enhanced LSTM, another LSTM network supplemented with the results of BERT processing, which is specifically designed to analyse text
data and their impact on financial market dynamics. The proposed model, which combines the capabilities of LSTM time series analysis with information obtained from BERT-processed headlines, enables the identification and consideration of the relationship between market trends, sentiment and external factors. Testing the proposed model on the data of Tesla has demonstrated its suitability for forecasting the price of Tesla's shares.

**Keywords:** forecasting, artificial intelligence, modelling, forecast accuracy, financial markets, share price.

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застосування для прогнозування показників. На основі проведеного дослідження було запропоновано модель прогнозування показників фінансових ринків з використанням систем штучного інтелекту. Дана модель складається з двох частин: 1) часові ряди LSTM, як мережа з довгою короткостроковою пам’яттю, предназначена для аналізу та прогнозування даних фінансових часових рядів шляхом фіксації часових залежностей та закономірностей, притаманих ринковим індикаторам; 2) NLP-Enhanced LSTM, як ще одна LSTM-мережа, доповнена результатами BERT-обробки, спеціально розроблена для аналізу текстових даних та їхнього впливу на динаміку фінансового ринку. Запропонована модель, зосереджуючи можливості аналізу часових рядів LSTM з інформацією, отриманою з оброблених BERT заголовків надає можливість виявляти та враховувати взаємозв’язок між ринковими тенденціями, настроями та зовнішніми факторами. Апробація запропонованої моделі на даних компанії Tesla довела дотримання її застосування під час прогнозування цін на акції даної компанії.

Ключові слова: прогнозування, штучний інтелект, модельювання, точність прогнозу, фінансові ринки, ціна на акції.

**Problem statement.** The contemporary evolution of society is marked by a proliferation of technological innovations and economic transformations. Consequently, the capacity to predict financial indicators with remarkable precision has become a matter of paramount importance, capable of significantly influencing the financial standing of investors and corporations [1]. The intricate interweaving of economic variables, geopolitical events and investor expectations renders traditional forecasting methods inadequate for the production of sufficiently accurate forecasts based on the dynamics of modern financial markets. Consequently, there is a pressing necessity for the development of innovative methodologies that can incorporate a multitude of variables to generate forecasts with high accuracy and flexibility in complex financial systems.

For a considerable period of time, financial markets have been the subject of interest to both academics and practitioners, acting as vital indicators of economic conditions and determining the drivers of economic development. The accurate forecasting of financial indicators plays a pivotal role in the decision-making processes of investors, policymakers, and financial institutions. It is therefore unsurprising that the search for forecasting models capable of providing high forecast accuracy is attracting the attention of specialists from various fields.

The utilisation of artificial intelligence represents a highly effective instrument that enables the identification of patterns, trends and the forecasting of market changes with a high degree of accuracy. The use of artificial intelligence (AI) systems enables the detection of previously unidentified correlations, the identification of emerging patterns, and the forecasting of market indicators with a
level of sophistication that surpasses traditional methods. This is achieved by analysing large volumes of data generated by financial systems. Consequently, the utilisation of AI-based forecasting models has extended beyond the domain of financial institutions to encompass businesses engaged in algorithmic trading. Even minor fluctuations in forecasting accuracy can have a significant impact on the potential for financial gain or loss.

Analysis of recent research and publications. The issue of financial market analysis was studied by many Ukrainian and foreign scientists, among whom should be noted Pandey D., Lucey B., Kumar S., Iorgachova M., Kovalova O., Kotsiurubenko G., Oparin V., Kovalenko U., Alekseenko L. and others. However, the variability of the external environment requires clarification of the issues of forecasting financial market indicators. Therefore, the problem of forecasting financial indicators with the use of artificial intelligence systems will contribute to improving the quality of forecasting and requires additional research.

The objective of this article is to analyse forecasting methods and develop a reliable forecasting model by studying the potential of artificial intelligence (AI) systems in the field of financial market forecasting.

Presentation of the main material. Time series forecasting represents a crucial aspect of financial analysis and decision-making. The use of historical data to predict future values of time series allows investors to make informed investment decisions, businesses to optimise their operations, and politicians to formulate effective strategies for the development of society. Prior to the application of forecasting techniques, it is essential to pre-process time series data in order to remove any extraneous noise or irregularities that may interfere with the forecasting process. The aforementioned process, designated as time series filtering, encompasses the following methodologies: moving average, digital filters, exponential filter, polynomial filter, median filter. The selection of pertinent features is of paramount importance for the effective forecasting of time series. A comprehensive set of features can facilitate the capture of the underlying dynamics of the data, thereby improving the accuracy of the forecasting process. However, including an excessive number of features can result in overfitting, whereby the model becomes overly complex and is unable to generalise to new data. In order to identify the most relevant features, it is possible to employ feature selection methods such as correlation analysis and feature importance measurements [2].

The selection of the number of attributes is a pivotal element in the process of time series forecasting. An excess of attributes may result in overfitting, whereas a deficiency may result in an inability to capture the full complexity of the data, leading to inaccurate predictions. A number of methods can be employed to ascertain the optimal number of attributes. These include statistical techniques such as Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC), which assess model complexity and favour simpler models with fewer attributes. Additionally, cross-validation and expert judgement can be utilised.
The absence of data can have a significant impact on the accuracy of time series forecasting. A number of methods can be employed to address this issue, including the calculation of the mean or median, interpolation, and model-based calculations. It is also important to consider the property of stationarity, which refers to the statistical stability of a time series over time [3]. When employing indicators of disparate dimensions and scales, it is imperative to normalise them. This entails scaling the data to a uniform range, typically spanning from 0 to 1, in order to guarantee that all variables exhibit comparable magnitude and distribution. This standardisation is of particular importance when utilising machine learning algorithms, as it prevents variables with larger values from exerting undue influence on the data [4].

A plethora of models can be employed to forecast time series, each exhibiting distinctive strengths and weaknesses. The selection of a model is contingent upon the characteristics of the data, the forecast horizon, and the desired level of accuracy. In particular, the following models were subjected to analysis as part of the study.

Moving average models are a relatively simple and widely used method for forecasting time series data. These models are predicated on the assumption that future values are influenced by recent past values. Moving average models are effective for identifying short-term trends and patterns, but may not be optimal for longer forecasting horizons.

Another class of widely used time series forecasting techniques is autoregressive models. These models assume that future values are determined by a linear combination of past values. Autoregressive models are effective at capturing linear trends and patterns, but may not be suitable for non-linear data.

ARIMA models integrate AR and MA models with a distinction to address non-stationary data. ARIMA models are considered versatile forecasting models that can cover a wide range of trends and patterns.

Recurrent neural networks (RNNs) constitute a class of neural networks that have been designed with the specific purpose of processing sequential data, such as time series. RNNs are particularly adept at capturing long-term dependencies and trends, rendering them well suited for longer-term forecasting.

LSTM networks represent a specific type of RNN that is particularly adept at addressing long-term dependencies in time series data. The incorporation of memory cells enables the models to retain past information over extended periods, thereby facilitating the capture of intricate patterns and the generation of accurate long-term predictions.

In addition to the aforementioned models, several other methods are employed to forecast time series, including support vector machines (SVMs), decision trees, and ensemble methods [5].

The selection of an appropriate methodology for forecasting financial markets is of paramount importance for the development of accurate and reliable forecasting.
models. Python, when combined with a wide range of different libraries and tools, has become a very attractive option among developers and analysts. This is due to its versatility, ease of use, extensive ecosystem, and robust support for data analytics, machine learning, and deep learning. Python is equipped with a wide range of libraries and frameworks that have been developed with the specific needs of data science, machine learning, and analytics in mind. Libraries such as Pandas, NumPy, and scikit-learn provide essential tools for data manipulation, numerical computing, and machine learning. Pandas is a versatile library for data manipulation and analysis, particularly suited to the analysis of time series data. It provides efficient data structures, such as DataFrame and Series, as well as intuitive functions for cleaning, filtering, aggregating, and transforming data, rendering it indispensable for pre-processing data for model building.

The study analysed historical archives of TESLA stock prices with the objective of assessing the effectiveness of current forecasting methods and identifying opportunities for improvement by incorporating news headlines. The dataset encompasses a comprehensive array of daily stock metrics, including date, opening, high, low, closing, volume, dividends, and stock splits. This rich and detailed historical market data source offers a valuable resource for analysis and forecasting.

The process of data preparation for research entails ensuring that the dataset is free from contamination, complete, and prepared for analysis. In the case of the TESLA stock dataset from Yahoo Finance, it is of the utmost importance to fill in missing values in order to maintain data integrity and facilitate accurate forecasting.

To fill in the missing values, the method of filling in with the average of the closest observed values from the previous and subsequent trading days was employed. This approach ensures that missing values are interpolated based on surrounding data points, thereby preserving the overall trend and dynamics of share prices. Following the interpolation of the missing values in the TESLA dataset, the subsequent step in the preparation process is to filter the data in order to enhance the quality of the dataset for modelling and analysis purposes. In order to achieve this, a digital low-pass filter was applied utilising the butter and filter functions of the SciPy library. The application of a filtered dataset to predictive models enhances their performance by reducing the likelihood of overtraining on short-term noise and improving the model's capacity to identify meaningful trends and patterns in the data. By training the model on a smoothed version of the dataset, we promote generalisation and improve the model's prediction accuracy on new data. Following the application of the digital low-pass filter to the TESLA stock data set, the subsequent crucial stage in the data preprocessing process is to assess the stationarity of the time series.

The Dickey-Fuller test can be applied to the filtered TESLA stock data set in order to ascertain whether the data set exhibits stationary behaviour. The p-value is
0.634, which is greater than the critical value of 0.05, indicating that the hypothesis of stationarity of the time series is rejected. To investigate the presence of seasonality in the TESLA stock data set, we employed seasonal decomposition, a method that decomposes a time series into three components: trend, seasonality, and residuals (or noise). The decomposition enabled the identification and analysis of the principal seasonal patterns in the data (Fig. 1).

![Fig. 1 The seasonal decomposition of the time series.](image)

In order to forecast financial market indicators, such models as WMA (weighted median average), SARMIAEX, MLP, RNN, LSTM were employed on the basis of the time series of TESLA shares. This approach permitted the development of a model for forecasting time series indicators, which incorporated processed news data to determine the sentiment of the data in the news and to enhance the forecasting performance. The overarching objective is to assess the relative merits and shortcomings of existing models and to propose novel approaches to enhance their efficacy.

In order to facilitate comparison, various performance metrics were employed to evaluate the predictive models, including mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). The final comparative results are presented in Table 1.
Table 1.

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE</th>
<th>Accuracy</th>
<th>MAPE</th>
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<tbody>
<tr>
<td>WMA</td>
<td>16.9626031214389</td>
<td>83.94%</td>
<td>1510.47%</td>
</tr>
<tr>
<td>SARIMAX</td>
<td>51.96154917116397</td>
<td>76.91%</td>
<td>20.40%</td>
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<td>MLP</td>
<td>25.14</td>
<td>89.59%</td>
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<td>RNN</td>
<td>19.26</td>
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Consequently, a comparative conclusion can be drawn regarding the accuracy of the models on the processed dataset in comparison to the accuracy assessment on the test data:

- The LSTM model demonstrated the greatest accuracy, exhibiting an improvement over the conventional recurrent model;
- The WMA and SARIMA models, however, performed less well on the complex dataset, as the identification of patterns in the data for forecasting long time intervals is not a straightforward process;
- The multilayer neural network, on the other hand, performed relatively well, given that this model is primarily used for forecasting other types of data.

The results of this study indicate that a new model for forecasting financial market indicators should be developed that employs artificial intelligence methods, in particular, natural language processing (NLP) methods with a deep learning architecture. The proposed model combines advanced NLP capabilities, such as sentiment analysis and contextual understanding of news headlines, with traditional time series forecasting methods. This integration is intended to enhance the accuracy and reliability of forecasts.

The proposed model employs nlptown's advanced Bidirectional Encoder Representations from Transformers (BERT) architecture, a state-of-the-art NLP model renowned for its capacity to comprehend the context and semantics of natural language text. The Bidirectional Encoder Representations from Transformers (BERT) model will be employed to process financial market news headlines, with the objective of extracting valuable insights, sentiment, and contextual information from textual data (Figure 2).
Fig. 2 Architecture graph of the created model
The proposed model comprises two principal components:

a. LSTM time series: a long short-term memory (LSTM) network designed to analyse and forecast financial time series data by capturing time dependencies and patterns inherent in market indicators.

b. NLP-Enhanced LSTM: another LSTM network augmented with BERT results, specifically designed to analyse textual data and its impact on financial market dynamics.

The resulting model integrates these components and employs fully connected layers to predict the final value of the neural network output.

The proposed model effectively reflects the complex relationship between market trends, sentiment, and external factors by combining the time-series analysis capabilities of LSTM with information obtained from BERT-processed news headlines (Figure 3).

![Prediction plot using the proposed model](image)

**Fig. 3** Prediction plot using the proposed model

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</tr>
<tr>
<td>BERT-LSTM</td>
<td>9.64</td>
<td>95.72%</td>
<td>3.64%</td>
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**Table 2. Comparison of the accuracy of the proposed model on the test case**
The utilisation of the proposed model markedly enhances the forecasting precision of the model. This is particularly the case given the potential for forecasting sharp changes in share prices for reasons that cannot be predicted from the time series itself. Moreover, despite the considerable length of the forecasting period, the sentiment data derived from the news headlines enabled the accurate prediction of the value of share prices for 2024.

**Conclusions.** The study conducted a comprehensive comparative analysis and evaluated the effectiveness of weighted mean average (WMA), SARIMAX, multilayer perceptron (MLP), recurrent neural networks (RNN) and long and short memory networks (LSTM) models in forecasting the dynamics of financial markets. Furthermore, a novel model is presented that integrates BERT-based natural language processing (NLP) techniques with the LSTM architecture, with the objective of enhancing the accuracy of financial market forecasting.

The analysis included a variety of metrics, such as mean absolute error (MAE), mean squared error (MSE), and others, which provided insight into the relative strengths and weaknesses of each model.

The proposed model for predicting financial market performance employs BERT’s capabilities to process news headlines and extract valuable information, sentiment, and contextual information, which is then incorporated into LSTM-based forecasting to enhance forecast accuracy. The BERT-NLP Enhanced LSTM model has demonstrated promising results, outperforming traditional models and offering a more holistic approach to financial market forecasting using textual information.

Future research may include the exploration of additional sources of textual data, the improvement of the architecture through the application of advanced deep learning techniques, and the extension of the application of NLP-based forecasting models to the broader area of financial market performance forecasting.

**References:**
Література:


