Forecasting stock market prices using deep learning methods

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ABSTRACT

The article focuses on enhancing stock market price prediction through artificial neural networks and machine learning. It underscores the significance of improving forecast accuracy by incorporating historical stock prices, macroeconomic indicators, news events, and technical indicators. Exploring deep learning principles, it delves into convolutional neural networks (CNN), recurrent neural networks (RNN), including long short-term memory (LSTM), and gated recurrent unit (GRU) modifications. This financial time series processing study covers data preprocessing, creating training/test sets, and selecting evaluation metrics. Results suggest promising applications for the developed forecasting models in stock markets, stressing the importance of considering various factors for precise forecasts in dynamic financial environments. Historical reserve data serves as the model foundation. Integration of macroeconomic, news, and technical indicators offers a holistic approach, aiding trend and anomaly identification for enhanced forecasts. The article recommends suitable deep learning architectures, highlighting LSTM and GRU's effectiveness in adapting to intricate data dependencies. Experimental outcomes showcase these architectures' benefits in predicting stock market prices, offering valuable insights for finance and asset management professionals in financial analysis and machine learning realms.

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1. INTRODUCTION

In the modern world, financial markets [1]–[3] are rapidly evolving, acquiring increasingly complex and dynamic features. This complexity, growing in parallel with the expansion of data volume and the introduction of new financial instruments [4], [5], is of particular importance. At the same time, artificial intelligence [6], [7], based on machine learning [8], [9] and deep learning [10]–[12] algorithms, penetrates various areas of human activity, exclusively transforming them and questioning traditional methodologies. In financial markets, this phenomenon takes on high significance, since the effectiveness of forecasting plays a key role in ensuring successful investments and strategic decisions. Stock market forecasting [13], [14] represents a cornerstone for investors, traders and analysts. It enables you to make informed decisions to acquire, divest or hold shares in order to optimize portfolios and maximize profits. However, with the increase in the volume and variety of data, as well as the acceleration of trade, traditional forecasting methods [15] show a gradual decrease in efficiency. In this work, machine learning and deep learning algorithms represent a significant tool capable of identifying complex patterns and regularities in data that may go undetected using traditional methods.

The use of machine learning and deep learning algorithms in the analysis of financial markets [16], [17] opens up new prospects for researchers and practitioners in the field of forecasting. Capable of processing vast amounts of data and automatically identifying relationships between various factors, these algorithms provide the tools to create more accurate and reliable forecasts. Moreover, deep learning algorithms [18]–[20] demonstrate the ability to automatically extract features from data, which provides them with the ability to adapt to changing market conditions and achieve high forecast accuracy even in the face of rapid variability and uncertainty. The development of machine learning and deep learning technologies in the field of financial market analysis [18], [21], [22] also attracts the attention of researchers and practitioners from various fields, including financial econometrics, computer science and statistics. Their collective efforts are aimed at finding new methods and models designed to improve the accuracy and reliability of forecasts, as well as developing tools for assessing the effectiveness and quality of such forecasts [23], [24].

The purpose of this work is to research and develop methods for predicting prices in the stock market using machine learning and deep learning algorithms. The main emphasis is on analyzing the potential and advantages of these methods in the context of predicting stock price movements and supporting investment decisions. To achieve this goal, the following tasks are envisaged, such as analyzing concepts and classifying machine learning algorithms and their application in the stock market, studying the characteristics of the stock market and comparing various forecasting methods to identify the most effective approaches to predicting stock prices, analyzing pre-processing methods and analysis of financial time series in order to optimize the forecasting process, study of artificial neural network architectures adapted for forecasting stock prices, assessing their potential and scope of application.

The relevance of this study is due to the key role that stock markets play in the global economy. In the context of the ever-increasing volume and variety of data, as well as the dynamic development of trading technologies, the use of machine learning and deep learning algorithms for predicting prices in the stock market seems to be a promising direction. This approach promises to improve the efficiency of investment strategies and investment portfolio management. The study is expected to make important contributions to the field of financial analysis and investment strategies, as well as improve the processes of investment portfolio management and informed investment decisions based on the analysis of stock market data.

2. METHOD

This research work applies a deep learning method for stock market price prediction based on recurrent neural networks using long-short-term memory (LSTM) and state update gate (GRU). The methodology includes data analysis, preparation of time series, selection of network architecture and optimization of hyperparameters. The model is trained on the training set, evaluated on the validation set, and then tested on the test set. The results are evaluated using various metrics, such as the coefficient of determination and mean absolute error, followed by interpretation of the accuracy of the forecasts. This approach provides a systematic study of the effectiveness of deep learning using LSTM and GRU for the task of forecasting price dynamics in the stock market.

Figure 1 shows the deployment of a recurrent neural network over time, where you can see the individual components and the connections between them. The central element of each time step is represented by a rectangle, denoted hh, which corresponds to the hidden state of the network. The hidden state at each time step is denoted as at−1, at, at+1, which reflects the evolution of the hidden state through successive time points. The recurrent neural networks (RNN) structure includes repeating blocks, where each block consists of a layer of neurons with a nonlinear activation function such as tanh or rectified linear unit (ReLU).

The processing of data in an RNN can be visualized through a time unfolding, where each instant is represented by a rectangle reflecting the hidden state of the network at the corresponding time step. This deployment illustrates how the network processes a sequence of data by taking into account the context and dependencies between elements of the sequence. Thus, RNN, LSTM, and GRU provide powerful tools for analysis and forecasting in various fields, especially in the context of stock market price forecasting, where taking into account time dependencies is critical. LSTMs and GRUs are types of recurrent neural networks equipped with memory and gate mechanisms that control the flow of information in the network. For example, an LSTM includes a memory cell, a forget filter, and input/output gates, allowing information to be efficiently managed and important aspects of a sequence to be preserved over time. These architectures are actively used in natural language processing, time series forecasting and other tasks. Figure 2 shows the structure of a single cell LSTM, which is a variation of a recurrent neural network. LSTM is designed to solve problems where it is necessary to take into account long-term dependencies in the data. It includes several interacting blocks and gates that control the flow of information.

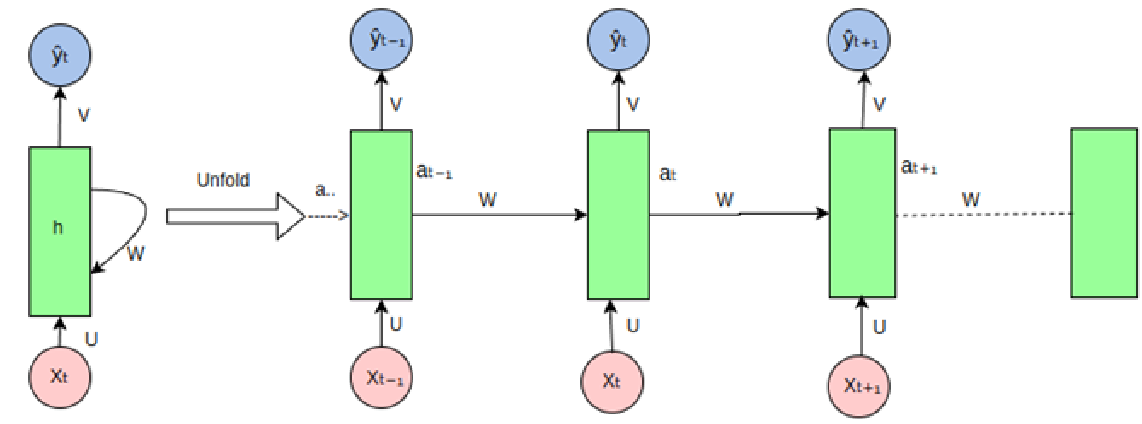
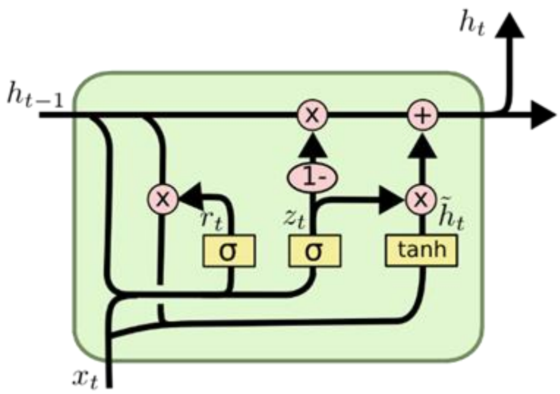


Figure 1. Architecture of recurrent neural networks



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Figure 2. LSTM architecture

A gated recurrent unit (GRU) is a type of recurrent neural network (RNN) designed to overcome the problems of decaying and exploding gradients found in standard RNNs. Designed to efficiently hold information over long periods of time and use it in sequential data, the GRU includes two key gates: an update gate and a reset gate. The first regulates how much the previous state transfers information to the new one, while the second determines how much of the previous information is discarded. These gates help the network determine when to update or discard state information. Such characteristics make GRU particularly effective for tasks where important temporal structure exists, such as language modeling, speech recognition, and time series forecasting. Figure 3 shows a schematic representation of a gated recurrent unit cell, which is one of the types of recurrent neural networks. GRU was designed to simplify long short-term memory while preserving its key properties and is typically used in sequence processing problems, such as language or time series modeling.

The research and development of stock market price prediction models using deep learning algorithms such as LSTM and GRU is an important field in the field of financial analysis. The complexity and dynamics of financial markets require effective forecasting tools, and deep neural networks that specialize in analyzing sequential data provide promising solutions. Recurrent neural networks (RNNs) such as LSTM and GRU excel at time series and sequence processing tasks, making them an ideal choice for stock market price forecasting.

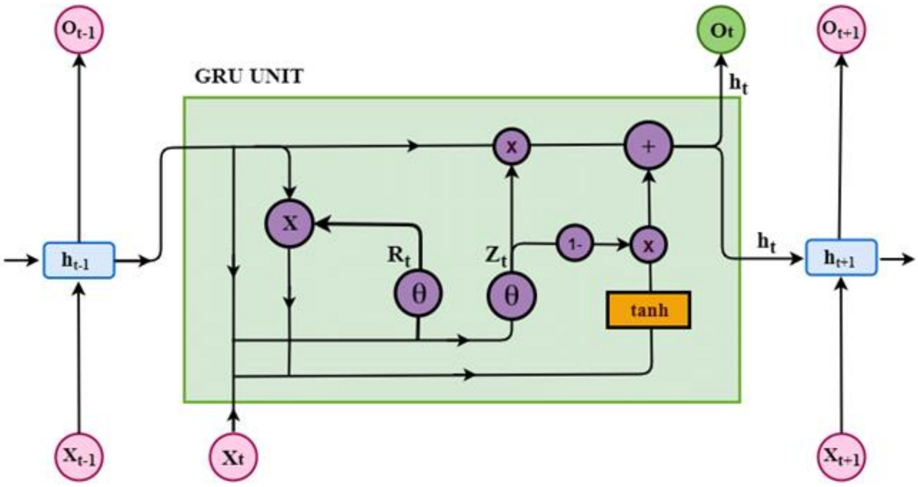


Figure 3. GRU architecture

3. RESULTS AND DISCUSSION

In this work, experiments were conducted with two different recurrent neural networks (RNNs): long short-term memory (LSTM) and gated recurrent units (GRU). The purpose of the work was to compare the learning process and the effectiveness of both models in predicting prices on the stock market. The models start with a 128-neuron layer that is capable of capturing dependencies in time series due to its ability to store information for long periods of time. The *return_sequences=True* option specifies that the next layer will also be an LSTM, GRU, and it requires the entire data sequence, not just the last output. The second LSTM, GRU layer contains 64 neurons and does not return sequences, which means it will only produce the latest output, which is suitable for passing data to a fully connected layer. Next comes a fully connected layer (Dense) with 25 neurons, which serves for additional data processing before the final output. The model is completed by an output fully connected layer with one neuron designed to predict the closing price of a stock, which is our target variable.

The model is compiled with the $'adam'$ optimizer, which is an efficient stochastic optimization method, and the $'mean\_squared\_error'$ loss function, which is often used in regression problems. The model is trained using the fit method, where x_train and y_train are the input and target data, respectively. $batch\_size = 1$ means that the model weights will be updated after each training example, making training more accurate but potentially more time-consuming. The $epochs = 5$ parameter specifies that the entire data set will be used to train the model ten times, allowing the model to better capture patterns in the data. Thus, we built and launched the process of training a neural network that is aimed at identifying complex patterns in data and is capable of predicting the future closing price of Apple shares.

In this work, experiments were conducted with two different recurrent neural networks (RNNs): long short-term memory (LSTM) and gate recurrent units (GRU). The purpose of the work was to compare the learning process and the effectiveness of both models in predicting prices on the stock market. Training for the LSTM model. The LSTM model was trained for five epochs. Figure 4 shows the training graph of the LSTM model. During training, there was a stable trend of improving the accuracy of the model with each epoch. The initial accuracy was 96.03%, which indicates the high predictive ability of the model already at the initial stages of training. As the epochs passed, the accuracy increased, reaching 99.39% in the fifth epoch. This indicates a high adaptation of the model to the training data set as shown in Figure 4.

Analysis of the training process of an LSTM model based on the presented data allows us to evaluate its effectiveness and ability to adapt to training data. Over the course of five training epochs, there was an improvement not only in model accuracy, but also in loss metrics and mean absolute deviation. In the first epoch, the model achieved an accuracy of 96.03%, which indicates that even at the initial stage of training it already demonstrated a high ability to predict prices in the stock market. It should be noted that the accuracy of the model increased at each subsequent epoch, reaching a value of 99.39% by the fifth epoch. This consistent increase in accuracy indicates that the model continues to improve its predictive abilities with additional training. In parallel with the increase in accuracy, the loss function decreased with each epoch, which is another indicator of the success of training. At the fifth epoch, the loss function was 0.00054795. This means that the model was able to minimize forecast error and achieve a high level of accuracy in estimating stock market prices.

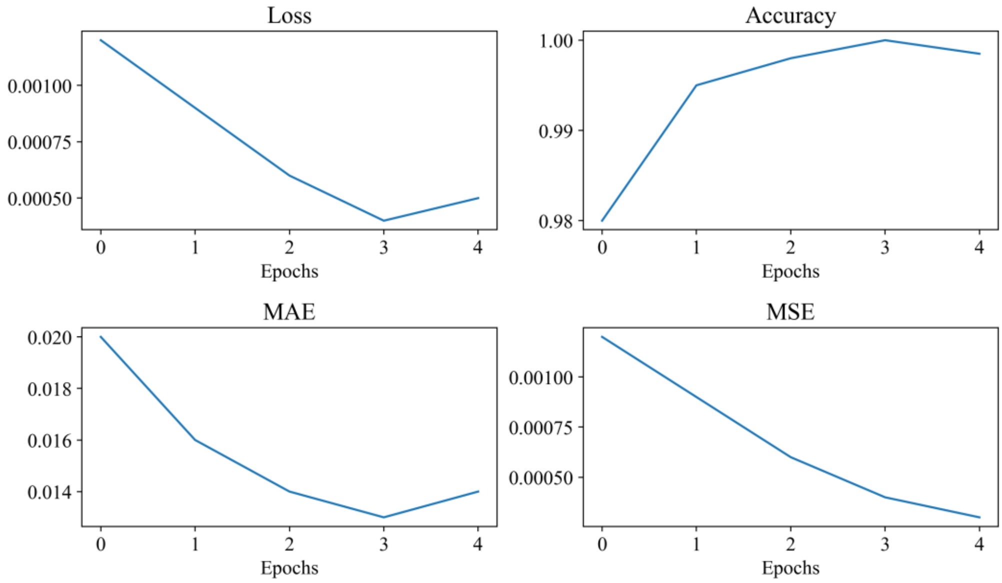


Figure 4. LSTM model training process

An important aspect of evaluating model performance is also the mean absolute deviation (MAE). This metric allows you to evaluate the average deviation of predicted values from actual values. At the fifth epoch, the LSTM model achieved an MAE of 0.0143, which also demonstrates its ability to make accurate predictions and minimize prediction errors. Additionally, it is important to note that the training process of the LSTM model was tracked using various metrics, including a custom accuracy metric (*custom_accuracy*). This metric is likely to take into account the specificity of the stock market price forecasting task and can provide greater insight into the model's performance in the context of financial data. Thus, in addition to standard loss metrics, the use of custom accuracy metrics allows you to get a more complete picture of the quality of forecasts. An important point is also the training time of the LSTM model at each epoch. Throughout the learning process, the time spent per epoch remained approximately the same, indicating the stability of the learning process. This is important to consider when planning to use the model in real-world scenarios where learning speed may be a critical factor. It is also worth noting that successful training of an LSTM model can be associated with the correct choice of hyperparameters, such as layer sizes, learning rate and number of epochs. This highlights the importance of carefully selecting model parameters to achieve optimal forecasting results.

The training results of the LSTM model shown in the data presented confirm its high efficiency and accuracy in predicting stock market prices. However, further testing on different datasets and use cases is required to fully understand its applicability and capabilities in real-world settings. Thus, the training results of the LSTM model indicate its high adaptability to training data and the ability to effectively predict prices in the stock market. Successful reduction of the loss function and achievement of high accuracy and MAE indicate high quality of forecasts, which makes this model promising for use in financial analytical tasks. The GRU model was also trained for five epochs. Figure 5 shows the training graph of the GRU model. As with LSTM, there was a trend of accuracy improving with each training epoch. By analyzing the training process of the GRU model based on the provided data, we can conclude that it is effective and adaptable to the training data set. The GRU model demonstrates high accuracy already in the initial stages of training, which is reflected in the accuracy of 98.56% in the first epoch. This indicator indicates the model's ability to make correct predictions in the early stages of training, which is an encouraging signal for its future effectiveness.

With each subsequent epoch, the accuracy of the GRU model continues to increase, reaching 99.88% by the fifth epoch. This trend indicates a continuous improvement in the model's ability to adapt to training data and prediction accuracy. In addition, by analyzing the loss function, you can see its consistent decrease with each training epoch. At the fifth epoch, the value of the loss function was 0.00027156, which indicates successful minimization of the prediction error and high accuracy of the model. The MAE also decreased with each epoch, reaching a value of 0.0110 at the last epoch. This indicates that the GRU model exhibits a stable and low error in forecasting stock market prices as shown in Figure 5.

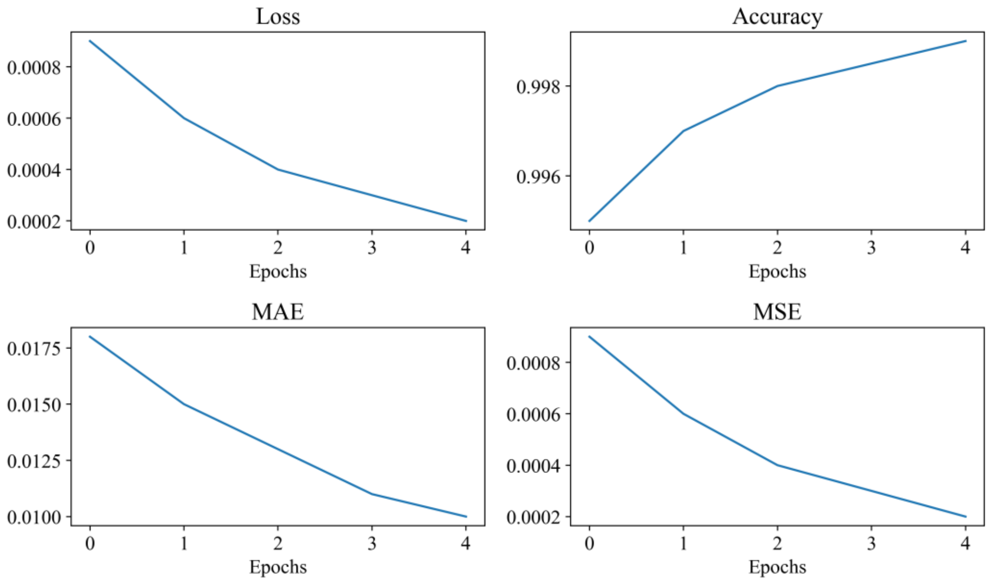


Figure 5. GRU model training process

Additionally, it is important to note the stability of the GRU model training time at each epoch. Throughout the training process, the time spent per epoch remained approximately the same, indicating that the training process was robust and that there were no anomalies that could affect its quality or stability. One of the important aspects is also the use of a custom accuracy metric (*custom_accuracy*), which probably takes into account the peculiarities of the problem of predicting prices on the stock market. This allows you to get a more complete picture of the quality of forecasts and evaluate the model taking into account the specifics of financial data. In addition, successful training of a GRU model can be attributed to the correct selection of hyperparameters such as layer sizes, learning rate, and number of epochs. This highlights the importance of carefully selecting model parameters to achieve optimal forecasting results. The training results of the GRU model indicate its high efficiency and accuracy in predicting stock market prices. However, further testing on different data sets and use cases is required to fully understand its applicability and capabilities in real-world settings.

Comparing both models, it can be noted that both of them demonstrated high accuracy and efficiency in predicting prices in the stock market. However, the GRU model achieved slightly higher accuracy than the LSTM both at the beginning of training and at the end of the five epochs. It is also worth noting that both models showed similar trends in the change in loss function and mean absolute deviation during training. At the beginning of training, LSTM and GRU showed high accuracy, but the GRU model achieved slightly higher accuracy values compared to LSTM in both the first and subsequent epochs. This may be due to the more efficient GRU architecture, which allows the model to train faster and make more accurate predictions. However, the differences in accuracy between the models were negligible, indicating the overall success of both models in the task of predicting stock market prices. Comparing the trends of the loss function and the mean absolute deviation also reveals similarities in the performance of both models. They both showed a decrease in the loss function with each training epoch, indicating that both models were successful in reducing prediction errors and improving their accuracy. Additionally, the mean absolute deviation also decreased as both models were trained, indicating their ability to make more accurate predictions and improve prediction quality.

However, despite the similarities in performance, the choice between LSTM and GRU may depend on the specific data characteristics and task requirements. For example, if learning speed and computational efficiency are important, then GRU may be preferable due to its simpler architecture and fewer parameters. However, if the problem requires a model with longer-term memory and the ability to handle longer-term dependencies in the data, then LSTM may be a more suitable choice. In general, a comparative analysis of LSTM and GRU allows us to better understand their advantages and disadvantages, as well as select the most suitable model depending on the specific conditions of the problem. Future research could deepen this comparison and examine other aspects of the performance and applicability of both models in different scenarios. After analyzing and evaluating the criteria of the neural network model for predicting stock market prices, we move on to integrating the model into a real-world application to test the model and make predictions. Our first step is to download all the necessary data from the Yahoo Finance server. Yahoo Finance is one of the most popular sources of financial data in the world, the server or site can be seen in Figure 6. It provides a wide range of financial information, including historical stock price data, company financial reports, news and market analysis. Yahoo Finance allows users to access timely and reliable data to conduct market analysis, make investment decisions and create forecasts.

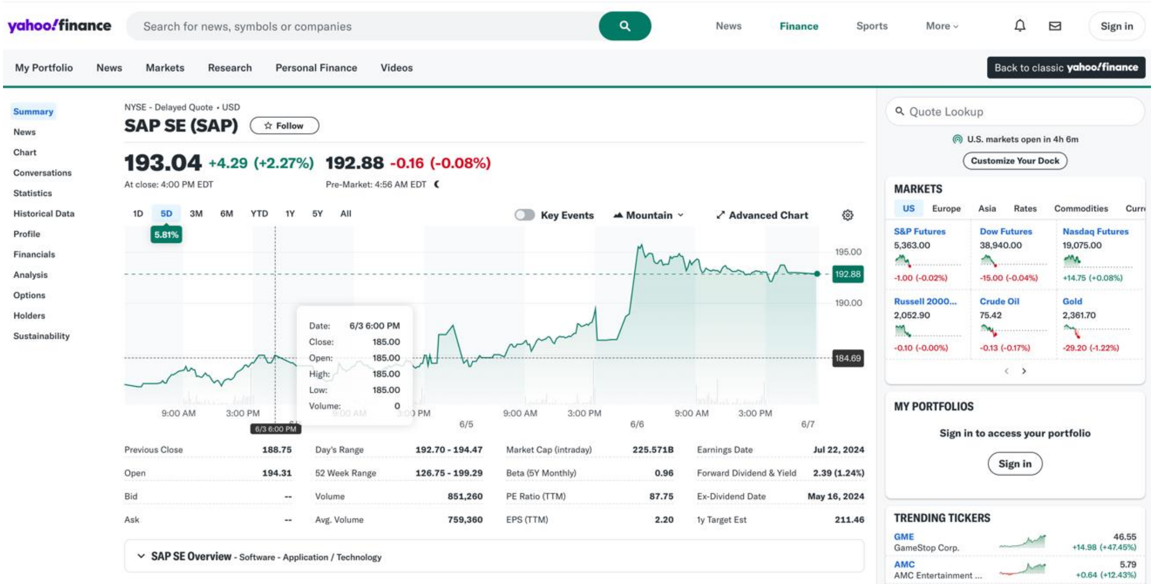


Figure 6. Yahoo finance main server

To efficiently load data from the Yahoo Finance server into our program, we resort to using the yfinance library, which provides a convenient interface for obtaining financial data directly from the source. In the process of downloading data, we follow several steps: starting with installing the yfinance library, then importing it into the program and using the download () function to obtain historical data on the stock prices of the selected company during the specified time period. This data, represented as a DataFrame object, becomes the basis for further analysis, visualization and forecasting of stock prices. The program, developed using the PyQt5 libraries for creating a graphical user interface (GUI) and the Keras library for implementing neural networks, provides users with a convenient tool for analyzing and predicting stock market prices. The main functionality of the program includes selecting a company from a provided list, such as "AAPL" (Apple), "GOOGL" (Google) and "MSFT" (Microsoft), as well as defining the time period of the analysis by specifying the start and end dates. The user interface as shown in Figure 7, ensures simplicity and intuitive accessibility, making the program an effective tool for investors, traders and analysts, allowing them to make informed investment decisions based on analysis of market dynamics.

To evaluate the quality of the neural network, the user can click the “Validation” button. The program validates the model using historical data, which allows you to evaluate the accuracy of forecasts and the quality of modeling. After predicting stock prices using a neural network, the user can evaluate the quality of the model by clicking the “Validation” button. This step is important to check the accuracy of the forecasts and the quality of the simulation, and the result can be seen in Figure 8.

During the model validation process, the program analyzes the predicted values of stock prices for a certain time period, comparing them with actual data. This step allows you to evaluate the accuracy of the model in predicting future values and its consistency with real changes in the market. The graph presented after validation shows three lines: the blue line represents the historical data for the last 60 days, used for training and forecasting; the next line is a forecast based on the analysis of time patterns; and finally, a validation line reflecting actual price values over the last 10 days. Although the differences are minimal, the shape of the forecast graph is consistent with historical data, indicating that the model successfully accounts for time dependencies and changes in the stock market. The program has a number of key advantages, including ease of use, high accuracy of forecasts and the ability to visually evaluate results. These characteristics make it a valuable tool for both experienced traders and investors, as well as for beginners interested in the stock market. Overall, the program presents itself as a useful asset for analyzing financial data and making informed decisions in the market, combining innovative forecasting methods with a userfriendly interface, making it accessible and useful to a wide range of users in the field of investing and trading in the stock markets.

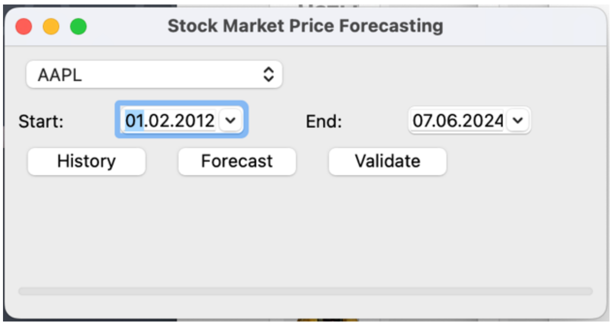


Figure 7. Interface with main elements for setting parameters

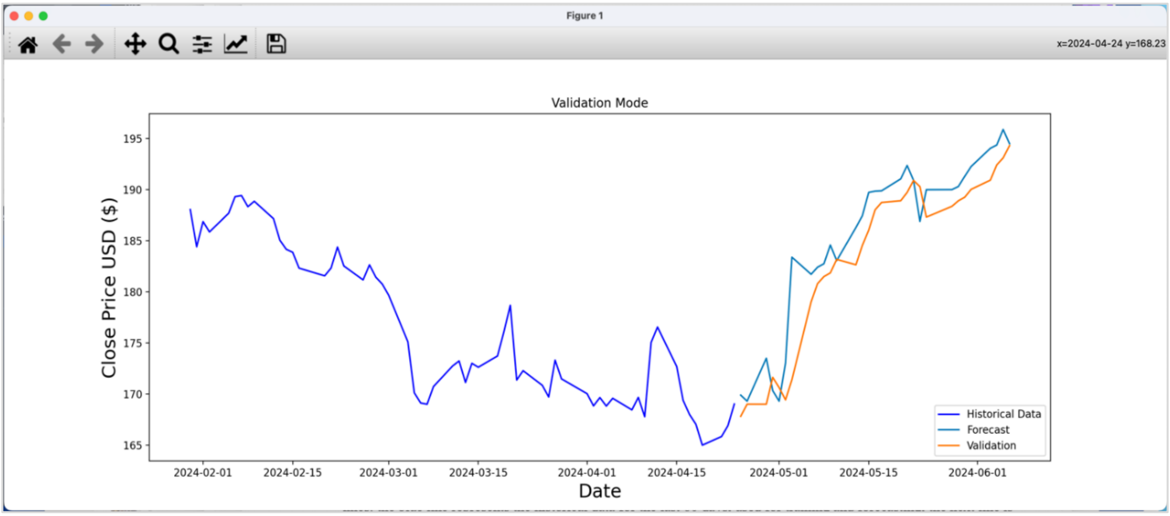


Figure 8. Displaying the validation graph

4. CONCLUSION

In this research paper, we have studied in detail the modern problem of predicting prices in the stock market in the context of rapid dynamic development and abundance of data, using machine learning and deep learning algorithms. Traditional methods of analysis have proven to be insufficient for modern financial markets, which highlights the need to develop more effective strategies, which has become our main goal. By exploring financial market analysis, evaluating forecasting methods, and applying recurrent neural networks such as LSTM and GRU, we aimed to provide innovative approaches to the problem of price forecasting, thereby improving the quality of investment decisions. Our experiments with LSTM and GRU models for stock price forecasting showed high accuracy and adaptability to changing market conditions. Both models effectively captured time dependencies in financial data, providing reliable forecasts that can significantly help investors and analysts. The LSTM model achieved an initial accuracy of 96.03%, which increased to 99.39% after five training epochs, indicating its high ability to learn and predict stock prices with minimal error. Similarly, the GRU model started with an accuracy of 98.56% and reached 99.88% by the fifth epoch, demonstrating its efficiency and slightly better performance compared to LSTM.

Software developed based on these methods offers a powerful tool for investors and analysts, providing detailed analytics and the ability to make informed decisions. This tool integrates historical stock price data, macroeconomic indicators and technical indicators, presenting a holistic approach to stock market forecasting. The use of deep learning architectures such as LSTM and GRU highlights their effectiveness in adapting to complex data dependencies and their superior performance in financial time series forecasting. Our research highlights the potential of deep learning algorithms to improve the accuracy and reliability of stock market forecasts. The results show that both LSTM and GRU are highly effective in predicting stock prices, with GRU having a slight performance advantage. However, the choice between these models may depend on the specific characteristics of the data and the requirements of the task. Future research can explore further improvements to model architectures, hyperparameter optimization, and real-world applications to fully realize the potential of deep learning in financial forecasting.

In conclusion, our work contributes to the field of financial analysis and investment strategies by providing advanced tools and techniques for stock market forecasting. The integration of machines and deep learning techniques opens up new opportunities to improve investment strategies and portfolio management, enabling more informed and strategic decision making in the dynamic environment of financial markets. This research lays the foundation for the continuous improvement of financial forecasting to improve accuracy, efficiency, and real-world applicability.

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