FORECASTING MARKET VOLATILITY USING AI AND ML MODELS

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Abstract
The article analyzes the application of artificial intelligence (AI) models for forecasting market volatility (MV). Examples of algorithms such as recurrent neural networks (RNN), long short-term memory (LSTM) networks, and regression methods are studied, demonstrating their effectiveness in processing time series and identifying complex data patterns. The importance of integrating machine learning (ML), as a class of AI methods, is emphasized for improving prediction accuracy and adapting to rapidly changing market conditions. The article also examines the advantages and limitations of using AI in financial analytics, including process automation, increased data processing speed, and challenges related to model interpretation.
Keywords: artificial intelligence (AI), machine learning (ML), volatility, forecasting, neural networks, financial markets, data analysis.

Introduction

Market volatility (MV) is a significant indicator reflecting the degree of fluctuations in the prices of financial assets over a certain period of time. It is important for risk assessment and the development of investment management strategies. High volatility indicates instability and increased market risks, whereas low volatility is associated with predictability and price stability. For financial market participants, accurate volatility forecasting is necessary for effective portfolio management, hedging and informed decision-making.

Traditional approaches to volatility forecasting, such as autoregression models with conditional heteroscedasticity and their modifications, are widely used to analyze historical data. However, they have their limitations, including assumptions about linearity and lack of flexibility in the face of sudden market changes. Given the current complexity and speed of changes in global financial markets, these methods are often insufficient to obtain accurate forecasts.

In recent years, artificial intelligence (AI) and machine learning (ML) models have attracted considerable attention due to their ability to analyze complex data and identify hidden patterns. These methods provide adaptability and the ability to work with large amounts of data, which allows them to surpass traditional approaches in predicting temporal and nonlinear dependencies.

The purpose of this article is to analyze the application of AI and ML models to predict MV, evaluate their advantages and disadvantages, and compare them with traditional methods. The article discusses the theoretical foundations of these approaches and examples of practical use.

The main part. An overview of traditional volatility forecasting methods

Volatility ratings are used to assess the degree of price volatility in financial markets. They reflect how quickly and significantly asset prices change over a certain period of time. Such ratings help investors and analysts assess the risks associated with investments and develop appropriate asset management strategies. They also serve as an indicator of instability in the markets and can be used to predict future fluctuations [1]. Various financial institutions and analytical companies develop their own methodologies and scales for determining and comparing volatility levels in various markets, which provides a comprehensive understanding of current economic conditions and helps to make informed decisions. For example, Figure 1 shows the USA MV rating according to the Cboe Volatility Index (VIX).

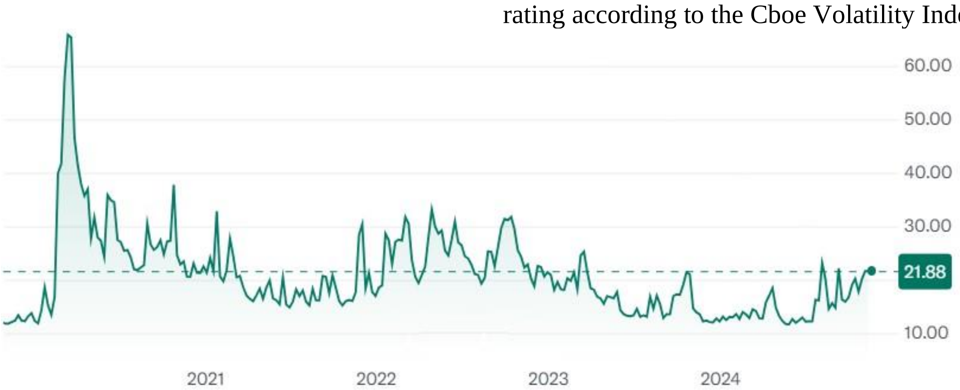

Figure 1. USA market volatility, %

Forecasting the volatility of financial markets for many years has been based on the use of traditional statistical methods that provide analysts and researchers with reliable and time-tested tools. Such methods include autoregression models with **conditional heteroscedasticity** and its derivatives, which remain important tools for modeling time series and forecasting volatility dynamics.

The Autoregressive Conditional Heteroscedasticity (ARCH) models, proposed in the early 1980s, became one of the first approaches to take into account the variability of the time series variance. They are based on the assumption that the current variance depends on the squares of the model's past error values. However, ARCH models required a significant number of parameters when describing data, which limited their use for long-term forecasts and complicated interpretation.

In 1986, the **Generalized ARCH (GARCH)** model was developed, which significantly expanded the analysis capabilities. It takes into account both past error values and previous variance values, which makes the model more stable and economical in terms of the number of parameters. The GARCH model is widely used due to its ability to effectively predict volatility in financial time series. However, its effectiveness decreases with sudden changes in the market, which is due to the limitations of the linear approach.

Over time, GARCH modifications have appeared, such as **EGARCH** (Exponential GARCH) and TGARCH (Threshold GARCH), which take into account the asymmetry in the distribution of volatility changes. These models help to take into account the phenomenon of the «leverage effect», when negative news has a greater impact on volatility compared to positive ones. EGARCH, for example, uses the logarithmic form of variance, which allows the model to be resistant to heteroscedasticity and take into account the asymmetric behavior of the market.

In addition to GARCH models, other statistical approaches are used in volatility forecasting, such as autoregressive integrated moving average (**ARIMA**) models and variations based on it. These methods provide flexibility in the analysis of stationary and non-stationary time series. ARIMA models can be useful for predicting short-term fluctuations, but with significant market changes and high volatility, they often turn out to be insufficiently accurate. Although traditional methods provide analysts with proven tools, they face a number of limitations (table 1).

Table 1.

Main characteristics and limitations of traditional volatility forecasting methods [2]

Method	Main characteristics	Main limitations
ARCH	Considers time series variance variability; depends on past errors.	Requires a significant number of parameters; difficult to use for long-term forecasts.
GARCH	Generalization of ARCH; takes into account both errors and previous variance values.	Sensitive to market regime changes; limited by the linear approach.
EGARCH	Exponential model that accounts for asymmetry in market reactions to news.	Complex interpretation; sensitive to parameter selection.
TGARCH	Model with a threshold value; considers leverage effect and asymmetry.	Limited applicability in cases of high volatility levels.
ARIMA	Used for stationary and non-stationary time series.	Limited accuracy in cases of high instability and non-linear data.

Modern challenges in financial markets require approaches that are able to adapt to complex and rapidly changing conditions. The limitations of traditional methods are pushing researchers to use more flexible and powerful tools, such as AI and ML algorithms, which are able to process large amounts of data and identify nonlinear dependencies.

The use of AI and ML for forecasting

The use of AI methods, including ML, to predict MV opens up new opportunities, significantly expanding traditional approaches. Modern ML algorithms demonstrate the ability to analyze large amounts of data and identify complex relationships, which makes them effective tools for financial modeling.

One of the most popular methods in forecasting is **linear and nonlinear regression**, which allows you to estimate the dependence between variables and make accurate predictions based on historical data (fig.2).

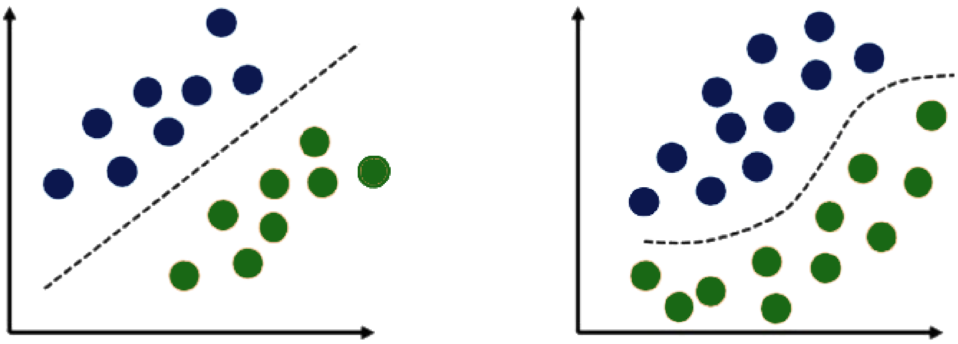

Figure 2. The scheme of linear and nonlinear regression

Regression algorithms can be used to build models that estimate the future behavior of volatility based on various factors, including macroeconomic indicators and market data. Regression models are often used in combination with more sophisticated methods to improve the accuracy of forecasts.

Decision trees and their improved versions, such as random forests and gradient boosting, are used for forecasting due to their ability to model nonlinear dependencies (fig.3).

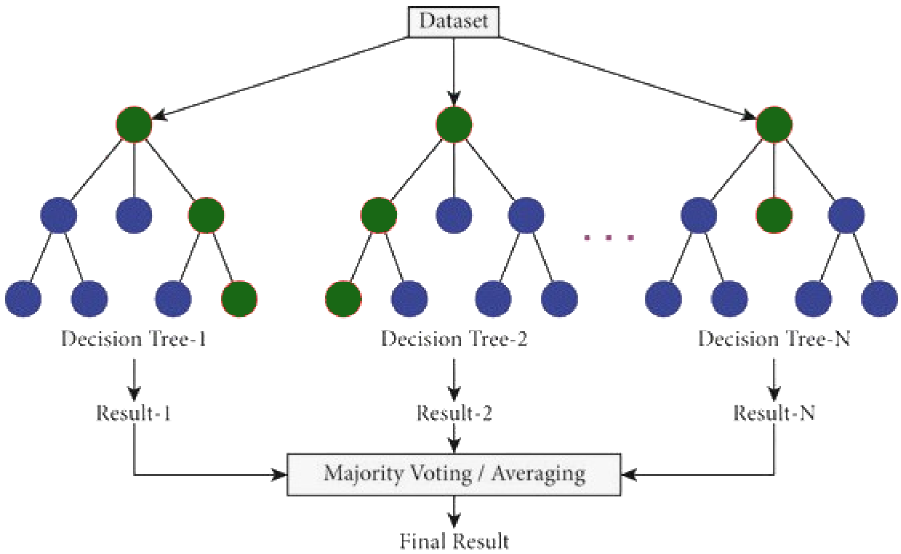

Figure 3. Diagram of decision trees

These algorithms have high interpretability and flexibility in processing data of different nature. Random forests build multiple decision trees and combine the results to produce a more stable forecast. Gradient boosting, in turn, consistently optimizes the model, improving accuracy through customizable learning stages.

Neural networks and deep learning have taken center stage in volatility forecasting due to their ability to learn complex and non-linear patterns. Multilayer perceptrons, which consist of several hidden layers, provide reliable tools for analyzing time series and predicting their behavior. However, such models require a large amount of data and computing resources for training. Deep neural networks can be used to create complex models that analyze the interactions of multiple factors affecting volatility.

Recurrent neural networks (RNN) and their improved versions, such as LSTM (Long Short-Term Memory), represent promising approaches for analyzing temporal data. RNN have built-in memory, which allows you to take into account previous states when predicting current values. This is especially useful in time series tasks where there is a relationship between successive observations. LSTM models solve the problem of fading gradients, which can occur in basic RNN, thanks to the built-in mechanisms of memorization and forgetting. Such networks demonstrate high accuracy in forecasting volatility, as they can take into account long-term dependencies and adapt to changing market conditions.

The specifics of using AI algorithms include the need to carefully configure hyperparameters and select the appropriate model architecture to ensure high accuracy of forecasts. ML requires extensive data to train and test models in order to avoid overfitting and ensure their generalizing ability. The integration of regularization methods such as dropout and L2 regularization helps to prevent overfitting and improve model performance.

Analysis of the advantages and disadvantages of using AI methods

AI technologies are able to take into account complex, non-linear relationships in data, which provides more accurate and adaptive forecasts. Nevertheless, the use of AI in financial analytics is associated with certain challenges and limitations that should be taken into account in order to achieve maximum efficiency (table 2).

Table 2.
Advantages and disadvantages of using AI methods to predict MV [3, 4]

Aspect	Advantages of AI methods	Disadvantages and challenges
Forecast accuracy	High accuracy due to the ability to analyze large amounts of data and identify hidden patterns.	Complexity in interpreting models; it can lead to a decrease in forecast reliability.
Adaptability	AI models can automatically adapt to changing conditions, ensuring accurate predictions.	High computational resource requirements; may not be suitable for all cases.
Data processing	Ability to analyze large data volumes and consider complex relationships between factors.	Data processing can be resource-intensive and time-consuming, especially for deep neural networks.
Process automation	AI automates the process of data analysis and forecasting, which improves responsiveness and reduces operational costs.	Models are often "black boxes" and difficult to interpret, reducing transparency.
Flexibility	Ability to work with non-linear and complex dependencies, making it useful for analyzing volatile markets.	Models may not provide stable results in case of insufficient training data and rapidly changing conditions.
Training settings	Models can be finely tuned to consider the statistical characteristics of risks and data.	The configuration and training process requires significant expertise and can increase implementation complexity.
Processing speed	Modern AI algorithms can quickly process data, speeding up decision-making processes.	High processing speed can lead to the need for specialized equipment, such as GPU and TPU.

The methods provide significant advantages in forecasting MV due to high accuracy, adaptability and the ability to analyze complex relationships. However, their use is subject to certain limitations, including the need for large amounts of data and the complexity of interpreting models. For the successful implementation of AI in financial models, it is important to take into account these challenges and develop strategies aimed at overcoming computational and analytical constraints.

Review of the practice of using AI in forecasting MV

In recent years, large American companies and financial institutions have been actively using AI methods to predict MV and other financial indicators. This approach provides not only higher accuracy of forecasts, but also adaptability to changes, which is critically important in conditions of high instability.

Investment banks, including **Goldman Sachs**, are actively investing in AI technologies to develop complex financial models. The Bank has implemented a number of initiatives aimed at using ML and deep neural networks to predict stock volatility and exchange rates. They included the introduction of analytical platforms capable of analyzing time series and correlations between assets, which allows for the rapid adaptation of hedging strategies [5]. The use of deep neural networks such as RNN and LSTM has helped Goldman Sachs improve its assessment of market risks and improve the accuracy of forecasts, reducing the likelihood of significant losses in the face of sudden market changes.

BlackRock, a large asset management company, also uses AI to analyze and predict MV. The Aladdin platform developed by this company includes the integration of ML methods to assess market risks and predict asset volatility. These algorithms help to analyze large amounts of market data, identify correlations and predict market behavior taking into account a variety of factors such as macroeconomic indicators and demand dynamics. One of the company's areas of work is to publish tips for investors on MV forecasts. For example, in July 2024, experts predicted a slowdown in economic growth against the background of an increase in the unemployment rate rose to 4.3%, and the average hourly wage by only 3,6%. Analysts also predict that AI will develop over the next 5-10 years, which can increase the profits of companies that spend significant funds on it today [6].

Fintech companies such as **Betterment** are also using AI to improve forecasts and provide more accurate recommendations to customers [7]. The use of ML algorithms allows these platforms to analyze historical data and current market conditions, predicting changes in volatility and helping clients adapt their investment strategies. Betterment uses AI technologies to automatically rebalance portfolios, minimize risks and increase profitability, especially during periods of instability. Such approaches give clients the opportunity to manage their assets more confidently, using personalized advice based on the analysis of a large amount of data and current market trends.

Stock market analytics companies, including **Bloomberg**, have also implemented AI to monitor and predict volatility. Bloomberg continues to develop its analytical platforms, such as Bloomberg Terminal, which use ML algorithms to process and analyze data in real time [8]. These technologies help traders and analysts track market fluctuations, predict spikes in volatility, and identify hidden trends.

Examples of American companies demonstrate that the use of AI methods to predict volatility in global markets significantly increases the effectiveness of analysis and reduces risks. AI helps to process large amounts of data, identify complex dependencies and adapt to changing conditions.

Conclusion

The use of AI models and ML methods to predict MV opens up new opportunities for financial institutions and companies, providing higher accuracy and adaptability compared to traditional methods. Modern algorithms allow us to take into account complex, nonlinear dependencies and analyze large amounts of data, which significantly improves the quality of forecasts and reduces the risk of uncertainty in a volatile market. The introduction of such technologies helps to improve asset management and allows for more effective development of hedging strategies that protect against unexpected market fluctuations.

Nevertheless, despite the obvious advantages, the use of AI in this field is associated with certain challenges, such as the need for significant computing resources, the complexity of interpreting models and the high need for qualified specialists. For successful implementation and use of AI models, it is important to take into account not only technical, but also organizational aspects, ensuring transparency of models and adaptability to rapidly changing conditions. These factors determine the need for an integrated approach, including constant updating and configuration of systems to maintain their relevance and high efficiency.

References

1. Dhingra B., Batra S., Aggarwal V., Yadav M., Kumar P. Stock market volatility: a systematic review // Journal of Modelling in Management. – 2024. – V. 19. – №. 3. – P. 925-952.

2. Bulut E. Market Volatility and Models for Forecasting Volatility // Business Continuity Management and Resilience: Theories, Models, and Processes. – IGI Global, 2024. – 2024. – P. 220-248.

3. Aluev A. Learning platforms for stock market trading: economic potential and growth opportunities // Trends in the development of science and education. – 2024. – №. 114(4). – P. 169-172.

4. Korostin O. Forecasting market trends in maritime shipping based on big data analysis // ISJ Theoretical & Applied Science. – 2024. – V. 137. – № 9. – P. 12-15.

5. Bian L. Harnessing the potential of ai to revolutionize productivity: unveiling opportunities and tackling challenges // Journal of productivity science. – 2024. – P. 12.

6. Navigating market volatility: Insights for investors / Blackrock // URL: https://www.blackrock.com/us/financial-professionals/insights/blackrock-volatility-summer-2024 (date of application: 21.10.2024).

7. Balaji K. Harnessing AI for Financial Innovations: Pioneering the Future of Financial Services // Modern Management Science Practices in the Age of AI. – IGI Global, 2024. – 2024. – P. 91-122.

8. Liu X., Wang X. Financial Market Volatility Forecasting and Volatility Adjustment Algorithm Combined with Time Series Analysis // Journal of Electrical Systems. – 2024. – V. 20. – №. 7s. – P. 3142-3157.