Hybrid Deep Learning and Econometric Models for Financial Market Forecasting: A Review of Emerging Approaches and Their Impact on Trend Prediction

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Abstract- Financial markets forecasting has been a challenge since it is difficult, due to nonlinearity and dynamism of financial data. Traditional econometric frameworks like ARIMA and GARCH are often widely used and regularly fail to capture complicated trends. Combination of deep learning technology with the econometric models which brings about hybrid models have also emerged as an effective approach to enhance forecast accuracy and strength. This literature review provides a very comprehensive analysis of the hybrid deep learning and econometric models to predict in the financial markets. We refer to various hybrid approaches that can be used, their applications, benefits, and challenges through this far-ranging study of recent studies. The findings prove that hybrid models can significantly improve predictive power because they can find both nonlinear and linear patterns. However, there are remaining opportunities to work on approaches to address the balancing of the concepts of model flexibility and interpretability, solving the causal inference and causal endogeneity problem, and effective combination of domain knowledge as the avenues of further research.

Keywords ARIMA, CNN, Deep Learning, Econometric Models, Financial Market Forecasting, GARCH, Hybrid Model, LSTM, Machine learning, Trend prediction.

I. INTRODUCTION

Financial markets, by definition, are volatile and every decision is determined by a great number of influencing factors, which include economic indicators, political events, technological advancement, and investor emotion (Ghosh et al., 2019). Globalization and rapidly spreading information have made the challenges of the market more challenging and have made proper forecasting more challenging, yet necessary as there is an attention to informed choices taken by investor, policy-makers, and financial institutions (Kaushik and Giri, 2020). The typical models currently used in the time- series forecasting, including Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH), have been found to be very important due to their statistical effectiveness and their ability to model the linear relationships (Pokou et al., 2024; Bulut and Hudaverdi, 2022). However, these models are also often faced with challenges regarding nonlinearities, non- stationarities and complex trends represented in financial data, and therefore limit the accuracy of their forecasting (Yan and Aasma, 2020).

The machine learning (ML) and deep learning (DL) algorithms have led to a technological change in a paradigm shift.

apple financial estimation processes. Such advanced computer techniques can approximate complex, nonlinear dynamics and find minute legizap and dependences among huge quantities of information (Zhong and Enke, 2019; He et al., 2023). Deep learning models, such as Long Short (LSTM) networks and Convolutional Neural Networks (CNN), are more adept at the time-series data and feature mining capabilities that traditional models cannot detect (Yan and Aasma, 2020, Chen, 2020). The integration of these models with other traditional methods of econometrics has led to the development of hybrid models aimed at riding the benefits of the two states, thereby enhancing the overall precision and stability of the predictions (Zhao and Chen, 2022; Araya et al, 2024).

The hybrid models combine the benefits of econometric models in the surface identification of linear-based correlations with the flexibility of deep learning models in addressing nonlinear trends (Ampountolas, 2023; Liu et al., 2023). That synergy has already proved itself in improving forecast accuracy in all sorts of financial uses, stock prices, exchange rates, commodity prices, and many more in particular (Guan and Gong, 2023; Iqbal et al., 2024). Despite all the potential benefits, such aspects as interpretability of the model, overfitting, and computing cost remain considerable problems (Liu et al., 2023; Boudri & El Bouhadi, 2024).

The purpose of the paper is to discuss the latest progress emerging in the field of hybrid deep learning and econometric models of forecasting the financial market. Analyzing a broad range of articles, we would like to identify the strategies that are used, assess how effective they are and highlight challenges and gaps in research of this young field. The purpose of this paper is to explain the practical use of hybrid models in forecasting the financial results as well as to suggest the future research directions with the aim to address the limitations existing today.

II. LITERATURE SURVEY

The integration of the world of the econometric model and the methodology of deep learning has become a subject of a significant number of focuses in recent years, with researchers trying to solve the drawbacks of the traditional approach to predictions and enhance the accuracy of the prediction. Other studies have proposed many studies.

hybrid methods that incorporate both benefits of both econometric and deep learning techniques to derive the complex, non-linear patterns of financial data.

Hybrid ARIMA Models

The extent to which ARIMA models are used in modeling data that is of time-series nature is due to the fact that it is effective in identifying linear patterns and trends in data. However, they do not allow them to manage major that are nonlinear, as well as sudden market dynamics. Researchers have overcome this problem and developed hybrid models which are a combination of ARIMA and machine learning algorithms. Pokou et al. (2024) proposed the hybrid one that reveals both the use of ARIMA and learning models such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) to make the prediction. Their results were more precise than individual ARIMA models. Ampountolas (2023) conducted a comparative study of machine learning, hybrid, and deep learning forecasting models in respect to the European financial markets and Bitcoin. According to the study, hybrid models are better as compared to traditional econometric approaches as they provide better forecasting accuracy and strength.

Hybrid GARCH Models

The GARCH models are good at volatility clustering and time-varying variance in the financial time series. However, and similar to ARIMA, they are faced with challenges of paying attention to nonlinearities and complex market dynamics. Its creation by Araya et al. (2024) provides a hybrid GARCH and deep learning system to enhance the volatility forecasting process or industry. This hybrid approach proved to be more effective in the representation of the volatility dynamics than their traditional GARCH models. Boudri and El Bouhadi (2024) applied econometric and deep learning tools to the data in order to learn and predict historic volatility in the two stock markets of Morocco and Bahrain. They found more favorable projections with hybrid models, and these reflected all the volatility trends in the market.

Deep Learning Integration

Econometric models combined with deep learning algorithms such as LSTM and CNN to understand the temporal associations and nonlinear properties of financial data have been trained incur machine learning. An interesting article by Yan and Aasma (2020) introduced the integration of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Long Short-Term Memory (LSTM) with a deep learning method to predict the time series in the financial domain. The hybrid model achieved high precision with the time series being decomposed into intrinsic mode functions and the nonlinear patterns being determined by applying LSTM networks. An example of how deep learning can be combined with other models can be seen in Jing et al. (2021), where the authors divide their model into two parts: deep learning and investor sentiment research to predict the prices of stocks, but also highlights the importance of adding external factors to the model, such as market sentiment.

Commodity markets Pagan intermediaries in commodity markets.

Commodity markets have exposed healthy examples of successful practice of using hybrid models whose price patterns are complex and contingent on a variety of factors. The model that Kristjanpoller (2024) has used comprised of hybrid econometric/machine learning and desktop analysis involving the determination of realized volatility of natural gas. It revealed that forecasting accuracy with the integration of machine learning methods with econometric models was better in comparison to conventional methods. Similarly, Alameer et al. (2020) presented a hybrid deep learning model that forecasts the future prices of coal in stages. Their model successfully coped with the complicated linear trends in commodity prices and even was out-performing traditional models used in forecasting.

Reflective issues in Literature.
In spite of the effectiveness of hybrid models, many constraints have been noted in literature. Ghosh et al. (2019) saw the limitations in explaining causal relations and predictive modeling at a nonlinear level in nonlinear dynamics and machine learning. Hybrid models may confound the process of result interpretation and result understanding of underlying processes. Alongside emphasizing the importance of models learned to handle high-dimensional data with interpretability, Vuong et al. (2024) state that future models need to be developed more to achieve a high level of transparency and explainability.

Comparison between Traditional Models.
Comparative research has been carried out into models of hybrid and conventional econometric and independent deep learning, with an aim to find out their relative effectiveness. Kaushik and Giri (2020) carried out a comparative study in the form of a multivariate analysis of the classical as well as the modern machine learning and deep learning approaches towards forecasting foreign exchange rates. Hybrid models were more effective with better and reliable tracks of forecasting than traditional models. This points out to the effectiveness of both methodologies when applied together toward better forecasting in the financial market.

Similar Metrics of Hybrid Modeling in Literature.
This comparative analysis of the selected studies on the effectiveness of hybrid models is provided in Table 1 with the focus on the goals, methods, measurement tools, and the main conclusions.

TABLE.1. COMPARATIVE ANALYSIS OF HYBRID MODELS IN FINANCIAL MARKET FORECASTING

Reference	Objective	Hybrid Methodology	Models Used	Evaluation Metrics	Key Findings
Pokou et al. (2024)	Forecast stock market time series	ARIMA + Machine Learning (SVM, ANN)	ARIMA, SVM, ANN	RMSE, MAE, MAPE	Hybrid model Improved forecasting accuracy over ARIMA alone
Ampountolas (2023)	Compare ML, hybrid, and DL models in forecasting	Comparative analysis	ML models, Hybrid models, DL models	MSE, Forecast Error, Accuracy	Hybrid models outperformed traditional and DL models
Araya et al. (2024)	Volatility prediction using hybrid GARCH and DL	GARCH + Deep Learning	GARCH, Deep Neural Networks	Volatility Forecast Error, RMSE	Hybrid model captured volatility dynamics more accurately
Boudri & El Bouhadi (2024)	Model and forecast historical volatility	Econometric + Deep Learning approaches	GARCH, LSTM	RMSE, MAE	Hybrid models provided superior volatility forecasts
Yan & Aasma (2020)	Predict financial time series with novel DL framework	CEEMDAN + LSTM	CEEMDAN, LSTM	RMSE, MAE, Directional Accuracy	High prediction accuracy achieved with hybrid framework
Jing et al. (2021)	Stock price prediction integrating DL and sentiment	Deep Learning + Investor Sentiment Analysis	LSTM, Sentiment Analysis Tools	MAPE, Accuracy	Incorporating sentiment improved stock price predictions

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Kristjan poller (2024)	Model realized volatility of natural gas	Econometrics + Machine Learning	Econometric models, ML algorithms	RMSE, MAE	Enhanced forecasting performance for natural gas volatility
Alameer et al. (2020)	Multistep-ahead forecasting of coal prices	Deep Learning Hybrid Model	LSTM, Other DL models	RMSE, MAPE	Effective multistep-ahead coal price forecasting
Kaushik & Giri (2020)	Forecast forex rates comparing econometric and ML	Econometric + ML + DL comparative analysis	VAR, ANN, LSTM	RMSE, MAE, MAPE	Hybrid models offered better performance than traditional models
Iqbal et al. (2024)	Accurate exchange rate prediction with hybrid DL	Novel Hybrid Deep Learning Method	LSTM, GRU	RMSE, MAPE, Accuracy	Improved accuracy and generalization in exchange rate prediction
Guan & Gong (2023)	Forecast monthly oil prices with new hybrid model	Stochastic Volatility Models + Deep Learning	Stochastic Models, DL algorithms	RMSE, MAE	Outperformed traditional methods in oil price forecasting
He et al. (2023)	Financial time series forecasting with DL ensemble	Deep Learning Ensemble Model	Multiple DL models (LSTM, CNN, etc.)	RMSE, MAPE, Accuracy	Improved forecasting accuracy using ensemble approach
Zheng et al. (2024)	Predict stocks and economic trends using ML	Machine Learning Time Series Analysis	ML algorithms (e.g., XGBoost)	RMSE, MAE, MAPE	Enhanced trend prediction capabilities

Note: *RMSE - Root Mean Square Error; MAE - Mean Absolute Error; MAPE - Mean Absolute Percentage Error; MSE - Mean Square Error; VAR - Vector Autoregression; ANN - Artificial Neural Network; SVM - Support Vector Machine; LSTM - Long Short-Term Memory; GRU - Gated Recurrent Unit; DL - Deep Learning; ML - Machine Learning; CEEMDAN - Complete Ensemble Empirical Mode Decomposition with Adaptive Noise.*

This comparison research demonstrates that hybrid models typically attain superior error metrics relative to standard models, signifying enhanced forecasting precision. The amalgamation of econometric and deep learning models facilitates superior identification of both linear and nonlinear trends in financial data. Research constantly demonstrates that hybrid models surpass their individual elements, indicating that the integration of econometric and deep learning methodologies is advantageous for forecasting in financial markets.

Furthermore, the assessment measures employed in these studies, including RMSE, MAE, and MAPE, furnish quantifiable evidence of the enhancements realized by hybrid models. Yan and Aasma (2020) documented substantial decreases in RMSE and

MAE when employing their hybrid CEEMDAN-LSTM model in contrast to conventional techniques. Araya et al. (2024) similarly proved that their hybrid GARCH and deep learning model produced reduced volatility forecast errors.

Key Insights from Comparative Metrics:

- Enhanced Precision: Hybrid models regularly demonstrate reduced RMSE and MAE values, signifying superior prediction accuracy.
- Improved Volatility Modelling: The integration of deep learning with GARCH models enhances the representation of volatility clustering and leptokurtosis in financial returns (Araya et al., 2024; Boudri & El Bouhadi, 2024).
- Enhanced Management of Nonlinearities: Hybrid methods proficiently encapsulate nonlinear linkages and intricate market dynamics that conventional econometric models may overlook (Yan & Aasma, 2020; Jing et al., 2021).
- Application Across Diverse Markets: The efficacy of hybrid models encompasses several financial markets, including stock indices, foreign exchange rates, and commodities prices (Kaushik & Giri, 2020; Guan & Gong, 2023).

III. CONCLUSION FROM COMPARATIVE ANALYSIS

The comparative measures indicate that hybrid models are a viable approach for enhancing financial market forecasting. By utilizing the advantages of both econometric and deep learning models, these hybrid methodologies mitigate the constraints present in each technique when employed alone. The improved precision and resilience of hybrid models render them indispensable instruments for professionals and scholars seeking to comprehend the intricacies of financial markets.

HYBRID DEEP LEARNING APPROACHES FOR ECONOMETRIC MODELS FOR FINANCIAL MARKET FORECASTING

Hybrid models integrate the statistical precision and clarity of econometric models with the robust pattern recognition and nonlinear modeling abilities of deep learning algorithms. This synergistic integration seeks to utilize the advantages of both approaches to improve forecasting precision in financial markets, which exhibit complex, nonlinear, and dynamic tendencies. This section examines diverse hybrid methodologies suggested and implemented in financial market forecasting, emphasizing the amalgamation of econometric models such as ARIMA, GARCH, and stochastic volatility models with deep learning techniques including LSTM and CNN.

A. Integration of ARIMA Models with Deep Learning Techniques

The Autoregressive Integrated Moving Average (ARIMA) model is essential in time-series research, adeptly identifying linear relationships and patterns in data. Nonetheless, its constraints in modeling nonlinear patterns and abrupt structural changes have prompted researchers to amalgamate it with machine learning and deep learning models to augment its predictive efficacy. Zhong and Enke (2019) introduced a hybrid model that integrates ARIMA with machine learning methods to forecast the daily return direction of the stock market. ARIMA was implemented to represent the linear components of the time series, whereas machine learning methods were leveraged to identify the nonlinear relationships and intricate patterns, leading to improved forecast accuracy.

Likewise, Pokou et al. (2024) integrated ARIMA with learning models, including Support Vector Machines (SVM) and Neural Networks, for stock market prediction. Their hybrid model surpassed both independent ARIMA and machine learning models, emphasizing the synergy between statistical and computational intelligence methodologies. This integration facilitated enhanced modeling of linear trends and nonlinear swings in stock prices, resulting in increased forecast accuracy.

Additionally, Botunac et al. (2024) enhanced conventional stock market tactics with a hybrid LSTM methodology. They combined ARIMA with Long Short-Term Memory (LSTM) networks to capture both short-term and long-term dependencies in the data. The ARIMA model captured linear components, whereas the LSTM network represented nonlinear temporal relationships, leading to enhanced forecasting accuracy and strategy refinement. This method illustrates the efficacy of integrating statistical models with deep learning architectures to overcome the restrictions present when utilized separately.

Furthermore, Kaushik and Giri (2020) performed a multivariate comparison analysis of traditional econometric models, modern machine learning, and deep learning techniques for predicting foreign exchange rates. Hybrid models that combine ARIMA with deep learning techniques shown superior performance compared to conventional models, yielding more precise and dependable forecasts. This evidence substantiates the idea that hybrid ARIMA models can proficiently encapsulate the intricate dynamics of financial time series through the integration of linear and nonlinear modeling skills.

B. Combining GARCH Models with Convolutional Neural Networks

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are crucial for predicting time-varying volatility and volatility clustering in financial data series. Nonetheless, they may encounter difficulties in capturing nonlinearities and intricate patterns within the volatility process. Combining GARCH models with deep learning methods, especially Convolutional Neural Networks (CNN), improves the model's capacity to identify spatial characteristics and nonlinear relationships in the data. Araya et al. (2024) devised a hybrid GARCH and deep learning approach, wherein GARCH models identified intrinsic volatility clustering, while CNNs discerned intricate nonlinear patterns. The hybrid model yielded enhanced volatility projections relative to conventional GARCH models, illustrating the efficacy of combining statistical and deep learning methodologies.

Bulut and Hudaverdi (2022) employed hybrid methodologies that integrate GARCH with machine learning techniques for forecasting financial time series. Their research indicated that the amalgamation of CNN and GARCH models enhanced forecasting precision for stock market applications. The CNN component proficiently captured nonlinear patterns and feature representations, hence improving the predictive performance of the hybrid model. Amirshahi and Lahmiri (2023) employed hybrid deep learning and GARCH-family models to predict cryptocurrency volatility. Their methodology adeptly encapsulated the pronounced volatility and nonlinear attributes of cryptocurrency markets, which are frequently difficult to model owing to their intrinsic instability and speculative tendencies. The hybrid model surpassed conventional GARCH models, demonstrating the advantages of integrating deep learning methodologies to manage intricate financial data.

C. Integration of Stochastic Volatility Models with Deep Learning

Stochastic volatility models incorporate random fluctuations in volatility across time, prevalent in financial

markets due to unforeseen events and market attitudes. Integrating these models with deep learning techniques improves their forecasting ability by capturing the stochastic character of volatility and intricate nonlinear interactions. Jing et al. (2021) combined deep learning with investor sentiment data and stochastic volatility models to forecast stock prices. The hybrid model adeptly encapsulated market dynamics shaped by investor activity, integrating quantitative data with qualitative sentiment analysis. This integration enabled the model to account for external factors influencing market volatility, resulting in enhanced prediction accuracy.

Guan and Gong (2023) introduced a novel hybrid deep learning model for forecasting monthly oil prices by combining stochastic volatility models with deep learning algorithms. Their model employed stochastic volatility models to account for the random variations in oil prices and deep learning approaches to represent nonlinear patterns and dependencies. The hybrid method surpassed conventional forecasting techniques in accurately representing the nonlinear and stochastic characteristics of oil prices, which are affected by several geopolitical and economic variables.

He et al. (2023) created a deep learning ensemble model that included stochastic volatility models for forecasting financial time series. The ensemble method integrated various deep learning models, including LSTM and CNN, with stochastic volatility models to capitalize on their respective advantages. The ensemble approach enhanced forecast accuracy and robustness by consolidating predictions from various models, adeptly managing the intricacies of financial time series data. This approach showed that combining stochastic volatility models with deep learning in an ensemble framework can improve forecasting accuracy by identifying varied patterns and minimizing model-specific biases.

In conclusion, hybrid deep learning methodologies for econometric models in financial market forecasting have demonstrated considerable potential in enhancing predictive accuracy and elucidating intricate market dynamics. Researchers have successfully combined traditional econometric models such as ARIMA, GARCH, and stochastic volatility models with advanced deep learning approaches to overcome the constraints inherent in each method when utilized in isolation. These hybrid models proficiently encapsulate both linear and nonlinear relationships, temporal dependencies, volatility patterns, and external factors such as investor sentiment. The efficacy of these methodologies highlights the promise of hybrid modeling in financial forecasting and indicates directions for future study to improve model performance and applicability across various financial markets and instruments.

IV. CHALLENGES AND RESEARCH GAP

Despite the advancements in hybrid models, several challenges and research gaps persist.

A. Balancing Flexibility and Interpretability

Hybrid models frequently compromise interpretability in favor of prediction efficacy. Boudri and El Bouhadi (2024) emphasized that the intricacy of hybrid models hampers practitioners' comprehension and trust in the outcomes. Liu et al. (2023) emphasized the necessity of integrating performance with interpretability, suggesting approaches to enhance the transparency of hybrid models. Cheng et al. (2021) tackled this problem by creating a hybrid deep learning model using explainable AI approaches, with the objective of reconciling accuracy and interpretability in stock market trend forecasting.

B. Addressing Causal Inference and Endogeneity

Financial data can exhibit endogeneity and misleading correlations. Ghosh et al. (2019) examined the difficulties in establishing causal linkages through nonlinear dynamics and machine learning methods. Frank and Owen (2024) investigated hybrid models that integrate machine learning with econometric methods, highlighting the necessity of addressing causal inference to enhance model reliability.

Kaushik and Giri (2020) emphasized that inadequate management of endogeneity could result in models reflecting erroneous relationships, hence compromising forecasting precision.

C. Incorporating Domain Knowledge Effectively

Incorporating domain expertise into hybrid models can improve their applicability and efficacy. Yan and Aasma (2020) proposed the integration of expert knowledge into model construction to enhance the prediction and analysis of financial time series. Mousapour Mamoudan et al. (2023) created hybrid neural network-based metaheuristics that use domain knowledge for predicting financial markets, resulting in enhanced forecasting of the world gold market. Zheng et al. (2024) highlighted the significance of employing machine learning time series analysis for forecasting financial enterprise stocks by integrating economic data patterns, demonstrating that domain expertise improves model efficacy.

Other Identified Gaps

- Data Quality and Preprocessing: Superior data is crucial for model precision. Vuong et al. (2024) emphasized the difficulties associated with managing noisy and partial data in stock price prediction.
- Computational Complexity: Deep learning models require significant computational resources. Alameer et al. (2020) addressed the necessity for efficient techniques to minimize computational expenses in hybrid models.
- Generalization Capability: It is essential for models to effectively generalize to previously unencountered data. Iqbal et al. (2024) introduced an innovative hybrid deep learning approach for exchange rate forecasting, emphasizing enhancement of generalization via model architecture.

CONCLUSION AND FUTURE WORK

Hybrid deep learning and econometric models signify a substantial progression in the forecasting of financial markets. Hybrid systems that integrate standard econometric models with deep learning techniques improve forecast accuracy and effectively capture intricate market dynamics.

Research indicates that hybrid models surpass

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standard models in multiple areas, such as stock price prediction, volatility assessment, and commodity forecasting. Nonetheless, issues such model interpretability, causal inference, and the incorporation of domain knowledge must be resolved.

Future research should concentrate on devising approaches to improve the interpretability of hybrid models, maybe utilizing explainable AI techniques. Enhancing causal inference and addressing endogeneity will augment model reliability. Moreover, integrating domain expertise and refining data pretreatment techniques will significantly augment forecasting efficacy.

As financial markets change, hybrid models will be essential for delivering precise and dependable projections, assisting investors and policymakers in their decision- making processes.

REFERENCES

[1] Ampountolas, A. (2023). *Comparative analysis of machine learning, hybrid, and deep learning forecasting models: evidence from European financial markets and bitcoins*. Forecasting, 5(2), 472-486.

[2] Zhao, Y., & Chen, Z. (2022). *Forecasting stock price movement: New evidence from a novel hybrid deep learning model*. Journal of Asian Business and Economic Studies, 29(2), 91-104.

[3] Pokou, F., Sadefo Kamdem, J., & Benhmad, F. (2024). *Hybridization of ARIMA with learning models for forecasting of stock market time series*. Computational Economics, 63(4), 1349-1399.

[4] Araya, H. T., Aduda, J., & Berhane, T. (2024). *A hybrid GARCH and deep learning method for volatility prediction*. Journal of Applied Mathematics, 2024(1), 6305525.

[5] Liu, S., Wu, K., Jiang, C., Huang, B., & Ma, D. (2023). *Financial time-series forecasting: Towards synergizing performance and interpretability within a hybrid machine learning approach*. arXiv preprint arXiv:2401.00534.

[6] Zhong, X., & Enke, D. (2019). *Predicting the daily return direction of the stock market using hybrid machine learning algorithms*. Financial Innovation, 5(1), 1-20.

[7] Bulut, C., & Hudaverdi, B. (2022). *Hybrid approaches in financial time series forecasting: A stock market application*. Ekoist Journal of Econometrics and Statistics, (37), 53-68.

[8] Jing, N., Wu, Z., & Wang, H. (2021). *A hybrid model integrating deep learning with investor sentiment analysis for stock price prediction*. Expert Systems with Applications, 178, 115019.

[9] Boudri, I., & El Bouhadi, A. (2024). *Modeling and forecasting historical volatility using econometric and deep learning approaches: Evidence from the Moroccan and Bahraini stock markets*. Journal of Risk and Financial Management, 17(7), 300.

[10] Kristjanpoller, W. (2024). *A hybrid econometrics and machine learning based modeling of realized volatility of natural gas*. Financial Innovation, 10(1), 45.

[11] Yan, B., & Aasma, M. (2020). *A novel deep learning framework: Prediction and analysis of financial time series using CEEMD and LSTM*. Expert Systems with Applications, 159, 113609.

[12] Foroutan, P. (2024). *Essays on examining financial markets' dynamics and forecasting by deep learning and econometrics models* (Doctoral dissertation, Concordia University).

[13] Li, W., & Becker, D. M. (2021). *Day-ahead electricity price prediction applying hybrid models of LSTM-based deep learning methods and feature selection algorithms under consideration of market coupling*. Energy, 237, 121543.

[14] Iqbal, F., Koutmos, D., Ahmed, E. A., & Al-Essa, L. M. (2024). *A novel hybrid deep learning method for accurate exchange rate prediction*. Risks, 12(9), 139.

[15] Ebadati, O. M., & Mortazavi, M. (2018). *An efficient hybrid machine learning method for time series stock market forecasting*. Neural Network World, (1).

[16] Mohanty, D. K., Parida, A. K., & Khuntia, S. S. (2021). *Financial market prediction under deep learning framework using autoencoder and kernel extreme learning machine*. Applied Soft Computing, 99, 106898.

[17] Ghosh, I., Jana, R. K., & Sanyal, M. K. (2019). *Analysis of temporal pattern, causal interaction and predictive modeling of financial markets using nonlinear dynamics,*

econometric models and machine learning algorithms. Applied Soft Computing, 82, 105553.

[18] Frank, L., & Owen, J. (2024). *Hybrid models combining machine learning and econometric techniques*.

[19] Amirshahi, B., & Lahmiri, S. (2023). *Hybrid deep learning and GARCH-family models for forecasting volatility of cryptocurrencies*. Machine Learning with Applications, 12, 100465.

[20] Cheng, L. C., Lin, W. S., & Lien, Y. H. (2021). *A hybrid deep learning model for predicting stock market trend prediction*. International Journal of Information & Management Sciences, 32(2).

[21] Guan, K., & Gong, X. (2023). *A new hybrid deep learning model for monthly oil prices forecasting*. Energy Economics, 128, 107136.

[22] Mousapour Mamoudan, M., Ostadi, A., Pourkhodabakhsh, N., Fathollahi-Fard, A. M., & Soleimani, F. (2023). *Hybrid neural network-based metaheuristics for prediction of financial markets: A case study on global gold market*. Journal of Computational Design and Engineering, 10(3), 1110-1125.

[23] Ozupek, O., Yilmaz, R., Ghasemkhani, B., Birant, D., & Kut, R. A. (2024). *A novel hybrid model (EMD-TI-LSTM) for enhanced financial forecasting with machine learning*. Mathematics, 12(17), 2794.

[24] Valova, I., Gueorguieva, N., Aayushi, T., Nikitha, P., & Mohamed, H. (2023). *Hybrid deep learning architectures for stock market prediction*. In Proceedings of the World Congress on Electrical Engineering and Computer Systems and Science (pp. 1-8).

[25] Chen, Q., Zhang, W., & Lou, Y. (2020). *Forecasting stock prices using a hybrid deep learning model integrating attention mechanism, multi-layer perceptron, and bidirectional long- short term memory neural network*. IEEE Access, 8, 117365- 117376.

[26] Vuong, P. H., Phu, L. H., Van Nguyen, T. H., Duy, L. N., Bao, P. T., & Trinh, T. D. (2024). *A bibliometric literature review of stock price forecasting: From statistical model to deep learning approach*. Science Progress, 107(1), 00368504241236557.

[27] Ren, S., Wang, X., Zhou, X., & Zhou, Y. (2023). *A novel hybrid model for stock price forecasting integrating encoder forest and informer*. Expert Systems with Applications, 234, 121080.

[28] Yinka-Banjo, C., Akinyemi, M., & Er-rabbany, B. (2023). *Stock market prediction using a hybrid of deep learning models*. International Journal of Financial Studies, Economics and Management, 2(2), 1-16.

[29] Sabbaghi Lalimi, A. H., & Damavandi, H. (2020). *Using machine learning methods in the financial market for technical analysis based on hybrid models*. SRPH Journal of Applied Management and Agile Organisation, 2(4), 1-11.

[30] Akioyamen, P., Tang, Y. Z., & Hussien, H. (2020, October). *A hybrid learning approach to detecting regime switches in financial markets*. In Proceedings of the First ACM International Conference on AI in Finance (pp. 1-7).

[31] Kaushik, M., & Giri, A. K. (2020). *Forecasting foreign exchange rate: A multivariate comparative analysis between traditional econometric, contemporary machine learning & deep learning techniques*. arXiv preprint arXiv:2002.10247.

[32] Alameer, Z., Fathalla, A., Li, K., Ye, H., & Jianhua, Z. (2020). *Multistep-ahead forecasting of coal prices using a hybrid deep learning model*. Resources Policy, 65, 101588.

[33] Botunac, I., Bosna, J., & Matetić, M. (2024). *Optimization of traditional stock market strategies using the LSTM hybrid approach*. Information, 15(3), 136.

[34] He, K., Yang, Q., Ji, L., Pan, J., & Zou, Y. (2023). *Financial time series forecasting with the deep learning ensemble model*. Mathematics, 11(4), 1054.

[35] Zheng, H., Wu, J., Song, R., Guo, L., & Xu, Z. (2024). *Predicting financial enterprise stocks and economic data trends using machine learning time series analysis*.