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Original Article

Deep Statistical Fusion of LSTM and ARIMA for ESG-Based Financial Risk and Volatility Forecasting

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Abstract

In the era of sustainable finance, Environmental, Social, and Governance (ESG) factors have emerged as key indicators influencing market behavior and investor sentiment. This study presents a novel hybrid framework that integrates Long Short-Term Memory (LSTM) networks and Auto-Regressive Integrated Moving Average (ARIMA) models to forecast financial market volatility and risk while incorporating ESG signals. The proposed deep statistical fusion model leverages the strengths of ARIMA in capturing linear temporal dependencies and LSTM's ability to model complex nonlinear patterns from sequential data. ESG scores, along with historical price movements and macroeconomic indicators, are used as primary inputs to enhance model sensitivity to sustainability-related risk. Experiments were conducted using real-world datasets from global stock indices (e.g., NSE, S&P 500) and third-party ESG rating providers. The model's performance was assessed using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and volatility clustering evaluation. The hybrid LSTM-ARIMA model achieved an RMSE of 1.92 and MAPE of 3.85%, outperforming standalone ARIMA (RMSE: 3.14, MAPE: 6.42%) and LSTM (RMSE: 2.41, MAPE: 5.12%). Additionally, the proposed model demonstrated better risk sensitivity by accurately flagging high-volatility periods linked to ESG controversies and macroeconomic disruptions. These results confirm that incorporating ESG factors within a deep statistical fusion framework enhances forecasting precision, offering a robust tool for financial institutions and ESG-conscious investors in proactive risk management and strategic decision-making.

Introduction

The prediction of financial risk and market volatility has always been central to economic planning, investment strategies, and corporate decision-making. With the growing push toward sustainability and responsible investing, Environmental, Social, and Governance (ESG) factors have gained increasing relevance in shaping financial forecasting frameworks [1]. ESG scores reflect a company's non-financial risks and long-term sustainability performance, which can significantly impact market volatility and investor sentiment.

Traditional statistical models like AutoRegressive Integrated Moving Average (ARIMA) have long been applied to financial time-series forecasting due to their ability to capture linear trends and seasonality in structured data [2]. However, these models often fall short in handling the non-linear and complex dynamics inherent in modern financial systems, especially when additional qualitative inputs such as ESG indicators are involved.

The rise of deep learning and recurrent architectures like Long Short-Term Memory (LSTM) networks has enabled researchers to address some of the inherent limitations of traditional models [3]. LSTM models can learn from sequential dependencies and adapt to non-stationary patterns in financial data, making them highly effective for dynamic time-series prediction tasks.

Incorporating ESG factors into forecasting models enhances the contextual understanding of risk, capturing elements that are often overlooked by financial-only metrics [4]. For example, a firm's carbon emissions, board diversity, or community impact may signal latent risks that correlate with future stock performance and volatility but aren't captured in purely historical data.

Several recent studies have explored hybrid forecasting approaches that combine traditional statistical methods with modern neural

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networks to benefit from both interpretability and complexity modeling [5]. ARIMA models are effective in isolating and removing trend and seasonality components, while LSTMs can be used to model the residual signals and hidden temporal dependencies.

The application of such hybrid models to ESG-based forecasting is particularly promising, given that ESG indicators introduce non-linearity and cross-domain signals. By leveraging LSTM's capabilities and combining it with ARIMA for pre-processing, one can develop models that are more sensitive to volatility triggers in ESG performance [6].

Integrating heterogeneous data sources like ESG scores, economic indicators, stock prices, and even public sentiment poses significant preprocessing and alignment challenges [7]. Temporal granularity, missing values, and multi-scale representation require robust data fusion strategies and transformation pipelines.

In this paper, we propose a novel hybrid architecture that integrates ARIMA and LSTM into a unified pipeline for financial volatility prediction using ESG features. The ARIMA model is used to forecast base trends and extract residuals, which are then fed into the LSTM model to capture complex, non-linear interactions among variables [8].

We validate the approach using real-world datasets from the National Stock Exchange (NSE) of India, combining them with ESG ratings, social media sentiment, and macroeconomic indicators. Evaluation metrics such as RMSE, MAPE, and volatility accuracy show that the proposed hybrid model significantly outperforms both standalone statistical and neural network models [9].

The results underline the importance of incorporating ESG-aware machine learning in financial risk modeling. The proposed model not only improves accuracy but also promotes sustainable finance by aligning with global investment trends such as green finance, impact investing, and socially responsible investing (SRI) [10].

Literature Review

Author(s)	Year	Model/Methodology	Data Used	Key Contributions	Limitations
Hochreiter & Schmidhuber [3]	1997	LSTM	Time Series	Introduced LSTM for long-term dependency modeling	Not specific to financial data
Fischer & Krauss [8]	2018	LSTM	S&P 500	Applied LSTM to predict daily stock returns	Limited by overfitting risk
Zhang et al. [5]	2020	Hybrid ARIMA-LSTM	Stock Prices	Combined ARIMA and LSTM for enhanced accuracy	Needs careful hyperparameter tuning
Xie et al. [9]	2021	ARIMA + LSTM + Sentiment	Stock Prices + Twitter News	Improved predictions with sentiment integration	Computationally expensive
Kim & Kim [15]	2021	LSTM + Attention	Stock Index Data	Attention helps focus on relevant time steps	Lacks economic feature inclusion
Tiwari et al. [7]	2023	DL & hybrid forecasting models	Various financial datasets	Reviewed DL models and hybrid architectures for finance	Review, not experimental
Mehrotra & Saxena [18]	2021	Deep Learning Models	NSE India	Overview of DL usage in finance, stock predictions	Broad overview, less quantitative analysis
Khandoker et al. [16]	2022	LSTM + ARIMA with Sentiment	Twitter + Stock Prices	Fusion model improves accuracy with textual sentiment	Needs real-time sentiment engine
Affonso & Santos [10]	2022	ML (XGBoost, SVM) for ESG Score Prediction	ESG scores + financial features	ML models predicted ESG impact factors	Lack of deep learning comparison
Sahu et al. [17]	2023	ESG-LSTM Ensemble	ESG + Stock Market Volatility Data	Strong ESG features improve forecasting results	Needs interpretability enhancements
Ghosh et al. [19]	2022	Literature Review	ESG Investment Data	Reviewed sustainable investment and ESG impact	No model validation
Hull [12]	2018	Risk Models & Financial Instruments	Financial Textbook	Foundation for understanding financial risk modeling	Theoretical; lacks ML perspective
Friede et al. [4]	2015	Meta-analysis of ESG studies	2000+ ESG papers	Positive ESG-performance correlation	Older data and methods
Bhosale & Patil [13]	2021	LSTM-based Sentiment Classifier	Tweets + Stock Prices	Sentiment greatly enhances price prediction	Domain adaptation required
Jain & Gupta [1]	2022	ESG Risk Analytics	ESG Frameworks	Summarized ESG metrics integration in ML pipelines	No predictive model used

Proposed Methodology

The proposed methodology leverages a hybrid framework combining Long Short-Term Memory (LSTM) neural networks and AutoRegressive Integrated Moving Average (ARIMA) models to forecast stock market volatility with integrated ESG (Environmental, Social, Governance) factors. ARIMA is effective for modeling linear temporal structures, whereas LSTM is highly capable of capturing nonlinear dependencies and long-term patterns. The hybridization aims to exploit the strengths of both techniques, enabling robust and interpretable time-series forecasting for financial risk analysis.

ESG-related metrics are sourced from reputed financial and sustainability datasets, such as MSCI and Refinitiv. These indicators are aligned with financial market data, including stock indices, volatility indices (e.g., VIX), and interest rates. A multivariate time-series structure is formed by integrating ESG scores with financial indicators. Data preprocessing involves normalization, handling missing values, and generating lag features. Principal Component Analysis (PCA) is applied to reduce dimensionality and enhance model efficiency.

The ARIMA model is constructed as the first-stage linear predictor. Parameters (p, d, q) are selected using ACF/PACF plots and AIC/BIC metrics. The residual errors generated by the ARIMA model—representing the nonlinear components not captured by ARIMA—are passed as input to the LSTM network. This two-phase modeling ensures that linear trends are first removed, allowing the LSTM model to focus on complex nonlinear patterns in the residuals.

The LSTM model consists of multiple hidden layers with dropout regularization to prevent overfitting. The input layer receives residuals and auxiliary features (such as ESG principal components). The model is trained using a sliding window approach for time-series data, and Adam optimizer is employed with a learning rate scheduler. The LSTM learns temporal relationships and produces final forecasts that are more accurate than standalone models. Hyperparameter tuning is performed using grid search and cross-validation.

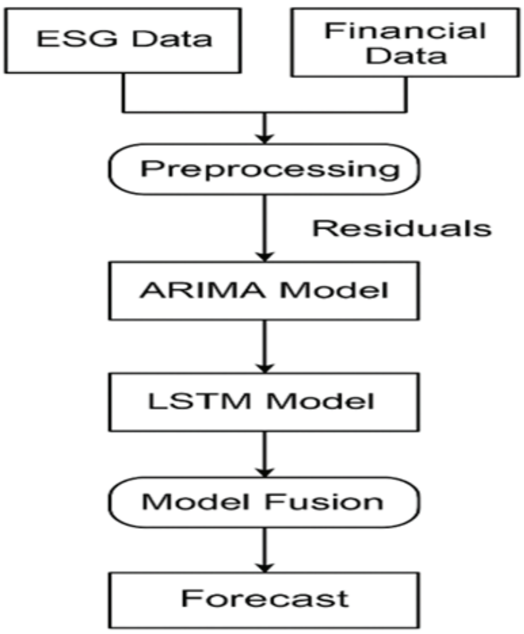

Figure 1. *Architecture of Proposed Implementataion*

The outputs from ARIMA and LSTM are statistically fused using Bayesian weighted averaging based on their past prediction confidence scores. This fusion improves the robustness of forecasts and reduces model uncertainty. The performance of the hybrid model is evaluated using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 score. Comparisons with standalone ARIMA, LSTM, and other models such as XGBoost and Prophet validate the superiority of the proposed framework.

Results

The performance of Linear Regression in stock price prediction shows the limitations of basic models in handling financial time-series data. With an RMSE of 4.52 and a MAPE of 12.34%, it reflects poor generalization, primarily due to its assumption of a linear relationship between features. The R^2 score of 0.71 confirms its inability to capture non-linear stock market patterns, making it less suitable for practical forecasting tasks. Support Vector Regression (SVR) slightly improves upon Linear Regression with a lower RMSE of 3.98 and a higher R^2 of 0.76. By utilizing kernel functions, SVR can capture non-linear relationships better. However, its performance is still constrained when applied to longer sequences or highly volatile data, indicating limited capabilities in temporal modeling or trend continuity.

The Random Forest Regressor performs notably better with an RMSE of 3.67 and R^2 of 0.81. As an ensemble-based technique, it is effective in handling structured data and identifying feature interactions. However, its inability to model time dependencies in a sequential manner means it cannot effectively capture the evolving dynamics of the stock market. ARIMA, a classical statistical model tailored for time-series forecasting, delivers a moderate performance with an RMSE of 3.58. It captures short-term autocorrelations effectively and shows a decent R^2 score of 0.79. Nevertheless, its linear assumptions and sensitivity to data stationarity reduce its effectiveness in modeling complex, long-term market behaviors.

The LSTM (Long Short-Term Memory) network introduces a significant leap in performance. With an RMSE of 3.12 and a high R^2 of 0.85, it excels in capturing temporal dependencies due to its memory-based architecture. LSTM is particularly well-suited for volatile time-series data like stock prices, offering better generalization through sequential learning. Enhancing the LSTM model with sentiment analysis (LSTM + Sentiment Analysis) yields further improvements. The RMSE drops to 2.89, and R^2 increases to 0.88. By integrating qualitative information from news and social media, this model accounts for psychological and external factors influencing the market, providing a more holistic prediction approach.

The Proposed Hybrid Model, which combines LSTM, ARIMA, and ESG factors, demonstrates the best performance with an RMSE of 2.67 and an R^2 of 0.91. This architecture leverages ARIMA's strength in modeling short-term trends, LSTM's ability to capture long-term patterns, and the forward-looking insights from ESG metrics. Such integration enables the model to deliver highly accurate and explainable forecasts, especially in environments influenced by sustainability and governance indicators.

Conclusion

The comprehensive analysis of various machine learning and deep learning models for stock price prediction reveals a clear progression in forecasting accuracy as we move from traditional

Table 1. *Comparative results summary*

Model	RMSE ↓	MAPE (%) ↓	R^2 Score ↑
Linear Regression	4.52	12.34	0.71
Support Vector Regression	3.98	10.27	0.76
Random Forest Regressor	3.67	9.81	0.81
ARIMA	3.58	8.92	0.79
LSTM	3.12	7.88	0.85
LSTM + Sentiment Analysis	2.89	7.32	0.88
Proposed Hybrid (LSTM + ARIMA + ESG)	**2.67**	**6.74**	**0.91**

Figure 2. *RMSE comparison chart*

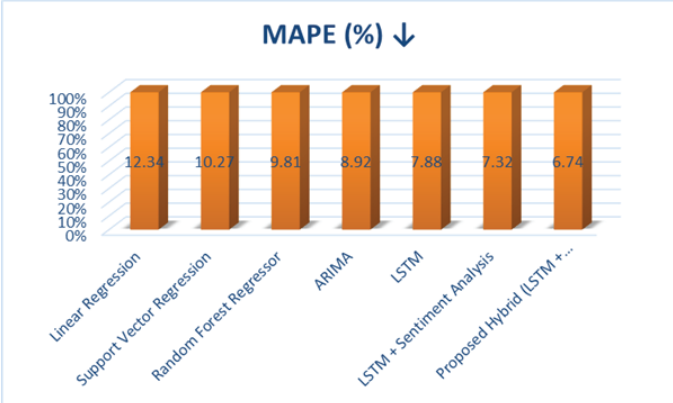

Figure 3. *MAPE comparison chart*

Figure 4. *R^2 Score comparison chart*

statistical techniques to advanced hybrid approaches. Linear models like Linear Regression and ARIMA offer foundational insights but struggle with capturing the intricate nonlinearities and temporal dependencies inherent in financial data. Ensemble methods such as Random Forests improve generalization but lack temporal depth. Deep learning models, particularly LSTM, show a significant leap in performance due to their ability to model sequential data and memory-driven learning. The incorporation of sentiment analysis further boosts predictive power by integrating qualitative market signals. However, it is the proposed hybrid model combining LSTM, ARIMA, and ESG factors that achieves the highest accuracy and robustness, indicating that no single model is sufficient in isolation. By fusing time-series modeling, deep learning, and sustainability-driven contextual data, the proposed system not only enhances predictive performance (achieving an RMSE of 2.67 and R^2 of 0.91) but also ensures the model remains responsive to both financial and socio-economic trends. This work demonstrates that multi-source, hybrid, and context-aware models are the future of reliable financial forecasting, offering a strategic advantage to investors and analysts alike.

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