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A Comparative Study of Deep Learning Models for ESG Index Volatility Prediction

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Abstract- The inclusion of Environmental, Social, and Governance (ESG) factors has achieved recognition in investment strategies, influencing market dynamics and investor behavior. However, predicting the volatility of ESG indices presents additional complexities due to heightened sensitivity to various external macroeconomic and geopolitical factors. This study develops an structured computational framework by utilizing deep learning architectures namely Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Convolutional Neural Network (CNN) to enhance ESG index volatility prediction. The models were rigorously evaluated using standard performance metrics and statistical validation through Welch's t-tests to ensure robustness and reliability of outcomes. Experimental results indicate that the GRU model achieved superior performance compared to both LSTM and CNN, while achieving superior accuracy and interpretability. These results provide meaningful insights for both investors and researchers looking for data-driven strategies for ESG market forecasting.

Keywords - ESG Investing, ESG Indices, Deep Learning, Volatility Prediction, Machine Learning

I. INTRODUCTION

In the rapidly evolving landscape of global financial markets, Environmental, Social, and Governance (ESG) investing has evolved as a transformative force, reshaping investment strategies and capital allocation decisions. ESG indices, which measures the performance of companies adhering to ESG principles, have gained significant importance among institutional and retail investors. These indices provide a benchmark for evaluating ESG-focused investments and serve as a key indicator of market sentiment toward sustainability-driven corporate practices. However, despite their growing relevance, ESG indices remain subject to market fluctuations and volatility, much like traditional financial indices. Understanding and forecasting ESG index volatility is crucial for risk management, portfolio optimization, and policy-making. Unlike conventional stock indices, ESG indices are impacted by a wide array of factors beyond financial and macroeconomic trends. External drivers such as regulatory changes, climate policies, social movements, and shifts in investor sentiment toward sustainability initiatives play a pivotal role in shaping their volatility. As ESG investing continues to evolve, developing robust strategies to navigate these complexities will be essential for investors seeking long- term, sustainable growth.

Over the past two decades, ESG investing has transitioned from a focused concept into a mainstream strategy, attracting trillions of dollars in assets under management. Institutional investors, pension funds, and asset managers are progressively considering ESG criteria into their investment decision-making, acknowledging the significant impact of sustainability factors on corporate performance and risk mitigation. Also, the regulatory frameworks worldwide are also evolving, with governments introducing and mandating ESG disclosures and sustainability reporting standards for corporations. Despite its increasing prominence, ESG investing presents distinct challenges, particularly in the context of market volatility.

While extensive body of research has explored ESG investing in developed countries like the Europe and United states, empirical studies on emerging economies particularly India remain limited. India's financial landscape offers a distinctive landscape for ESG investing shaped by its evolving sustainability regulations, increasing foreign institutional investment in ESG- focused funds, and the country's broader commitment to climate action and social responsibility. A key milestone in India's ESG journey is the mandate of Business Responsibility and Sustainability Reporting (BRSR) for the top 1,000 listed companies by Securities and exchange board of India (SEBI). This regulatory reform further enhances the structure and transparency of ESG disclosures, providing investors with more comprehensive sustainability data. As India strengthens its ESG framework, there is a growing need to examine how ESG aspects influence stock market performance, investor behaviour, and market volatility within this dynamic and rapidly developing financial environment.

The evolution of artificial intelligence (AI) and deep learning has revolutionized financial modelling, marking a transformative shift in financial modelling, redefining how market volatility is predicted. Traditional statistical models, which have long been employed for market volatility prediction, tends to face difficulties in capturing the complex, non-linear relationships that characterize ESG-driven indices. In contrast, deep learning models and Transformer-based architectures, have demonstrated exceptional proficiency in identifying complex patterns within vast amount of historical data. These models offer a more advanced and sophisticated approach to volatility forecasting, significantly enhancing predictive accuracy and offering valuable insights for investors and policymakers. As a subset of machine learning, deep learning has revolutionized the field of financial forecasting by enabling models to uncover intricate complex patterns, detect anomalies, and efficiently process vast volumes of time-series data with exceptional accuracy. Unlike conventional econometric models, deep learning algorithms operate without relying on predefined assumptions about market behavior. Instead, deep learning algorithms continuously adapt and self-learn from historical data. This flexibility makes them particularly appropriate for the dynamic, non- linear essence of financial markets, allowing for more robust and adaptive volatility predictions in ESG-driven investments.

An increasing number of studies has examined the deployment of machine learning and deep learning techniques in developing effective predictive models for financial markets. Studies by those by Nabipour et al., (2020), Wang et al., (2020), and Sen, (2018) have demonstrated the effectiveness of these advanced methods in forecasting price movements and market volatility. Within the domain of ESG related indices, research by Guo et al., (2020), Cho & Lee, (2022), and Raman et al., (2020) have investigated the use of deep learning models to predict price fluctuations and volatility, yielding varying degree of success. The accuracy and robustness of these predictive models depend on several key factors, encompassing the choice of deep learning architecture, the quality and granularity of input data, and the fine-tuning of model parameters. Among the most extensively utilized deep learning techniques are Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), Gated Recurrent Units (GRUs). Additionally, hybrid models that integrate multiple architectures have gained popularity for their ability to enhance predictive performance and capture complex market dynamics (S. L. Lin & Jin, 2023). As research in this field advances, optimizing model architectures and leveraging high- quality ESG datasets will be crucial for improving forecasting accuracy and developing more resilient financial strategies.

Although substantial advancements have made in this field, several critical challenges and gaps still persists in the literature. A major issue is the absence of a standardized evaluation framework, which poses obstacles to objectively compare different predictive models- even when they utilize similar deep learning techniques. Many studies emphasize their model's predictive accuracy without providing a standardized framework for evaluation, leading to inconsistencies in performance assessment of different models. Moreover, many researchers often do not disclose a transparent, data-driven approach to hyperparameter tuning, which is essential for optimizing model performance. Another critical limitation is that most existing studies have predominantly focus on price prediction rather than volatility forecasting, despite the fact that ESG-conscious investors are more concerned with risk management and ensuring market stability, emphasizing the need for accurate volatility forecasts rather than short-term returns. To overcome these shortcomings, this study seeks to construct a comphrensive deep learning framework for ESG index volatility prediction, ensuring that all models are implemented within a consistent and controlled environment.by standardizing model evaluation and implementation, this approach will enable objective comparisons across different deep learning techniques, enhancing the consistency and resilience of volatility forecasts.

II. LITERATURE REVIEW

Environmental, Social, and Governance (ESG) factors represent a set of non-financial criteria that assess a company's environmental sustainability, social responsibility, and corporate governance practices (Yu & Xiao, 2022). These factors play a crucial role in modern investment strategies as corporations increasingly recognize the importance of incorporating ESG principles into their business models. ESG investing is grounded in the idea that companies demonstrating strong commitments to sustainability, ethical governance, and social impact are better positioned for long-term success. As a result, investor interest in ESG disclosures and responsible investment practices has grown significantly in recent years (Dalal & Thaker, 2019; Gangi et al., 2022).

From a financial theory perspective, the trade-off theory suggests that companies primarily focus on profit maximization and wealth accumulation, while legitimacy theory views ESG investments and disclosures as a way for firms to build credibility and attract investors (Behl et al., 2022). The global financial crisis of 2008 heightened awareness about corporate ethics, risk management, and responsible business practices, drawing greater attention to the ESG risks and governance structures of publicly traded firms (Sultana et al., 2018). With increasing investor demand for transparency, corporations are now expected to provide more comprehensive ESG disclosures (Espahbodi et al., 2019). Research suggests that firms with higher ESG disclosure levels tend to experience higher valuations and greater investor confidence (Li et al., 2018). Furthermore, ESG performance has been linked to stronger corporate governance and enhanced stock returns, reinforcing its significance in investment decision-making (Khan, 2019). As noted by Khalil & Nimmanunta, (2023), ESG factors have become a key component in risk management, company valuation, and regulatory compliance.

Investor interest in ESG investments is primarily driven by two factors: ethical considerations and portfolio performance (Broadstock et al., 2021). ESG-focused investments are perceived as safer alternatives, particularly during periods of economic uncertainty, as they tend to be less volatile and more resilient to external shocks (Mousa et al., 2022). Given the increasing reliance on ESG criteria in portfolio selection, understanding the volatility of ESG indices has become a critical area of research. While ESG disclosure and investor interest continue to grow, ESG research is still in its early stages, largely due to the evolving nature of ESG reporting standards and data availability (Zhou & Zhou, 2022).
The study of financial market volatility has long been a key area of research, with time-series models frequently used to assess market uncertainty and risk fluctuations. Conventional models for instance, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been broadly applied to identify volatility patterns in stock markets. For instance, Yong et al., (2021) analyzed stock return volatility in Malaysia and Singapore, while Endri et al., (2021) examined market fluctuations in Indonesia during the COVID-19 pandemic using GARCH-based models. These models are effective in characterizing the statistical properties of financial time series, helping researchers and investors better understand market dynamics (Z. Lin, 2018). However, conventional econometric models have certain limitations, particularly in tackling intricate, high-dimensional, and non-linear relationships within financial data.

With transformative improvements in technology, artificial intelligence (AI) and deep learning models have gained attention as powerful approaches to traditional econometric approaches. These modern techniques offer superior feature extraction capabilities and greater flexibility in identifying hidden patterns in large datasets (Lin et al., 2022). In particular, neural networks have been shown to improve upon traditional GARCH forecasts, reducing error rates and enhancing the accuracy of volatility predictions (Kristjanpoller & Hernández, 2017).

Among deep learning models, Long Short-Term Memory (LSTM) networks have exhibited remarkable proficiency in learning temporal dependencies from financial time-series data. Kim & Won, (2018) suggested a hybrid model that integrates LSTM and GARCH, revealing that LSTMs excel at capturing long-term patterns and improving realized volatility predictions. Similarly, Koo & Kim, (2022) suggested an LSTM-GARCH hybrid model to address extreme biases in volatility distribution, offering a more robust solution for forecasting market fluctuations.

Market volatility tends to rise sharply during periods of systemic crises, such as economic recessions, pandemics, and geopolitical conflicts. To accurately capture these fluctuations, it is crucial to incorporate relevant external factors into predictive models. Research by Umar & Gubareva, (2021) examined how social media coverage of the COVID-19 pandemic influenced ESG leader indices across different regions, identifying distinct phases of low, medium, and high coherence between media coverage and ESG index price movements. Their findings suggest that during periods of low coherence, ESG investments may offer diversification advantages, potentially serving as a stabilizing force in times of global uncertainty. Similarly, Akhtaruzzaman et al., (2022) explored the impact of media coverage on financial contagion and found that both advanced and emerging equity markets experienced increased volatility, with the U.S. market being the most significantly affected. These studies highlight the growing role of media sentiment and public perception in shaping financial market dynamics, particularly in relation to ESG investments.

Academic literature has extensively examined the link between ESG policies and systematic risk. Albuquerque et al., (2019) examined how corporate social responsibility (CSR) and ESG strategies influence firms' exposure to systemic risks, proposing that strong ESG-oriented companies face lower price elasticity in demand due to their differentiated product strategies. Their study suggests that firms with strong ESG commitments may experience reduced volatility, as they tend to attract loyal consumers who prioritize sustainability and ethical business practices. This reinforces the idea that ESG-conscious companies may be more resilient during economic downturns due to greater investor and consumer confidence.

Despite these valuable insights, research on ESG-related stock portfolios and volatility forecasting remains relatively underdeveloped compared to traditional stock market volatility models (Cho & Lee, 2022; Koo & Kim, 2023; Lu et al., 2022; Mittnik et al., 2015). While prior studies have made meaningful contributions in areas such as ESG portfolio construction, optimization, performance evaluation, and risk assessment, many have primarily focused on building highly complex models or implementing machine learning techniques without careful feature selection. The absence of a well-balanced approach in prior research has led to inefficiencies in model performance and interpretability.

To address these challenges, our study objective is to develop an integrated framework for ESG volatility prediction, leveraging state-of-the-art deep learning techniques while ensuring that models are trained on a carefully curated set of influencing factors. Our goal is to provide a thorough insight of ESG investment portfolio behavior from diverse perspectives and to offer key perspectives that can inform both future academic research and practical investment strategies. By maintaining a balance between model complexity and interpretability, this research seeks to bridge existing gaps and enhance the reliability of ESG index volatility predictions.

III. THEORETICAL FRAMEWORK

Financial markets are inherently volatile, with fluctuations driven by macroeconomic conditions, investor sentiment, and external shocks such as recessions, pandemics, and regulatory changes. The upsurge of Environmental, Social, and Governance (ESG) investing has established new dimensions to market volatility, as ESG indices are influenced by both traditional financial factors and sustainability-related disclosures, corporate governance practices, and ethical investment trends. Understanding and predicting ESG index volatility requires a multi-dimensional theoretical framework that integrates financial theories, risk management principles, and advanced deep learning methodologies.

Modern Portfolio Theory (MPT) provides an initial foundation by emphasizing the diversification benefits of ESG investments. Research suggests that firms with strong ESG commitments often exhibit lower risk exposure during financial crises, as they attract long-term investors focused on sustainable returns. However, MPT does not account for the role of ESG-related news, social movements, and investor sentiment, which can drive volatility independently of financial performance. The Efficient Market Hypothesis (EMH) further contributes to this framework by suggesting that ESG-related disclosures are increasingly priced into financial markets, yet market inefficiencies persist due to inconsistent reporting standards and investor perceptions. These inefficiencies may lead to unexpected volatility spikes, particularly when sustainability reports or regulatory changes trigger rapid market reactions.

Trade-Off Theory and Legitimacy Theory offer additional insights into the behavior of ESG indices. Trade-Off Theory highlights the risk-return trade-offs that companies face when implementing ESG strategies, as sustainability initiatives require financial investment that may impact short-term profitability. Firms balancing profit maximization with sustainability commitments must navigate these trade-offs, influencing their stock price stability. On the other hand, Legitimacy Theory explains how corporate ESG reputation affects investor sentiment, where firms with strong ESG credentials benefit from lower volatility, while those accused of greenwashing or weak governance experience heightened market fluctuations.

Traditional models have been widely used to forecast financial volatility but often struggle with non-linear relationships and high-dimensional financial data. Deep learning approaches have become apparent as more effective tools for capturing complex dependencies in ESG time-series data. LSTM models can identify patterns in historical ESG index movements, economic indicators, and sustainability reports, making them appropriate for volatility prediction. Hybrid deep learning models, namely LSTM-GARCH and Transformer-GARCH, further enhance prediction accuracy by combining AI-driven pattern recognition with traditional econometric techniques.

Given the increasing role of ESG disclosures, regulatory shifts, and investor sentiment in market behavior, this study proposes an integrated framework for ESG index volatility prediction employing deep learning techniques.

IV. DATA

This study focuses on the S&P BSE 100 ESG Index, a widely recognized ESG-concentrated index in India. The index is a market-cap-weighted benchmark designed to assess the performance of securities that meet sustainability criteria, while maintaining a sectoral composition similar to that of the S&P BSE 100 (S&P Dow Jones Indices, 2016). This Index is maintained to offer investors a structured approach to ESG investment in the Indian market. The index was introduced to provide a sustainability-oriented alternative to traditional stock indices while ensuring industry diversification remains intact.

Several factors influence fluctuations in the S&P BSE 100 ESG Index, including fundamental dataset, technical indicators, and macroeconomic variables. Fundamental data reflects the financial health and ESG compliance of underlying companies, while technical indicators include closing price, relative strength index (RSI), moving average convergence divergence (MACD) and its components (MACD Signal and MACD Histogram), Bollinger Bands (Upper Band, Middle Band, Lower Band), rolling volatility, daily return, excess return, and Sharpe ratio. These indicators were chosen based on their ability to capture momentum, volatility, and trend-based movements in the stock market, which are essential for accurate forecasting of ESG index fluctuations. Macroeconomic variables, like, the India VIX index, and the USD/INR exchange rate, capture broader economic conditions and investor

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sentiment. The India VIX index, which measures market volatility, provides insights into investor risk perception, while the USD/INR exchange rate reflects currency fluctuations that impact foreign investment and trade dynamics.

Integrating multiple data sources enhances the predictive accuracy of deep learning models, allowing for a more holistic analysis of ESG index behavior. Fundamental and technical indicators provide insights into stock performance, while macroeconomic variables account for external market influences. This multi-dimensional approach strengthens model reliability, improving forecasts of ESG index volatility and supporting informed investment decisions.

The study uses data from December, 2017 to February, 2025, encompassing key market fluctuations, including the COVID-19 pandemic-induced bear market of 2020. By considering both bull and bear market conditions, the deep learning model ensures a comprehensive representation of ESG index dynamics across economic cycles.

As a sustainability-focused benchmark, the S&P BSE 100 ESG Index offers meaningful insights into the performance of ESG-compliant firms in India. With increasing regulatory emphasis on corporate sustainability and responsible investing, accurately forecasting ESG- related volatility is crucial for investor seeking to balance financial gins with ethical and sustainable investment strategies. A precise understanding of volatility helps investors manage risks effectively, improve portfolio resilience, and align their investments with long-term sustainability goals, ensuring both financial performance and positive societal impact.

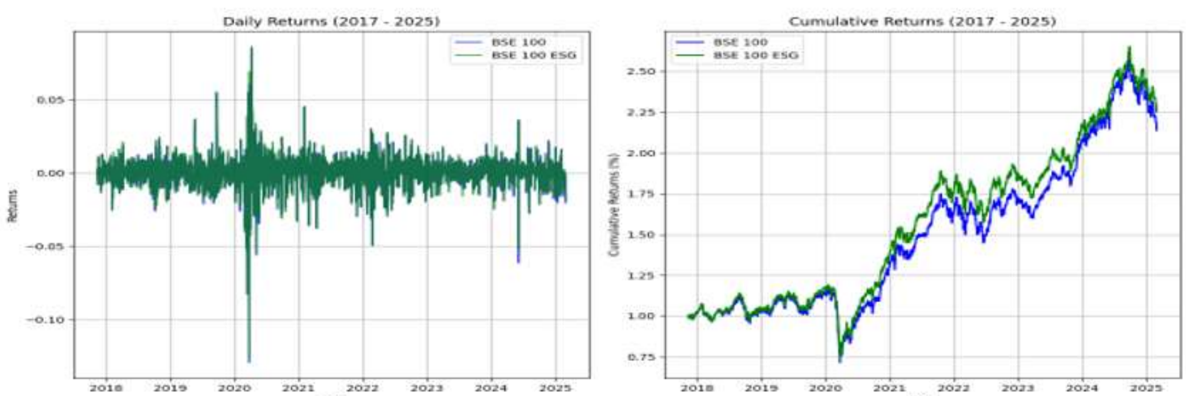

Figure. 1 Performance analysis of daily and cumulative returns of BSE 100 and S&P BSE 100 ESG indices

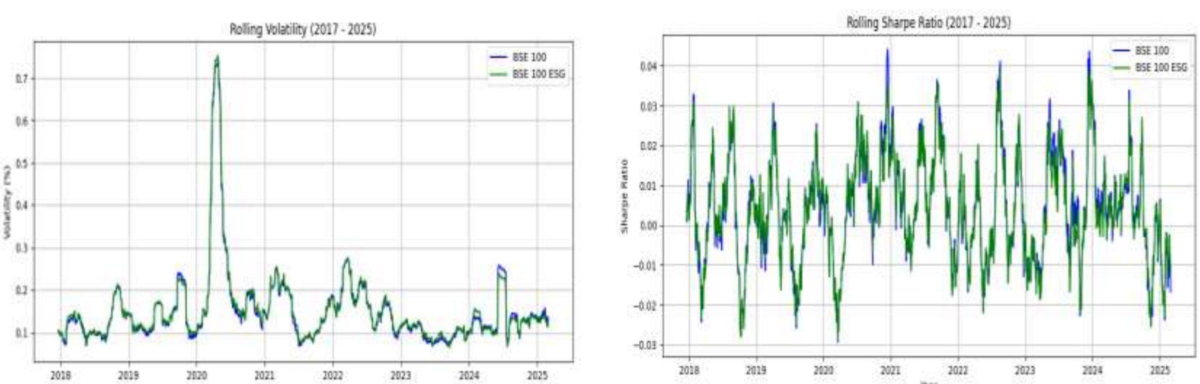

Figure. 2 Rolling volatility and Sharpe ratio of BSE 100 and S&P BSE 100 ESG indices

Based on an in-depth review of the relevant literature and insights gained from exploratory data analysis, the following key findings can be identified.

1: BSE 100 and S &P BSE 100 ESG have nearly mirrored trends in terms of daily returns and cumulative returns, as exhibited in Figure. 1.

2: Figure. 2 demonstrates similar pattern in annualized rolling volatility and Sharpe ratio of these two indices in the given time interval.

The Fig. 3 presents correlation heatmaps for S&P BSE 100 ESG and BSE 100, visualizing relationships between technical indicators such as RSI, MACD, Bollinger Bands, and Sharpe Ratio. The colour intensity indicates correlation strength, with red indicating strong positive correlation and blue depicting strong negative correlation, aiding in understanding market dynamics.

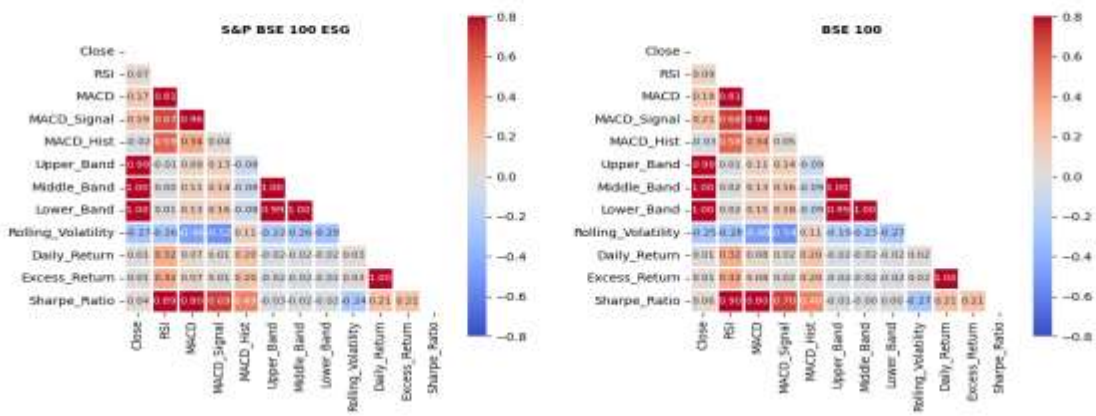

Fig. 3 Correlation heatmaps (Left: S&P BSE 100 ESG, right: BSE 100)

V. METHODOLOGY

In present study, three deep learning models—Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Networks (CNN)—were implemented to predict the volatility of the S&P BSE 100 ESG Index. They were chosen based on their proven effectiveness in handling time-series forecasting tasks, especially in financial markets. The approach consists of multiple steps, involving data collection, preprocessing, feature engineering, model development, model evaluation, and result visualization. Every step has a pivotal role in ensuring the accuracy and reliability of the predictive models.

The LSTM model was designed to capture long-term dependencies and sequential patterns in ESG index data. LSTM networks mitigate the shortcomings of traditional recurrent neural networks (RNNs) by using a memory cell mechanism that regulates the flow of information through forget, input, and output gates. The LSTM model in this study comprises of two stacked LSTM layers with 50 neurons each, followed by a fully connected dense layer to generate the final output. The activation function employed in the LSTM layers is tanh, while the gate operations use the sigmoid function. The model is configured with the Adam optimizer and Mean Squared Error (MSE) loss function, which are commonly used for time-series regression tasks. Similarly, the GRU model was employed as a substitute to LSTM. GRUs simplify the memory cell mechanism by merging the forget and input gates into a single update gate, minimizing computational complexity while preserving the ability to model long-term dependencies. The GRU model in this study follows a structure similar to the LSTM model, with two

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GRU layers of 50 neurons each, followed by a dense output layer. The activation functions and optimizer settings remain the same as those used in the LSTM model.

In contrast, the CNN model, which is traditionally utilized for image processing, was adopted for time-series forecasting by leveraging 1D convolutional layers to draw out meaningful patterns from the ESG index data. The CNN model consists of a 1D convolutional layer with 64 filters and a kernel size of 2, followed by a flattening layer that converts the extracted features into a format suitable for dense layers. A fully connected dense layer was added at the output to generate predictions. The ReLU activation function was applied to the convolutional layer to enhance non-linearity, and the model utilized the Adam optimizer and Mean Squared error (MSE) for loss computation.

The dataset was pre-processed for all models and classified into 80% training and 20% testing sets, ensuring that the models learned from past trends and were evaluated on unseen data. The input data for LSTM and GRU was reshaped into a three-dimensional format of (samples, timesteps, features) to account for temporal dependencies, whereas the CNN model was trained using a two-dimensional input format of (samples, features). The models were trained for 50 epochs with a standard batch size of 32, allowing sufficient updates to the model parameters while preventing overfitting.

After training, the models performance was measured using three key performance metrics: Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 Score. These metrics offer key perspectives into the accuracy, consistency, and explanatory power of the models in predicting ESG index volatility. The performance of LSTM, GRU, and CNN was compared based on these statistical measures to determine which architecture offered the most reliable forecasts. By implementing these models using standard configurations, this study establishes a structured approach to ESG index volatility forecasting while maintaining computational efficiency and interpretability. The results obtained provide meaningful perspectives into the suitability of deep learning architectures for financial time-series analysis.

To statistically validate the model performance, Welch's two-sample t-test was conducted to contrast prediction errors across models. Unlike traditional t-tests, Welch's test accounts for unequal sample variances, making it suitable for evaluating deep learning models. Statistical significance was determined using a 5% significance level ($\alpha=0.05$). A p-value less than 0.05 suggested a significant difference in predictive performance, confirming that one model outperformed the other. The test was applied separately to compare LSTM vs. GRU, LSTM vs. CNN, and GRU vs. CNN, providing empirical support for identifying the most effective deep learning model.

By utilizing this structured process, the study reinforces a robust and data-driven approach to ESG index volatility forecasting. The integration of deep learning architectures, financial feature engineering, and statistical validation strengthen the reliability of the findings, offering valuable insights into ESG-driven market dynamics.

VI. EXPERIMENTAL APPROACH AND FINDINGS

The primary objective of our study was to perform a comparative study of the predictive performance of LSTM, GRU, and CNN models in forecasting the volatility of the S&P BSE 100 ESG Index.

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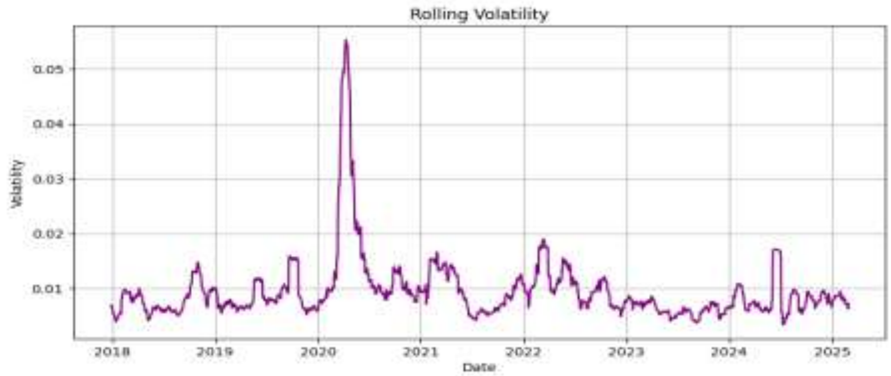

Figure. 4 S&P BSE 100 ESG annualized rolling volatility

The annualized rolling volatility of the index as depicted in figure 4 for the period December 2017 to February 2025, exhibits a highly complex, noisy, and volatile pattern, making it an interesting case for deep learning-based forecasting. To achieve this, the study was carried out in five main steps. First, the data was prepared, including cleaning and structuring it for analysis. Next, the models were built using standard settings. Then, their performance was evaluated using accuracy metrics consisting of RMSE, MAPE, and R^2 score. After that, the best-performing model was identified based on prediction accuracy. Finally, a statistical analysis was conducted using Welch's t-test to check if the differences in model performance were significant. This structured approach ensured a thorough and fair comparison of deep learning models for predicting ESG index volatility.

VII. SYSTEM CONFIGURATION AND INPUT DATA PREPARATION

Table 1 outlines the computational structure used for the experiments. The study was conducted in a Python environment, leveraging TensorFlow and Keras APIs for model implementation. The hardware and software configuration utilized for experimentation is listed in Table 1.

SYSTEM CONFIGURATION	ENVIRONMENT	ARCHITECTURE
GOOGLE COLAB WITH NVIDIA-SMI 495.44 GPU	Python 3.x, TensorFlow, and Keras APIs	LSTM, GRU, CNN

Table 1: Computing Environmental Setup

The original dataset was divided among training, validation, and test sets in an 80:10:10 ratio. Specifically, 80% of the data was allocated for training, out of which 10% was utilized for validation, ensuring a balanced learning process. The test set, encompassing 10% of the data, was deployed to evaluate the model's generalization capability. The dataset's overall distribution is presented in Table 2.

DATA	DATES	NUMBER OF SAMPLES
COMPLETE DATA	2017-12-26 to 2025-02-28	1,779
TRAINING	2017-12-26 to 2023-09-22	1,423
VALIDATION	2023-09-25 to 2024-06-13	177
TEST	2024-06-14 to 2025-02-28	179

Table 2: Proportion of Training, Validation, and Test Data

VIII. RESULTS AND DISCUSSION

Assessing and identifying the best performing model for volatility forecasting is crucial for ensuring accurate financial predictions. In this study, LSTM, GRU, and CNN models were systematically evaluated based on Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE),

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and R^2 Score. The empirical findings indicate that GRU is the overall best-performing model, outperforming LSTM and CNN in all key performance metrics.

Table 1: Model Performance Comparison

MODEL	RMSE	MAPE	R^2 SCORE
LSTM	0.0765	0.0806	-1.7882
GRU	0.0444	0.0443	0.0613
CNN	0.0671	0.0587	-1.1451

As presented in Table 1, GRU achieved the lowest RMSE (0.0444) and MAPE (0.0443), suggesting its superior predictive accuracy and robustness in capturing stock price fluctuations. Furthermore, GRU is the only model with a positive R^2 score (0.0613), suggesting that it effectively explains some of the variance in stock price movements. In contrast, LSTM (-1.7882) and CNN (-1.1451) exhibit negative R^2 scores, implying that their predictions are significantly less reliable and do not accurately capture market trends.

The superior performance of GRU can be attributed to its efficient gated architecture, which effectively overcomes the vanishing gradient issue and maintains long-term dependencies in financial time series dataset. Unlike LSTM, which has a higher computational cost due to its additional memory cell mechanisms, GRU's simplified gating structure enables faster training and improved generalization. CNN, on the other hand, primarily excels in spatial data processing but lacks the capability to fully capture sequential patterns inherent in stock price movements, leading to suboptimal forecasting accuracy.

The results suggest that, GRU is identified as the utmost effective model for volatility prediction, demonstrating higher accuracy, better generalization, and statistically significant improvements over LSTM and CNN.

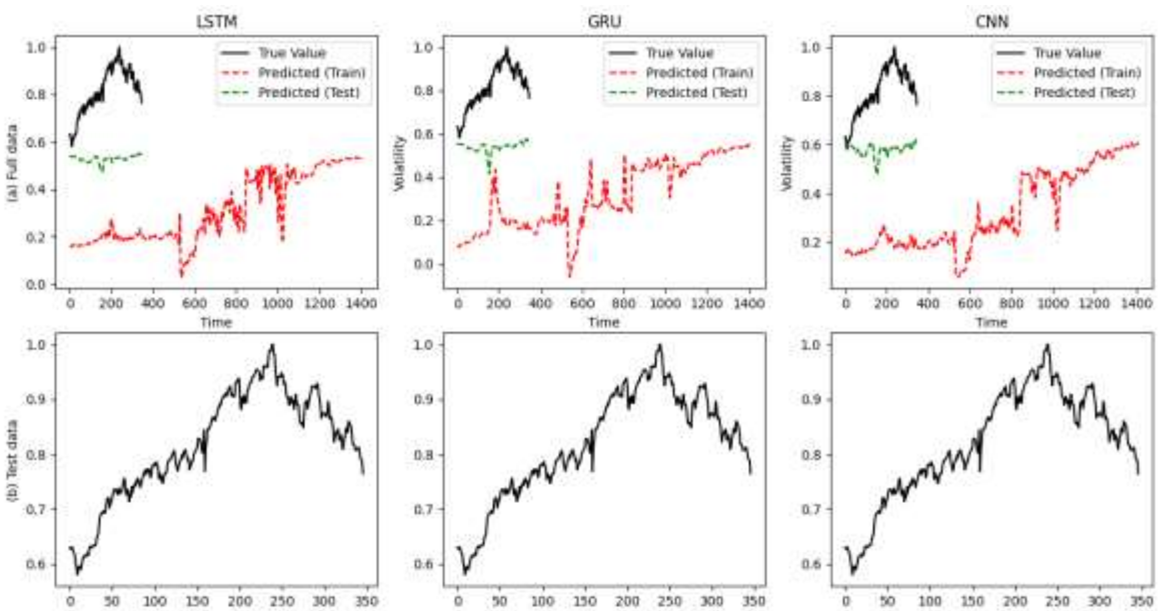

Figure. 15 Time series plots of the deep learning models

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Table 2: Welch's T-Test Results

Model comparison	t-statistic	p-value
LSTM VS GRU	12.5156	0.0000
LSTM VS CNN	4.9293	0.0000
GRU VS CNN	-2.8384	0.0051

To assess the significance of the performance differences among the LSTM, GRU, and CNN models, a Welch's two-sample t-test was conducted on the absolute prediction errors. This statistical test was selected due to its effectiveness against unequal variances and different sample sizes, making it appropriate for comparing the forecasting accuracy of distinct deep learning models. The results indicate that all pairwise comparisons yielded p-values below 0.05, confirming that the differences in predictive accuracy among the models are statistically significant. The largest performance difference was observed between LSTM and GRU ($T = 12.5156$, $p = 0.0000$), suggesting that LSTM produces significantly higher prediction errors than GRU. Similarly, the LSTM vs. CNN comparison ($T = 4.9293$, $p = 0.0000$) indicates that CNN outperforms LSTM, albeit with a smaller margin. Additionally, the GRU vs. CNN comparison ($T = -2.8384$, $p = 0.0051$) further confirms that GRU consistently yields lower prediction errors than CNN, reinforcing its superior forecasting capability.

IX. CONCLUSION

This study compared the performance of LSTM, GRU, and CNN models for stock price prediction using technical indicators. The results revealed that GRU outperforms both LSTM and CNN, achieving the lowest prediction errors (RMSE: 0.0444, MAPE: 0.0443) and the only positive R^2 score (0.0613). In contrast, LSTM and CNN struggled to accurately capture stock price movements, leading to higher errors and negative R^2 scores.

To ensure these differences were not due to random variation, Welch's t-test was conducted, confirming that GRU's advantage is statistically significant ($p < 0.05$). The largest gap was between LSTM and GRU ($T = 12.5156$, $p = 0.0000$), reinforcing that GRU consistently makes better predictions. GRU's superior performance can be attributed to its efficient gating mechanism, which helps capture long-term trends without excessive computational cost.

While LSTM tends to overfit and CNN struggles with time-series data, GRU strikes the right balance, positioning it as the most robust model for ESG index volatility prediction. Moving forward, hybrid models combining GRU with attention mechanisms or sentiment analysis from financial news could further enhance accuracy.
In conclusion, GRU stands out as the best choice for stock price forecasting, offering both accuracy and efficiency. Future advancements in deep learning and AI-driven financial modelling will likely build upon these findings to develop even more reliable prediction systems. Future research should investigate hybrid GRU-based architectures and advanced hyperparameter optimization techniques to further improve predictive performance in financial markets.

X. IMPLICATIONS

This study provides meaningful perspectives on deep learning models applications for stock market forecasting, emphasizing the importance of transparency, integrity, and interpretability in financial modelling. By utilizing publicly available data, the findings contribute to investor confidence and serve as an additional tool for informed decision-making. However, investment strategies should not rely solely on model predictions, as market conditions remain highly volatile, influenced by factors such as geopolitical instability, and economic crises.

For equity traders, portfolio managers, and individual investors, the study highlights the potential of neural networks to capture market volatility and enhance risk assessment. Moreover, academic researchers can further refine these models by integrating alternative data sources, sentiment analysis, and hybrid architectures to improve predictive accuracy. Ultimately, aligning AI-driven forecasting models with real-world financial complexities can lead to more reliable and adaptive investment strategies in dynamic market environments.

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