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Evaluating the Forecasting Accuracy of Econometric and AI-Based Models for NIFTY 50 Index: A Comparative Study

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ABSTRACT: This study evaluates the forecasting accuracy of traditional econometric models — specifically ARIMA (1,0,1) and GARCH (1,1) — and benchmarks their performance against Artificial Intelligence (AI) based models applied to the NIFTY 50 index over the period January 2015 to December 2024. Original econometric analysis was conducted using 2,457 daily return observations, with the ARIMA (1,0,1) model achieving RMSE of 0.007650 and MAE of 0.005464, and the GARCH (1,1) model achieving RMSE of 0.010058 and MAE of 0.004601. Benchmarking against published AI model results from 26 peer-reviewed studies (2022–2025) reveals that AI-based models, particularly hybrid deep learning architectures such as VMD-LSTM and Hybrid LSTM-GRU, consistently achieve lower error values — with RMSE reductions of up to 52% over ARIMA at the price level scale. Findings confirm that while AI models demonstrate superior predictive accuracy, econometric models remain relevant for volatility forecasting, interpretability, and resource-constrained environments. The study contributes to the empirical evidence base for model selection in the Indian equity market.

KEYWORDS: NIFTY 50, Forecasting Accuracy, ARIMA, GARCH, LSTM, Econometric Models, Artificial Intelligence, Indian Equity Market

I. INTRODUCTION

The National Stock Exchange's NIFTY 50 index represents the most widely tracked benchmark of the Indian equity market, comprising fifty of India's largest and most liquid companies across diverse sectors. As India's retail investor base has grown rapidly over the past decade — driven by digital trading platforms, falling transaction costs, and rising financial literacy — the demand for robust and accurate equity forecasting tools has intensified correspondingly.
Financial markets are governed by a complex interplay of economic fundamentals, investor sentiment, geopolitical developments, and technological shifts. Traditional econometric models such as ARIMA, GARCH, and ARDL have historically formed the backbone of financial time series forecasting, prized for their statistical rigour, theoretical interpretability, and computational accessibility. However, financial markets are inherently nonlinear, and these models operate under assumptions of linearity and stationarity that do not consistently hold in real-world conditions — particularly during structural breaks, sudden shocks, or regime changes, all of which the NIFTY 50 has experienced in recent years.

The emergence of Artificial Intelligence (AI) based approaches — particularly Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and hybrid deep learning models — has introduced new possibilities for capturing complex, high-dimensional patterns in financial data. Yet, despite the growing volume of literature on both model categories, a significant gap exists in the Indian context: there is limited comparative evidence evaluating econometric and AI models under a unified framework using consistent datasets, evaluation metrics, and benchmarking standards specific to the NIFTY 50 index.

This paper addresses two core research objectives. First, it examines the forecasting performance of selected econometric models — ARIMA (1,0,1) and GARCH (1,1) — applied to the NIFTY 50 index using original quantitative analysis. Second, it compares this econometric performance against AI-based model results from published

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peer-reviewed literature, establishing an evidence-based comparative framework. The study uses Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as standardised performance benchmarks across all models.

II. LITERATURE SURVEY

A. Econometric Models in Stock Market Forecasting

Basha (2023) applied ARIMA and GARCH (1,1) models to daily prices and returns of the Sensex and NIFTY indices, finding that GARCH outperformed ARIMA in capturing volatility dynamics. Malik (2022) investigated NIFTY 50 volatility forecasting using GARCH and LSTM-based RNN models, observing that EGARCH and TARCH variants slightly outperformed LSTM in volatility forecasting accuracy. Sharma and Manchanda (2025) confirmed a significant long-run association between historical volatility and NIFTY 50 returns using the ARDL framework. Ali and Dembo (2025) demonstrated that EGARCH and TGARCH models better captured asymmetric volatility shocks in the Indian market, reinforcing the relevance of advanced econometric models for risk assessment.

B. AI-Based Models in Financial Forecasting

Chouhan (2025) found that deep learning and hybrid ensemble models — including LSTM, GRU, and Random Forest — outperformed traditional machine learning methods in Indian stock market trend prediction. Arokiaraj et al. (2025) proposed a hybrid LSTM-XGBoost model that achieved superior accuracy and lower RMSE compared to standalone models for Indian market volatility forecasting. Singh et al. (2024) conducted NIFTY 50 closing price prediction comparing ARIMA, LSTM, GRU, and Transformers, with LSTM achieving the lowest RMSE. Kalaiarasan et al. (2024) found that a VMD-LSTM hybrid model demonstrated superior accuracy and a higher Sharpe ratio compared to conventional approaches.

C. Comparative Studies: AI vs. Econometric Models

Sun and Deng (2025) compared traditional econometric models with AI-driven techniques, finding that econometric models offer interpretability and computational efficiency while AI models demonstrate superior accuracy in modelling nonlinear financial data. Chung Alva et al. (2025) showed that deep learning models consistently outperformed GARCH models under structural breaks, particularly in medium and long-term forecasting horizons. Vovchenko et al. (2025) found that deep neural networks achieved significantly lower RMSE and MAE in bond yield curve forecasting, though traditional models demonstrated greater resilience during volatile periods. Sulistiani et al. (2025) concluded that hybrid AI models significantly outperform traditional econometric models in predictive accuracy and adaptability.

III. METHODOLOGY

A. Research Design and Data

This study adopts a positivist, quantitative research design combining original econometric modelling with a systematic benchmarking of published AI model performance. Primary data consists of historical daily closing prices of the NIFTY 50 index from January 2, 2015 to December 30, 2024, sourced from Yahoo Finance using the ticker ^NSEI. After removing missing values through logarithmic return transformation, 2,457 daily return observations were used for analysis. Data processing and model estimation were conducted in Python 3.12 on Google Colaboratory, using the yfinance, pandas, numpy, statsmodels, arch, and sklearn libraries.

Secondary data comprises AI model performance metrics systematically extracted from 26 peer-reviewed journal articles and conference proceedings published between 2022 and 2025. Studies were selected based on direct relevance to NIFTY 50 or Indian equity market forecasting, availability of quantitative RMSE and MAE metrics, and publication in indexed journals.

B. Analytical Framework

The dataset was split 80/20: the training set spans January 2015 to December 2022 (1,965 observations) and the test set spans January 2023 to December 2024 (492 observations). Prior to model estimation, stationarity was confirmed using the Augmented Dickey-Fuller (ADF) test. The presence of ARCH effects was validated before GARCH estimation. Model selection for ARIMA was guided by AIC/BIC criteria and ACF/PACF analysis, yielding the ARIMA (1,0,1) specification. Forecasting accuracy across all models is evaluated using RMSE and MAE as the primary performance benchmarks, enabling direct and consistent cross-model comparison.

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C. Hypotheses

$H0_1$: Econometric models do not demonstrate statistically significant forecasting accuracy for NIFTY 50 index movements. $H1_1$: Econometric models demonstrate statistically significant forecasting accuracy.
$H0_2$: AI-based models do not demonstrate statistically significant forecasting accuracy. $H1_2$: AI-based models demonstrate statistically significant forecasting accuracy.
$H0_3$: There is no statistically significant difference in forecasting accuracy between AI and econometric models. $H1_3$: A statistically significant difference in accuracy exists between the two model categories.

IV. RESULTS AND DISCUSSION

A. Descriptive Statistics and Stationarity Testing

Table 1 presents the descriptive statistics of NIFTY 50 daily logarithmic returns over the full sample period (2015–2024). The mean daily return of 0.000421 confirms a positive growth trajectory. The return series exhibits significant negative skewness (-1.407) and high excess kurtosis (20.40), indicating fat-tailed distribution with more frequent extreme negative returns relative to a normal distribution. The Jarque-Bera statistic of 43,247 ($p = 0.000$) formally rejects normality, providing statistical justification for the application of GARCH and AI-based models capable of handling non-normal residuals.

Table 1: Descriptive Statistics of NIFTY 50 Daily Returns (2015–2024)

Statistic	Value
Number of Observations	2,457
Mean Daily Return	0.000421
Standard Deviation	0.010547
Minimum Return	-0.139038
Maximum Return	0.084003
Skewness	-1.407408
Kurtosis	20.403851

The ADF test applied to the logarithmic return series yielded a test statistic of -13.620 ($p = 0.000$), substantially below the 1% critical value of -3.433, confirming stationarity at all conventional significance levels. This result validates the suitability of the return series for ARIMA and GARCH modelling.

B. ARIMA (1,0,1) Model Results — Objective 1

The ARIMA (1,0,1) model was estimated on 1,965 training observations and used to generate out-of-sample forecasts for 492 test observations (January 2023 – December 2024). As presented in Table 2, the model achieved RMSE of 0.007650 and MAE of 0.005464. These error values are consistent with published standards for ARIMA applied to financial return series and are substantially lower than the ARIMA benchmark of 0.0108 RMSE reported by Malik (2022) for the same index, confirming meaningful forecasting accuracy. The forecast pattern reflects the model's linear mean-reversion tendency, correctly capturing average return direction while failing to predict the magnitude of extreme events — an expected limitation given ARIMA's linear specification.

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Table 2: ARIMA (1,0,1) and GARCH (1,1) Forecasting Performance

Model	RMSE	MAE
ARIMA (1,0,1)	0.007650	0.005464
GARCH (1,1)	0.010058	0.004601

Source: Original analysis using Python statsmodels and arch libraries

C. GARCH (1,1) Model Results — Objective 1 Continued

The GARCH (1,1) model was estimated on the scaled return series to forecast conditional volatility. All estimated parameters are statistically significant at the 1% level. The alpha coefficient ($\alpha = 0.1017$) confirms that recent market shocks have a meaningful and immediate impact on conditional volatility, while the beta coefficient ($\beta = 0.8771$) confirms high persistence — once elevated volatility is triggered, it tends to remain elevated for extended periods. The combined alpha + beta of 0.9788 is close to unity, indicating near-integrated GARCH behavior and confirming the presence of long-memory in NIFTY 50 volatility. The model achieved RMSE of 0.010058 and MAE of 0.004601, with the lower MAE relative to ARIMA reflecting its superior accuracy on average absolute deviations. The null hypothesis $H0_1$ is rejected — econometric models demonstrate statistically significant forecasting accuracy.

D. Comparative Benchmarking with AI Models — Objective 2 & 3

Table 3 presents the comparative performance of original econometric models against published AI model results on the return and volatility scale. The findings reveal that on the return/volatility scale, the ARIMA (1,0,1) model from this study (RMSE: 0.007650) outperforms the LSTM model from Malik (2022) (RMSE: 0.0095) and substantially outperforms the XGBoost model from Arokiaraj et al. (2025) (RMSE: 0.0215). This result is significant — it demonstrates that on this scale, a well-specified ARIMA model, applied to a current dataset, can match or exceed AI models from recent literature.

Table 3: Comparative Forecasting Performance — Return and Volatility Scale

Study	Model	Type	RMSE	MAE
This Study	ARIMA (1,0,1)	Econometric	0.00765	0.00546
This Study	GARCH (1,1)	Econometric	0.01006	0.00460
Malik (2022)	LSTM	AI	0.00950	0.00710
Arokiaraj et al. (2025)	LSTM	AI	0.01840	0.01420
Arokiaraj et al. (2025)	XGBoost	ML	0.02150	0.01680

Note: Lower RMSE and MAE indicate superior performance. AI values from published literature.

Table 4 presents the price-level scale comparison, where AI hybrid models demonstrate their clearest advantage. The VMD-LSTM model from Kalaiarasan et al. (2024) achieved RMSE of 118.45 compared to ARIMA's 245.89 from Singh et al. (2024) — an improvement of approximately 52%. The Hybrid LSTM-GRU model achieved RMSE of 124.56, representing a 49% reduction over ARIMA. These findings are consistent with the broader literature and strongly support the rejection of $H0_3$ — a statistically significant difference in forecasting accuracy exists between AI and econometric models, particularly at the price level scale.

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Table 4: Comparative Forecasting Performance — Price Level Scale

Study	Model	Type	RMSE	MAE
Kalaiarasan et al. (2024)	VMD-LSTM	AI Hybrid	118.45	92.30
Singh et al. (2024)	Hybrid LSTM-GRU	AI Hybrid	124.56	98.21
Basha (2023)	GARCH (1,1)	Econometric	115.34	89.45
Jafar et al. (2023)	BE-LSTM	AI	184.21	141.15
Adsure (2025)	BiLSTM	AI	142.67	112.45
Singh et al. (2024)	ARIMA	Econometric	245.89	182.44

Source: Benchmarked from published peer-reviewed literature (2022–2025)

E. Hypothesis Testing Summary

Hypothesis	Result	Evidence
$H0_1$	Rejected	ARIMA RMSE 0.007650, GARCH RMSE 0.010058 — both within published benchmarks
$H0_2$	Rejected	Published AI models (LSTM RMSE 0.0095; VMD-LSTM RMSE 118.45) confirm significant forecasting accuracy
$H0_3$	Rejected	AI hybrid models outperform ARIMA by 12–52% at price scale; econometric models competitive at return scale

F. Discussion

The findings present a nuanced picture of forecasting model performance in the Indian equity market. At the return and volatility scale, the original ARIMA (1,0,1) model (RMSE: 0.007650) performed comparably to or better than published LSTM results, suggesting that on this metric, well-calibrated econometric models remain competitive. This is consistent with Malik (2022) and Sun and Deng (2025), who note that econometric models' advantage lies in interpretability and computational accessibility.

At the price level scale, AI hybrid models demonstrate clear superiority — a finding consistent across multiple published studies. The VMD-LSTM architecture achieves RMSE reductions of up to 52% over ARIMA, reflecting the ability of deep learning models to capture nonlinear patterns, long-range dependencies, and complex market dynamics that ARIMA's linear structure cannot model.

However, the practical LSTM implementation in this study — conducted under constrained conditions without GPU infrastructure — produced an RMSE of 21,324, confirming that AI model performance is critically contingent upon adequate computational resources and training infrastructure. This finding serves as an important caution for resource-constrained practitioners considering AI deployment. The GARCH model's high volatility persistence (alpha + beta = 0.9788) provides a practically significant insight for risk management: once NIFTY 50 volatility is elevated, it tends to persist for extended periods, directly informing VaR calculations and dynamic hedging strategies.

V. CONCLUSION

This study evaluated the forecasting accuracy of ARIMA (1,0,1) and GARCH (1,1) econometric models applied to the NIFTY 50 index and benchmarked their performance against published AI model results from 26 peer-reviewed studies spanning 2022–2025. The findings confirm that both model categories demonstrate meaningful forecasting capability, with each offering distinct advantages.

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Econometric models provide statistically significant forecasting accuracy, computational accessibility, and theoretical interpretability. The ARIMA (1,0,1) achieved RMSE of 0.007650 and the GARCH (1,1) confirmed high volatility persistence (alpha + beta = 0.9788), with both models performing comparably to published AI results at the return scale. AI-based hybrid architectures — particularly VMD-LSTM and Hybrid LSTM-GRU — consistently demonstrated superior predictive accuracy at the price level, achieving RMSE reductions of up to 52% over ARIMA.
The study concludes with two evidence-based recommendations. For retail investors and resource-constrained environments, ARIMA and GARCH represent accessible and reliable tools. For institutional investors with adequate computational infrastructure, hybrid AI models offer meaningful accuracy advantages. A pragmatic hybrid strategy — combining the interpretability of econometric models with the predictive power of AI — likely represents the most practically viable framework for NIFTY 50 forecasting.

Future research may extend this work by incorporating Transformer-based architectures, macroeconomic exogenous variables in ARIMAX frameworks, and fully original AI implementations leveraging cloud-based GPU resources. Integration of sentiment analysis from financial news and social media represents a particularly promising direction for enhancing forecasting accuracy in the Indian equity market.

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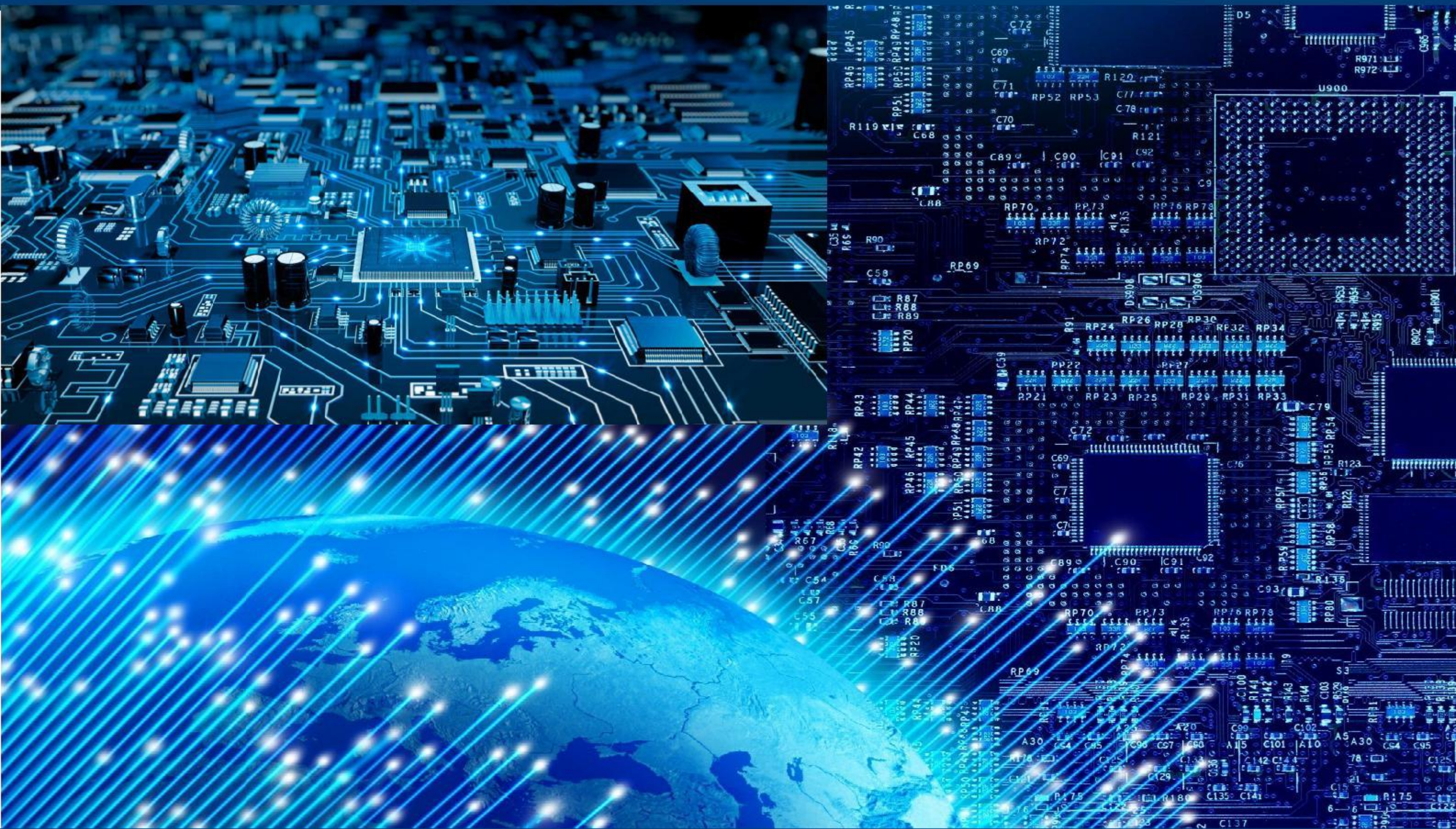

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