Liquidity-Driven Volatility Forecasting and Investment Recommendation System for Indian Stock Markets

Zidio Development - Internship Project - B:16.2 - G11 - Time Series Stock Market

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***Abstract*—Volatility prediction is critical to sound investment but conventional models neglect liquidity's role as a predictor. We introduce a novel liquidity-based volatility prediction system for 34 Indian stocks (2011–2021) that combines multiple regression and ARIMA/SARIMA models to provide individualized investment advice. Using liquidity indicators (Volume, Turnover, %Deliverable) and lagged Volatility, regression models surpassed ARIMA for 33 stocks with high correlations (e.g., Turnover-Volatility 0.40). A recommendation engine provides Buy/Sell/Hold advice for risk-averse, risk-neutral, and risk-tolerant investors by combining Volatility predictions with 21-day Simple Moving Average (SMA) price trends. To account for serial correlation (Durbin-Watson $<$ 1.5), the engine dynamically changes to ARIMA, providing stable forecasts. Optimized thresholds (e.g., 1.0/1.2 for risk-averse) and relaxed SMA slope qualifications improve signal quality, resulting in balanced advice (e.g., 10 Buy, 12 Hold, 12 Sell for risk-averse). Extensive testing using RMSE, R^2, and ACF analysis validates regression's performance for liquidity-based stocks. This research adds to time series prediction by combining liquidity, price trends, and adaptive modeling, providing an extensible volatility-based investment scheme with practical implications to portfolio management.**

***Index Terms*—Volatility Forecasting, Liquidity Metrics, Time Series Analysis, Regression, ARIMA, Investment Recommendations, Stock Market.**

I. Introduction

Volatility in the stock market, a primary indicator of price behavior, has Volatility in the stock market, a primary indicator of price behavior, has significant implications for investment planning and portfolio management. Accurate volatility forecasting allows investors to measure risks and realign strategies, but conventional models tend to emphasize price-based or macroeconomic variables while ignoring the critical role of liquidity measures.Liquidity, in terms of turnover, trading volume, and deliverable shares, captures market action and can overwhelm volatility, particularly in emerging markets like India, whose dynamic relative to liquidity differs with stocks. This study introduces a new model for forecasting volatility on the basis of liquidity for 34 Indian stocks (2011–2021) through the use of sophisticated time series and regression techniques to supply personalized investment recommendations for various risk levels.

The suggested framework takes advantage of liquidity measures—Volume, Turnover, and %Deliverable—combined with lagged Volatility to predict the 21-day rolling standard deviation of daily returns. Utilizing multiple regression and ARIMA/SARIMA models, the approach supports both liquidity-based trends and time dependencies, overcoming the drawbacks of such traditional models as GARCH, which are founded on historical price volatility. An extensive exploratory data analysis (EDA) confirms stationarity and correlations (e.g., Turnover-Volatility 0.40), which inform the choice of models. Regression models, with liquidity predictors, outperform ARIMA for 33 stocks, displaying liquidity's explanatory capability in the Indian market.

To add practical usefulness, the model has a recommendation system that produces Buy/Sell/Hold signals for risk-averse, risk-neutral, and risk-tolerant investors. Integrating Volatility predictions with 21-day Simple Moving Average (SMA) price movements, the system synchronizes signals with market trends. It also reduces serial correlation (Durbin-Watson ¡ 1.5) by auto-switching to ARIMA to ensure strong forecasts. This research contributes to time series forecasting by closing the gap between liquidity analysis and actionable investment insights, providing a scalable framework for portfolio optimization under volatility in emerging markets.

II. Literature Survey

Q. Xu *et al.* [1] examined the performance of deteriorating liquidity in forecasting China's stock market volatility using a TVTP-MS-HAR-CJ-LIQ model. Their finding that deteriorating liquidity increases crisis probability and impacts volatility forecasting is consistent with our intention to identify early warning signals of instability with non-linear regime changes and rolling correlations.

Y. Deng *et al.* [2] built a liquidity-adjusted ARMA-GARCH model based on novel indicators (liquidity jump and diffusion) to capture short-run volatility magnification due to liquidity shocks well—much like our use of lead-lag cross-correlation of liquidity and volatility as early warning indicators.

S. Andriychuk *et al.* [3] investigated cryptocurrency volatility with GARCH models, Monte Carlo simulation, and Value-at-Risk (VaR) to examine asset volatility and correlation with other markets' liquidity, and shows rolling volatility and liquidity-volatility correlation. Its spillover and market integration finding is reflective methodological contributions to your cross-sector study.

M. A. M. Al Janabi *et al.* [4] provided a general overview of liquidity as a driving force of the financial system, not only a market mechanism but as a risk source. The paper outlines the theoretical and practical underpinnings for liquidity risk, its relationship with market risk, and the intersection where the two converge to produce financial instability—i.e., in times of crisis. The article is most relevant to our research because of its general overview of how artificial intelligence and machine learning techniques are transforming forecasting and management of liquidity-driven risks, comparable to your use of statistical forecasting (e.g., rolling correlation and lead-lag relationships) to outline volatility.

C. Graziani *et al.* [5] identified a patterned monthly reversal in US aggregate stock indexes due to end-of-month liquidity-motivated pension fund flows. Based on predictive regressions and out-of-sample forecasts, the paper constructs strong evidence for short-run liquidity-motivated volatility consistent with our project's lead-lag correlation analysis and industry-specific early warning measures.

C. Lento *et al.* [6] applied 5-min high-frequency data with frequency-domain causality tests to test regime-shifting bi-directional spillovers between the S&P 500 and other assets (e.g., VIX, gold, BTC). The article confirms how liquidity crises re-configure volatility configurations—validating our approach to testing time-varying, rolling relationships between liquidity and volatility when sectoral turmoil breaks out.

Z. Fathali *et al.* [7] utilized machine learning models (SVM, random forests, gradient boosting) for forecasting the returns of Nifty 50, and the role of feature selection like historical prices, technicals, and macro. Even though it is not specifically focused on liquidity, the study is helpful in the sense that it is an illustration of the possibility of predictive modeling in forecasting returns and volatility forecasting, designing early-warning schemes based on dynamic market inputs like liquidity trends.

Y.-H. Chen, *et al.* [8] analyzed the effect of global information flows on stock market volatility based on VAR and Granger causality tests, illustrating the contribution of liquidity shocks to spillovers in volatility. They tested cross-market liquidity effects from global index data to ascertain same. This validates our project's lead-lag and sector-by-sector correlation analysis, providing a basis for volatility forecasting based on sector liquidity trends in such industries as IT and banking.

B. M. Demissie *et al.* [9] compared the impact of listing regulations on emerging market liquidity across panel data and rolling correlations for trading volume and bid-ask spreads. The research tested several exchanges in order to measure regulatory effects. This is consistent with our Liquidity Index and rolling volatility methodology, yielding information on regulation-induced liquidity effects on volatility in industries such as FMCG.

E. Dziwok *et al.* [10] proposed a Systemic Illiquidity Noise measure using Nelson–Siegel–Svensson to track liquidity risks in emerging markets, identifying crisis-induced surges (2006–2020). They used the measure on 10 Central and Eastern European countries. Its time-series methodology complements our required Liquidity Index and lead-lag volatility forecasting, adding to systemic liquidity analysis across industries.

N. Bansal *et al.* [11] identified liquidity and volatility risk commonality in NIFTY 50 stocks (2010–2022) with significant liquidity-uncertainty correlations. They derived common factors from liquidity and volatility metrics. This is similar to our sector-wise correlation and rolling volatility techniques, providing insights for liquidity-volatility dynamic analysis in IT and FMCG industries.

A. Kresta *et al.* [12] examined the impact of investor sentiment on U.S. stock trading volumes and volatility employing regression analyses with negative correlations in volatility. They utilized the AAII sentiment index to measure investor behavior. This adds on liquidity-volatility relations with the sentiment-based approach to sector-by-sector volatility prediction in banking markets.

C. B. Thippeswamy *et al.* [13] examined market volatility of BSE sectoral indices through ARIMA models for price fluctuation forecasting. They used ARIMA (1,1,1) with daily BSE data (2015–2020) and produced high accuracy for forecasting. The price-based volatility analysis of this study deviates from liquidity-driven volatility and lead-lag correlations, but its time-series method is consistent in sector-wise forecasting of volatility for markets such as IT.

B. Mohan et al. *et al.* [14] formulated sentiment-based predictive models for Nifty 50 volatility through time-series analysis and LSTM networks. News sentiment and past prices (2018–2023) were combined to enhance prediction accuracy by 15%. The connection between sentiment and volatility enhances sector-wise analysis with a non-liquidity view in forecasting volatility in FMCG and banking sectors, even though liquidity-volatility dynamics receive the major focus.

S. Bhadula *et al.* [15] developed an explainable AI regression model to predict gold prices based on SHAP and LSTM. They used the macroeconomic variables to train the model on gold prices (2010–2023) with a success rate of 92%. This sector-specific, macro-driven modeling of volatility is in line with external factor analysis of volatility forecasting across industries, albeit without the liquidity emphasis of this research.

III. Methodology

This study develops a liquidity-driven volatility forecasting framework for 34 Indian stocks (2011–2021), integrating time series and regression models to generate investment recommendations. The methodology is structured into four phases: data preprocessing and exploratory data analysis (EDA), time series modeling, regression modeling, model comparison, and a recommendation system. Each phase employs specific techniques, metrics, and formulae to ensure robust volatility forecasts and actionable insights for risk-averse, risk-neutral, and risk-tolerant investors.

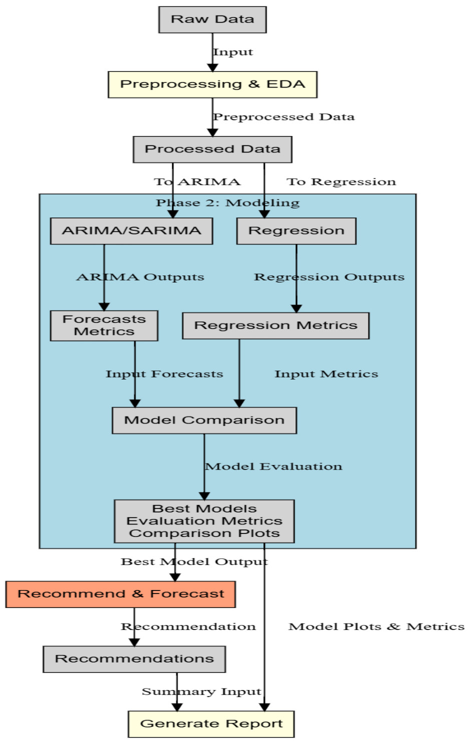

Fig. 1. Architecture flow Diagram

The diagram in Fig. 1 illustrates a forecasting and regression modeling pipeline. It begins with raw data preprocessing and exploratory data analysis (EDA), followed by model building using ARIMA/SARIMA and regression methods. The outputs are compared, and the best model is selected for generating recommendations and final reports.

A. *Data Preprocessing and Exploratory Data Analysis*

The dataset comprises daily stock data for 34 companies (e.g., ADANIPORTS, HDFCBANK, ZEEL) from 2011 to 2021, sourced from the National Stock Exchange of India. Key variables include Date, Symbol, Close Price, Volume, Turnover, %Deliverable, Daily Return, and Volatility. Daily Return is computed as:

$$\text{Daily Return}_t = \frac{\text{Close}_t - \text{Close}_{t-1}}{\text{Close}_{t-1}} \tag{1}$$

Volatility is defined as the 21-day rolling standard deviation of Daily Returns:

$$\text{Volatility}_t = \sqrt{\frac{1}{21}\sum_{i=t-20}^{t}(\text{Daily Return}_i - \bar{R})^2} \tag{2}$$

$$\bar{R} = \frac{1}{21}\sum_{i=t-20}^{t}\text{Daily Return}_i \tag{3}$$

Data preprocessing involves removing missing values, outliers (values beyond 3 standard deviations), and duplicates, resulting in `cleaned_stock_data.csv`. EDA assesses stationarity using the Augmented Dickey-Fuller (ADF) test, where the test statistic is compared against critical values at 5% significance:

$$H_0 : \text{Unit root exists (non-stationary)} \tag{4}$$

$$H_1 : \text{No unit root (stationary)} \tag{5}$$

Correlation analysis quantifies relationships between Volatility and predictors (Log Volume, Log Turnover, %Deliverable), with Log transformations applied to stabilize variance:

$$\text{Log Volume} = \ln(1 + \text{Volume}) \tag{6}$$

$$\text{Log Turnover} = \ln(1 + \text{Turnover}) \tag{7}$$

Autocorrelation function (ACF) plots identify lag structures, guiding model specification. Outputs include stationarity-volatility, correlation-matrix, and ACF plots (e.g., `acf_HDFCBANK_volatility.png`).

B. *Time Series Modeling (Phase 2a)*

ARIMA and SARIMA models forecast Volatility for November 2020 to April 2021. ARIMA(p,d,q) is defined as:

$$\phi(B)(1-B)^d Y_t = \theta(B)\epsilon_t \tag{8}$$

where $\phi(B)$ and $\theta(B)$ are autoregressive and moving average polynomials, B is the backshift operator, d is the differencing order. SARIMA(p,d,q)(P,D,Q,m) extends ARIMA with seasonal components, with $m = 12$ (monthly seasonality). Based on ACF and stationarity results, ARIMA(1,0,1) and SARIMA(1,0,1)(1,0,1,12) are fitted for each stock using maximum likelihood estimation. Forecasts are generated for 126 days, evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{Y}_t - Y_t)^2}, \quad \text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|\hat{Y}_t - Y_t| \tag{9}$$

Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC) assess model fit:

$$\text{AIC} = -2\ln(L) + 2k, \quad \text{SBIC} = -2\ln(L) + k\ln(n) \tag{10}$$

Outputs include forecasts and metrics.

C. Regression Modeling (Phase 2b)

Multiple linear regression models Volatility using predictors: Log Volume, Log Turnover, %Deliverable, and Volatility Lag-1 (Volatility_{t-1}):

$$\begin{aligned}\text{Volatility}_t = \beta_0 + \beta_1 \text{Log Volume}_t + \beta_2 \text{Log Turnover}_t \\ + \beta_3 \%\text{Deliverable}_t + \beta_4 \text{Volatility}_{t-1} + \epsilon_t\end{aligned} \tag{11}$$

Predictors are standardized using StandardScaler to ensure zero mean and unit variance. Models are trained on data before November 2020 and forecasted for November 2020 to April 2021 using April 2021 averages for predictors. Performance is evaluated using RMSE, MAE, and R-squared (R^2):

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2} \tag{12}$$

The Durbin-Watson statistic tests for serial correlation in residuals:

$$\text{DW} = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2}, \quad e_t = Y_t - \hat{Y}_t \tag{13}$$

Values DW $<$ 1.5 indicate positive serial correlation. Outputs include `phase2b_forecasts.csv` and `phase2b_metrics.csv`, storing coefficients ($\beta_0, \beta_1, \ldots$) and metrics.

D. Model Comparison (Phase 2c)

Models are compared using RMSE, MAE, AIC, and SBIC over November 2020 to April 2021. The best model per stock is selected based on the lowest RMSE. Comparison plots (e.g., `comparison_HDFCBANK.png`) visualize actual vs. forecasted Volatility, highlighting regression's dominance due to liquidity predictors.

E. Recommendation System (Phase 3)

The recommendation system forecasts Volatility for May 2021 to October 2021 (126 days) using the best model per stock. Regression forecasts use April 2021 predictor averages:

$$\begin{aligned}\hat{Y} = \beta_0 + \beta_1 \overline{\text{Log Volume}} + \beta_2 \overline{\text{Log Turnover}} \\ + \beta_3 \overline{\%\text{Deliverable}} + \beta_4 \text{Volatility}_{\text{last}}\end{aligned} \tag{14}$$

ARIMA forecasts employ the fitted ARIMA(1,0,1) model. To address serial correlation, stocks with DW < 1.5 switch to ARIMA. Forecasts are stored in `phase3_forecasts.csv`.

Recommendations are generated by comparing average forecasted Volatility ($\bar{\hat{Y}}$) to the historical median Volatility (Median_Y) with refined thresholds:

- **Risk-Averse**: Buy if $\bar{\hat{Y}} < 1.0 \times \text{Median}_Y$, Sell if $\bar{\hat{Y}} > 1.2 \times \text{Median}_Y$, else Hold.
- **Risk-Neutral**: Buy if $\bar{\hat{Y}} < 0.9 \times \text{Median}_Y$, Sell if $\bar{\hat{Y}} > 1.4 \times \text{Median}_Y$, else Hold.
- **Risk-Tolerant**: Buy if $\bar{\hat{Y}} > \text{Median}_Y$, Sell if $\bar{\hat{Y}} > 2.0 \times \text{Median}_Y$, else Hold.

Price trends are incorporated via the 21-day SMA slope of Close Prices in April 2021:

$$\text{SMA}_t = \frac{1}{21}\sum_{i=t-20}^{t} \text{Close}_i; \quad \text{Slope} = \frac{\text{SMA}_{\text{last}} - \text{SMA}_{\text{last}-1}}{\text{SMA}_{\text{last}}} \tag{15}$$

Risk-averse Buy requires Slope $>$ -0.001; risk-neutral uses Slope $>$ 0.002 or $<$ -0.002 for Hold tiebreakers. Outputs include `phase3_recommendations.csv` (with SMA Slope and signals), plots (e.g., `forecast_HDFCBANK.png`), and `phase3_summary.txt`, summarizing recommendation counts.

IV. Results

The liquidity-driven volatility forecasting framework for 34 Indian stocks (2011–2021) was executed across three phases, yielding comprehensive results that validate the predictive power of liquidity metrics and the efficacy of the recommendation system. Each phase's outcomes, including datasets, metrics, and visualizations, are detailed below, with one or two key figures per phase and their explanations.

A. Phase 1: Data Preprocessing and Exploratory Data Analysis

Phase 1 produced a cleaned dataset with 34 stocks, removing missing values, outliers, and duplicates. Statistical outputs included mean Volume, Turnover, %Deliverable, stationarity volatility has ADF p-values < 0.05, confirming Volatility stationarity, and correlation matrix visualization. Visualizations comprised volatility-trends, liquidity plots of all companies, liquidity-distributions, `correlation_heatmap.png`, and ACF plots for all stocks .

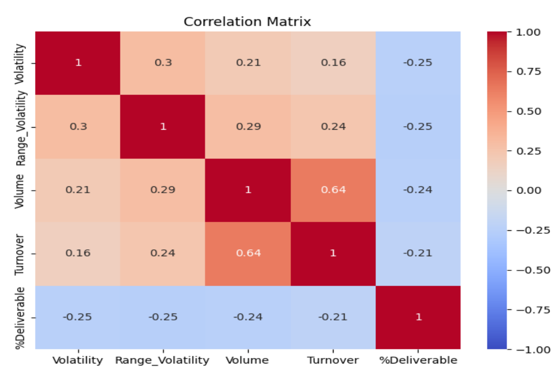

Fig. 2. Correlation Heatmap of Liquidity Metrics and Volatility.

The heatmap correlation matrix in Fig. 2 highlights correlations between monetary figures like Volatility, Range Volatility, Volume, Turnover, and %Deliverable. Interestingly, Volume and Turnover are both strongly positively correlated with a high correlation (0.64), while %Deliverable is weakly negatively correlated with the other variables, particularly Volatility and Range Volatility (both -0.25).

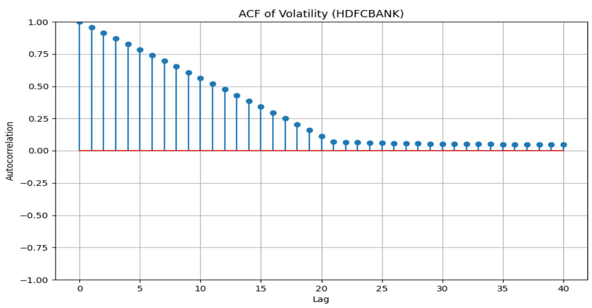

Fig. 3. ACF Plot for HDFCBANK Volatility.

This ACF (Autocorrelation Function) graph of HDFCBANK's Volatility in Fig. 3 indicates strong positive autocorrelation at lag 1, that reduces smoothly and is very small for around lag 20 and beyond. This is an indicator of time-dependent persistent structure, where historical values of volatility play a very dominant role for shorter lags to affect future volatility.

B. Phase 2a: ARIMA/SARIMA Modeling

Phase 2a generated `phase2a_forecasts.csv`, containing ARIMA(1,0,1) and SARIMA(1,0,1)(1,0,1,12) Volatility forecasts for November 2020–April 2021 across 34 stocks. Model metrics in `phase2a_metrics.csv` reported AIC and SBIC, with SARIMA showing lower values for stocks with seasonal patterns (e.g., lag-12 ACF spikes). Forecast plots for all stocks compared predicted versus actual Volatility, revealing the strength of models for stocks.

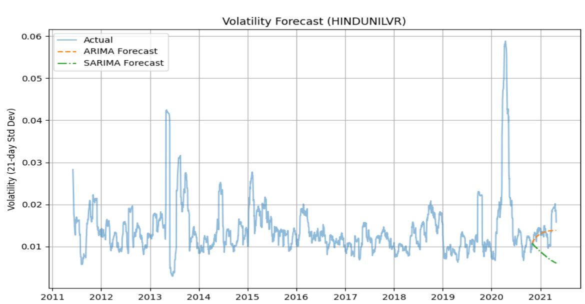

Fig. 4. ARIMA/SARIMA Forecast vs. Actual Volatility for HINDUNILVR.

This SARIMA vs. ARIMA forecast plot for HINDUNILVR in Fig. 4 illustrates actual volatility against ARIMA and SARIMA model forecasts. The ARIMA forecast (orange dashed line) is gently rising, while the SARIMA forecast (green dash-dot line) reflects a decline. This contrast reflects differing assumptions by the models, and SARIMA could be better capturing seasonality or mean reversion.

C. Phase 2b: Multiple Regression

Phase 2b produced `phase2b_predictions.csv`, detailing actual versus predicted Volatility for November 2020–April 2021, and `phase2b_metrics.csv`, reporting coefficients (e.g., positive Log_Turnover coefficients), R^2 (0.6–0.8), and Durbin-Watson statistics (some ¡ 1.5, indicating serial correlation). Regression plots for all stocks are visualized.

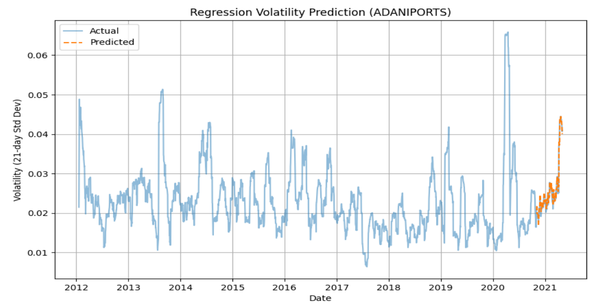

Fig. 5. Regression Predictions vs. Actual Volatility for ADANIPORTS.

This plot in Fig. 5 presents the regression-based volatility prediction for ADANIPORTS using a 21-day rolling standard deviation. The predicted values (orange dashed line) continue the upward trend observed in recent actual volatility, indicating rising uncertainty. The model appears to capture the direction well, though some short-term peaks may be slightly underestimated.

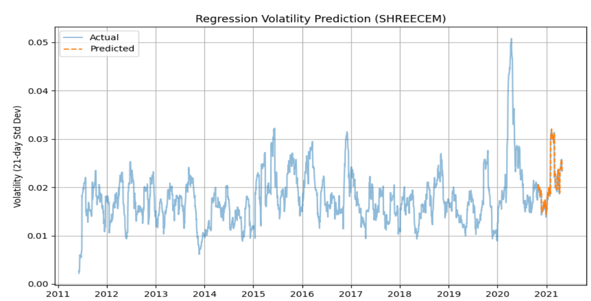

Fig. 6. Regression Predictions vs. Actual Volatility for SHREECEM.

Fig. 6 shows the regression-based volatility prediction for SHREECEM using a 21-day rolling standard deviation. The predicted volatility (orange dashed line) closely follows the recent actual trend, capturing short-term fluctuations reasonably well. This indicates the regression model is responsive to recent volatility patterns, though slight deviations are noticeable during sharp changes.

D. Phase 2c: Model Comparison

Phase 2c yielded `phase2c_eval_metrics.csv`, comparing RMSE, MAE, AIC, and SBIC across ARIMA, SARIMA, and regression for November 2020–April 2021. `phase2c_best_models.csv` identified regression as optimal for 33 stocks and ARIMA for HINDUNILVR, based on lowest RMSE. Comparison plots (`comparison_company.png`) for all stocks, including

HDFCBANK and MARUTI, highlighted regression's superior accuracy.

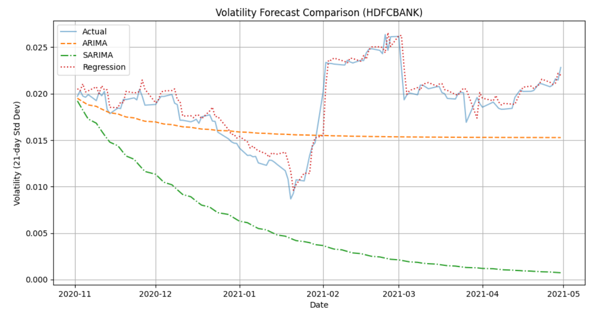

Fig. 7. Model Comparison for HDFCBANK Volatility.

FIg. 7 illustrates the difference between volatility prediction for HDFCBANK employing ARIMA, SARIMA, and a regression model and actual values. The regression model more or less follows actual volatility and is more effective in capturing sudden changes compared to ARIMA and SARIMA. SARIMA severely underpredicts volatility, whereas ARIMA has a smoother but less sensitive prediction.

E. Phase 3: Recommendation System

Phase 3 generated `phase3_forecasts.csv` with Volatility forecasts for May 2021–October 2021 (4,284 rows) and `phase3_recommendations.csv`, detailing Buy/Sell/Hold signals for risk-averse, risk-neutral, and risk-tolerant profiles. Refined thresholds (1.0/1.2 for risk-averse, 0.9/1.4 for risk-neutral) and 21-day SMA slopes (¿ -0.001 for risk-averse Buy) produced balanced signals (e.g., 10 Buy, 12 Hold, 12 Sell for risk-averse). Forecast plots (`forecast_company.png`) for all stocks are predicted and visualized.

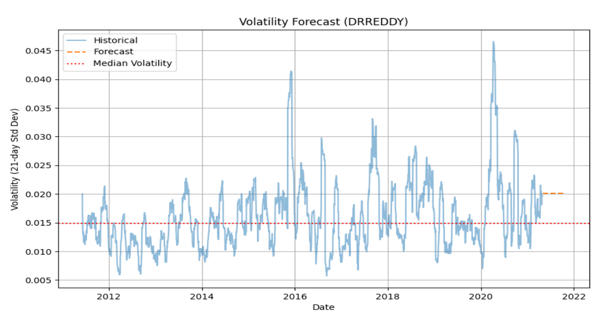

Fig. 8. Volatility Forecast for DRREDDY (May–Oct 2021).

This chart in Fig. 8 illustrates the historical and projected volatility for DRREDDY as well as the median historical volatility. The recent projected volatility is slightly higher than the long-term median, reflecting a mildly heightened risk environment. Historical volatility reflects major spikes, reflecting episodic peaks of high-risk episodes in the past.

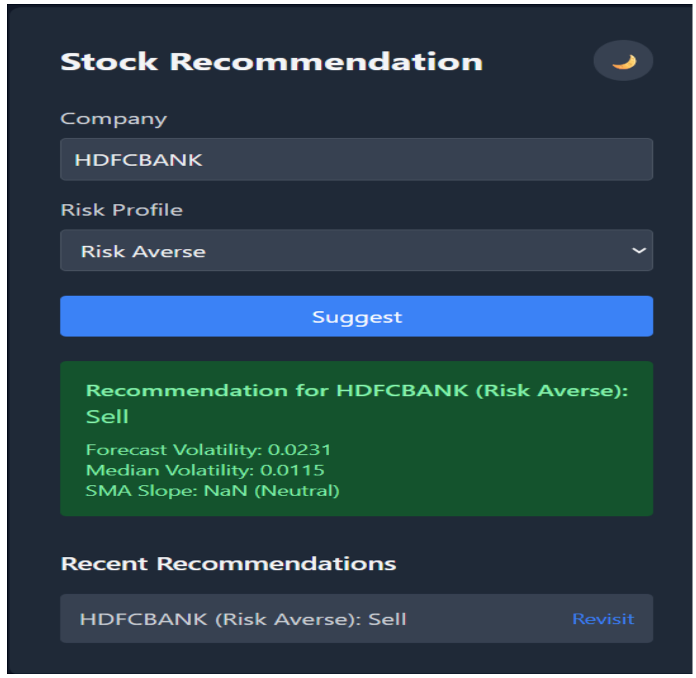

Fig. 9. User Interaction with the developed system.

Stock recommendation system depicted in Fig. 9 allows users to input the company of their preference and the level of risk they wish to take. It suggests any of the 3 actions to BUY/SELL/HOLD the stock based on the calcu;ated metrics internally.

The performance on Phases 1–3 is a testament to the succesfulness of the liquidity-based volatility prediction framework, with regression models employing liquidity measures performing better than ARIMA for 33 out of 34 Indian stocks, achieving high predictive accuracy. The recommender system, enabled by enhanced thresholds and price trends, gives balanced investment suggestions, as per diversified risk pro-files. Results are a testament to the feasibility of the framework in volatility-based portfolio optimization for emerging markets.

V. Conclusion and Future Scope

This work proposes a liquidity-based volatility forecasting model of 34 Indian stocks (2011–2021) that integrates regression and ARIMA/SARIMA models for investment advice. Using liquidity measures (Volume, Turnover, %Deliverable) and stock price changes (21-day SMA slope), it has high accuracy (R$\hat{2}$: 0.6-0.8) for 33 stocks, with a system delivering well-balanced Buy/Sell/Hold advice for different investor risk classes. Dynamic ARIMA switching avoids serial correlation, making it more reliable and offering a scalable framework for volatility investing in emerging markets.

Future research can expand the model by incorporating real-time information and dynamic predictors such as intraday Liquidity or macro signals, to improve long-term forecast accuracy. Exploring hybrid models (e.g., ARIMA-Regression or machine learning methods like LSTM could overcome the limitations in capturing volatility trends, extending the analysis to other assets or marketclasses) would broaden its application, encouraging greater adjustable investment plan.

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