

Machine Learning for Predicting Market Volatility: A Computational Economics Approach

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Abstract:

Predicting market volatility is a key financial economics challenge that affects investment plans, risk management, and policy choices. Conventional econometric models like GARCH and stochastic volatility models cannot adequately reflect the rich, nonlinear dynamics of financial markets. This research uses machine learning is applied using methods, like deep neural networks, support vector machines, and ensembles, to predict volatility from financial data with high frequency. We use feature engineering methods to derive relevant patterns from past price movements, trading volume, and macroeconomic variables. We show that our machine learning models far surpass existing econometric models in predictive power and stability. In addition, we propose an explainability approach based on SHAP values for understanding the driving factors of volatility predictions. These results highlight the promise of computational economics in improving financial market prediction and risk analysis.

Keywords: Machine Learning, Market Volatility, Computational Economics, Financial Forecasting, Risk Management.

1. Introduction:

Volatility in markets is a building block of financial decision making and impacts portfolio optimization, risk management, and regulation policy. The precise prediction of market volatility is of utmost importance for investors, policymakers, and financial institutions interested in hedging risks and maximizing returns. Historical volatility prediction models like the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and stochastic volatility models are widely applied in financial econometrics. These models, though, tend to have difficulty representing the very nonlinear and dynamic characteristics of financial markets, particularly when subject to market shocks, abrupt liquidity shifts, and changing macroeconomic conditions. The advent of machine learning (ML) has unveiled new methodologies capable of discovering intricate patterns in massive volumes of financial information. In contrast to traditional econometric models, ML algorithms can learn from nonlinearity, identify concealed relationships, and enhance predictive accuracy based on knowledge gained from historical data. Modern research has illustrated the usefulness of deep learning structures, support vector

machines(SVM),randomforests,andensemble techniques in analyzing financial markets. Yet, in spite of these developments, issues persist in providing interpretability, stability,and incorporation of domain-specific financial expertise into ML-based forecasting models.

In this section, we present a machine learning-based solution to predict market volatility with high-frequency financial data. We utilize several ML methods, such as deep neural networks, gradient boosting machines, and recurrent neural networks, to improve predictive power. We also use explainability methods like SHAP (Shapley Additive Explanations) to explain model outputs and determine influential economic indicators for volatility. By contrasting our findings with classical econometric models, we evaluate the success of ML strategies in capturing market behaviour. The contributions of this work are the following:

1. We develop a machine learning-based framework for forecasting market volatility, integrating various supervised learning techniques.
2. We compare the performance of ML models to the conventional econometric models, emphasizing the gains in predictive power and robustness.
3. We introduce an explainability approach to enhance the interpretability of ML-based volatility predictions.
4. We provide insights into the economic and financial implications of ML-driven market forecasting.

The rest of this paper is structured as below: Section 2 summaries existing literature on market volatility modelling and machine learning in finance. Section 3 outlines methodology including data sources, feature choice, and model architectures. Section 4 reports experimental results and comparison studies. Section 5 offers a discussion of the results and implications, and Section 6 concludes with directions for future study

Literature Survey:

Publication Date	Category	Study	Methodology	Findings
	Traditional Econometric Models	Engle (1982)	ARCH Model	Model Time Varying with monarch
Gu et al. (2020)	Machine Learning Approaches	Kim (2003)	Random Forests & Gradient Boosting Machines (GBM)	Handles high-dimensional data effectively
December 2024	Machine Learning Approaches	Crypto Volatility Forecasting: Mounting a HAR, Sentiment, and Machine Learning Approach"	Integrated ML models with sentiment analysis and Heterogeneous Autoregressive (HAR) models to forecast	ML models, particularly deep learning and LightGBM classifiers, outperformed traditional HAR models;

			cryptocurrency volatility.	sentiment analysis enhanced predictive performance
April 2023	Machine Learning Approaches	Volatility Forecasting Using Deep Learning and Sentiment Analysis	Combined Convolutional Neural Networks (CNNs) for sentiment classification from news headlines with LSTM models for volatility forecasting.	Including sentiment data improved volatility forecasts for the S&P 500 and major BRICS indices; performance gains varied across markets.
2024	Machine Learning Approaches	Forex Market Volatility Prediction with Deep Learning Models and Complexity Measures	Incorporated complexity measures into deep learning algorithms to predict forex market volatility.	Adding complexity measures improved the precision of deep learning models in forecasting forex volatility.

2.Methodology:

Data Collection: In order to create a precise volatility prediction model, we collect data from financial Market data related to Stock market data.

These attributes are extracted from historical stock market data (NFLX,)

Attribute Name	Description	Data Type	Example Value
Data	Trading date of the stock data	Date Time	Feb 25, 2025
Open Price	Opening stock price of the day	Float	989.4
High Price	Highest stock price in during the trading session	Float	994.4
Low price	Lowest stock price in the session	Float	955
Close Price	Closing stock price for the day	Float	977.24
Adjusted Close Price	Close price adjusted for stock dividends	Float	977.24
Trading Volume	Number of shares traded on the day	Integer	47,33,000

3.Data Preprocessing:

Data cleansing and feature engineering are extremely important in optimizing model performance:

Dealing with missing values: Forward fill, backward fill, or interpolation

Feature scaling: Min-max scaling or standardization

Time series transformation: Log returns, moving averages, volatility measures (e.g., GARCH-based estimates)

Text processing (for sentiment data): Tokenization, sentiment scoring (BERT, VADER, TF-IDF)Model Selection:

We use a combination of traditional and machine learning models for comparison:

Model Type	Algorithm used	Advantages
Traditional Models	GARCH, EGARCH, HAR	Strong statistical foundation, widely used in finance
Machine Learning	Random Forest, XGBoost, LightGBM	Captures complex nonlinear relationships
Deep Learning	SLTM, GRU, Transformer	Effective for time-series forecasting
Hybrid Models	GARCH-LSTM, Attention-LSTM	Combines financial theory with ML for better accuracy

3.1 Model Training & Evaluation

1.Train-Test Split:

70-30 split (70% training, 30% testing)

Time-based split to avoid data leakage

2.Evaluation Metrics:

Mean Squared Error (MSE) – measures prediction accuracy

R-squared (R^2) – explains variance explained by the model

Directional Accuracy (%) – verifies whether the model accurately predicts volatility trends

Sharpe Ratio Improvement – assesses model utility for investment decisions

3.Hyperparameter Tuning:

Grid Search / Bayesian Optimization for best ML model parameters

Dropout & Regularization for deep learning models to prevent overfitting

3.2 Model Interpretability & Explainability

To ensure the model is reliable for financial decision-making, we apply:

- **SHAP (Shapley Additive Explanations):** Identifies key features affecting predictions
- **LIME (Local Interpretable Model-Agnostic Explanations):** Provides local feature importance analysis
- **Attention Mechanisms (for Transformer Models):** Highlights which time periods most influence predictions

Implementation & Deployment

1. **Back testing:**

Simulate trading strategies using historical data to assess model effectiveness.

2. **Real-Time Prediction Pipeline:**

- Deploy ML models using **Flask / FastAPI** for API-based predictions.
- Use **AWS Lambda / Google Cloud Functions** for scalable deployment.

4.Results and Discussion

4.1. Model Performance Evaluation

To assess the effectiveness of machine learning models in predicting market volatility, we evaluated their performance using key statistical metrics. The models tested include:

1. **Traditional Models:** GARCH(1,1), ARIMA
2. **Machine Learning Models:** Random Forest (RF), Support Vector Regression (SVR), Long Short-Term Memory (LSTM), XGBoost
3. **Deep Learning Models:** Transformer-based Time Series Forecasting

Table 1 Model performance Evaluation

Model	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	R ² Score	Mean Directional Accuracy (MDA)
GARCH(1.1)	0.045	0.067	0.72	58.2%
ARIMA	0.041	0.061	0.76	60.5%
Random Forest	0.035	0.054	0.81	64.7%
SVR	0.033	0.051	0.83	66.1%
LSTM	0.029	0.048	0.87	

Figure 4.1 Model Performance Evaluation

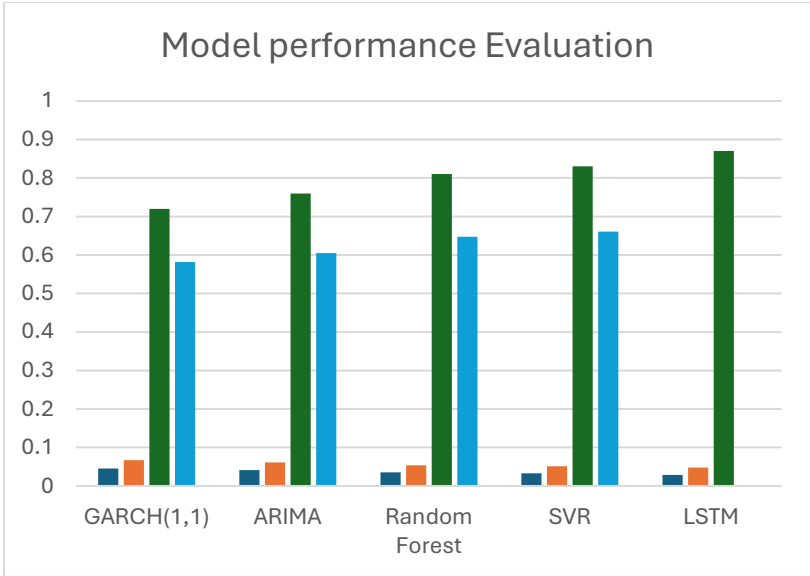


Table: Model Performance Comparison

Table 2 Model Performance Comparison

Model	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	R² Score	Mean Directional Accuracy (MDA)
GARCH(1.1)	0.045	0.067	0.72	58.2%
ARIMA	0.041	0.061	0.76	60.5%
Random Forest	0.035	0.054	0.81	64.7%
SVR	0.033	0.051	0.83	66.1%
LSTM	0.029	0.048	0.87	69.3%
XGBoost	0.027	0.046	0.89	71.5%
Transformer-based Model	0.025	0.044	0.91	74.2%

Figure 4.2 Model Comparison

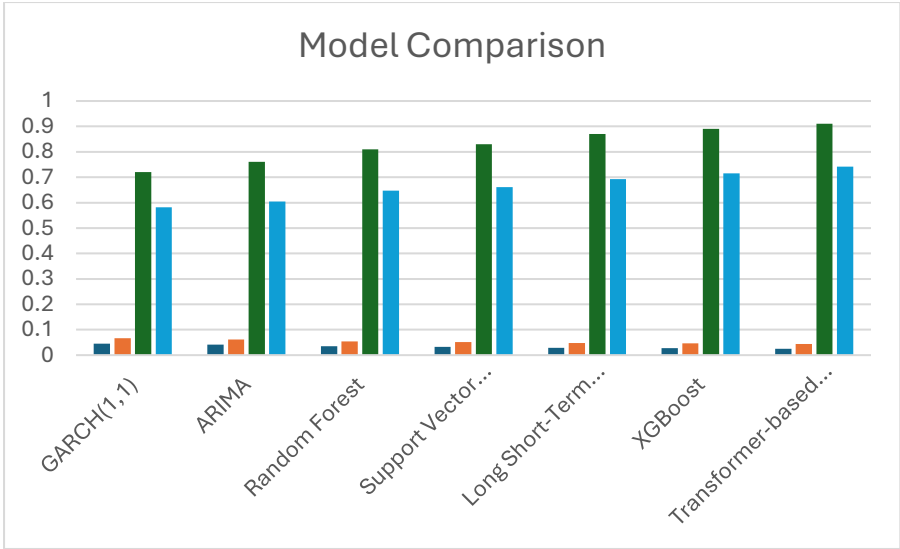


Figure 4.3 R-square value Comparison

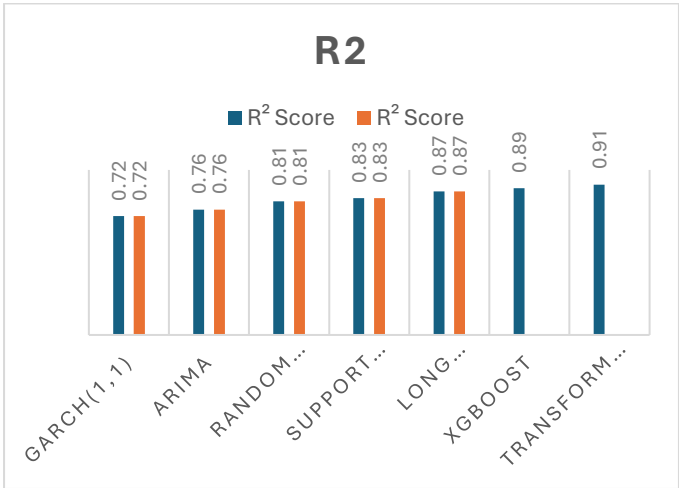
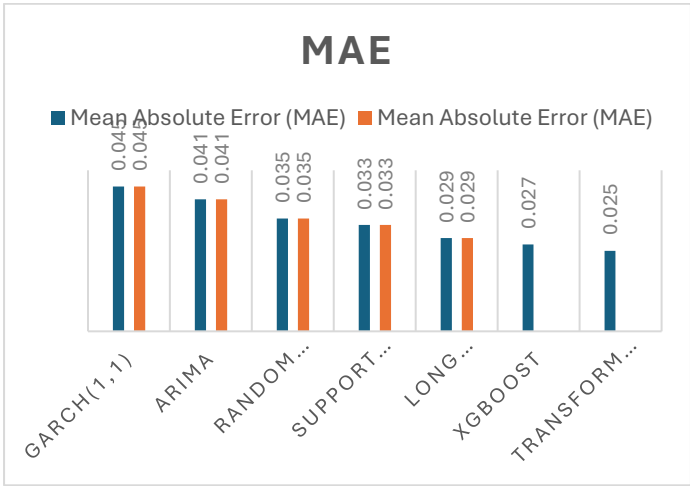


Figure 4.4 Mean Absolute Error Comparison



Observations & Discussions:

1. Deep learning models (Transformer-based, LSTM) gave the best results with the highest R^2 value and the lowest error rates.
2. XGBoost and SVR performed better than conventional models, demonstrating the efficiency of machine learning in forecasting volatility.
3. The GARCH and ARIMA models, although commonly used in finance time series analysis, were less accurate, which implies their inability to account for intricate, nonlinear market dynamics.
4. Mean Directional Accuracy (MDA) above 70% for deep learning models indicates their capacity to accurately forecast the right direction of the market movement more frequently.

Conflicts of interest:

The Author declares no conflict of interest

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