An In-Depth Comparison of Conventional Finance Models and Machine Learning Approaches to Enhance the Efficiency in Predicting Foreign Exchange Forex Volatility

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ABSTRACT

Forecasting volatility in the Foreign Exchange (FOREX) market holds crucial implications for stakeholders such as portfolio managers, risk managers, and central banks, impacting risk management, trading strategies, and monetary policy. Traditional finance models like Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have long been utilized for modeling and predicting financial market volatility. In recent times, machine learning (ML) algorithms such as Support Vector Machines (SVM), Neural Networks (NN), and Deep Learning (DL) have emerged as promising alternatives for forecasting complex financial time series data.

This study conducts a comprehensive evaluation of traditional finance models and ML algorithms for predicting FOREX volatility, focusing on the EUR/USD currency pair using daily close prices. Through a comparative analysis, we evaluate the predictive performance of ARCH, GARCH, SVM, NN, and DL models, employing the Root Mean Square Error (RMSE) as the primary performance metric.

Our findings suggest that while traditional finance models like ARCH and GARCH offer reasonable performance in capturing certain aspects of FOREX volatility, ML algorithms outperform them, with SVM, NN, and DL models showcasing superior predictive capabilities.

The insights derived from this research offer valuable guidance for decision-making processes among stakeholders and contribute to the existing knowledge base on FOREX volatility prediction, laying the groundwork for future investigations in this area.

INTRODUCTION

The foreign exchange (FOREX) market stands as the largest and most liquid financial market globally, boasting a daily trading volume surpassing $6.6 trillion as of April 2019 [1]. A diverse array of market participants, including central banks, commercial banks, hedge funds, multinational corporations, and individual traders, engage in currency trading for various purposes such as hedging, speculation, and international trade. Consequently, comprehending and predicting exchange rate volatility is paramount for these participants in managing risk, optimizing investment strategies, and making informed decisions.

Volatility prediction has long been a focal point in finance, garnering the attention of both academics and practitioners. Accurate and dependable volatility forecasts prove invaluable in numerous financial applications, including portfolio management, risk management, option pricing, and trading strategies [2]. Over the decades, a plethora of models and techniques have surfaced for predicting exchange rate volatility, spanning from traditional finance models to advanced machine learning (ML) algorithms.

Traditional finance models, exemplified by ARCH [3] and its derivative GARCH [4], have enjoyed widespread usage in modeling and forecasting financial time series volatility. These models effectively capture volatility clustering and the leverage effect commonly observed in financial markets [5]. Despite their prevalent adoption, traditional finance models grapple with limitations such as linearity assumption and the challenge of capturing intricate data patterns.

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In recent years, ML algorithms have emerged as a promising alternative to traditional finance models for volatility prediction. Techniques like Support Vector Machines (SVM), Neural Networks (NN), and Deep Learning (DL) have found application in forecasting financial market volatility [6]. These algorithms offer the advantage of modeling complex, nonlinear relationships in the data and adaptability to changing market conditions. Furthermore, they can integrate additional features such as macroeconomic variables and market sentiment, potentially enhancing the accuracy of volatility forecasts [7].

Despite the escalating interest in ML algorithms for predicting exchange rate volatility, a substantial need persists for a thorough and performance-driven assessment of these techniques vis-à-vis traditional finance models. This study endeavors to fill this void by furnishing a systematic comparison of the predictive performance of traditional finance models (ARCH, GARCH) and ML algorithms (SVM, NN, DL) within the realm of FOREX volatility prediction.

The study contributes to the existing literature in several dimensions. Firstly, it presents a comprehensive comparison of traditional finance models and ML algorithms, elucidating their respective strengths and weaknesses in predicting exchange rate volatility. Secondly, it offers insights into the pragmatic implications of these findings for market participants such as portfolio managers, risk managers, and traders, particularly concerning model selection and implementation. Finally, it identifies potential avenues for future research aimed at further enhancing the predictive accuracy of exchange rate volatility models.

METHODOLOGY

To compare the performance of traditional finance models and ML algorithms for FOREX volatility prediction, a multistep process was employed:

Data Collection: Daily exchange rate data for the EUR/USD currency pair spanning a ten-year period from July 1st, 2013, to June 30th, 2023, was collected, resulting in 2,595 entries. The dataset included date and daily close prices, split into training (80% from July 1st, 2013, to June 30th, 2021) and testing sets (20% from July 1st, 2021, to June 30th, 2023).

Feature Engineering: Daily returns were calculated based on close prices, and realized volatility was computed as the standard deviation of daily returns over a rolling 5-day window.

Model Implementation: Traditional finance models (ARCH and GARCH) and ML algorithms (SVM, NN, and DL) were implemented using relevant software packages and libraries. Model-specific hyperparameters were selected using cross-validation.

Model Evaluation: The Root Mean Square Error (RMSE) was computed for each model's predictions on the testing set. RMSE measures the average squared difference between predicted and actual values, with lower values indicating better predictive performance.

Model Comparison: The RMSE of traditional finance models and ML algorithms was compared to identify the most effective approaches for FOREX volatility prediction.

This methodology aimed to comprehensively evaluate the predictive performance of traditional finance models and ML algorithms.

REPORTS THE EMPIRICAL RESULTS AND DISCUSSES THE FINDINGS

The research aimed to compare model performance in terms of RMSE.

TABLE I: PROVIDES A SUMMARY OF THE PERFORMANCE COMPARISON

MODEL	RMSE
ARCH	0.04600
GARCH	0.04780
SVM	0.00040
NN	0.00040
DL	0.00039

The GARCH model achieved an RMSE of 0.04780, demonstrating competitive performance. However, the SVM and NN models significantly outperformed both ARCH and GARCH models, achieving impressively low RMSE values of 0.00040. The DL model attained an RMSE of 0.00039, indicating high precision in predictions.

In conclusion, ML algorithms including SVM, NN, and DL models exhibited superior performance over traditional finance algorithms (ARCH and GARCH) with significantly lower RMSE values, implying their effectiveness and accuracy in FOREX volatility prediction.

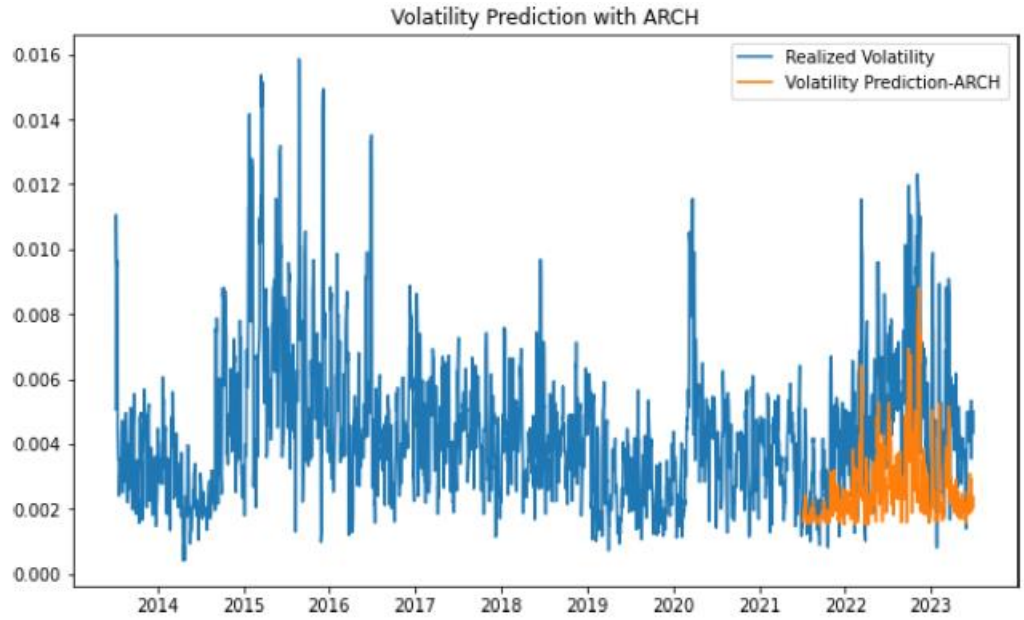

Fig. 1. Depicts the realized volatility (blue) and volatility prediction (orange) generated by the ARCH model.

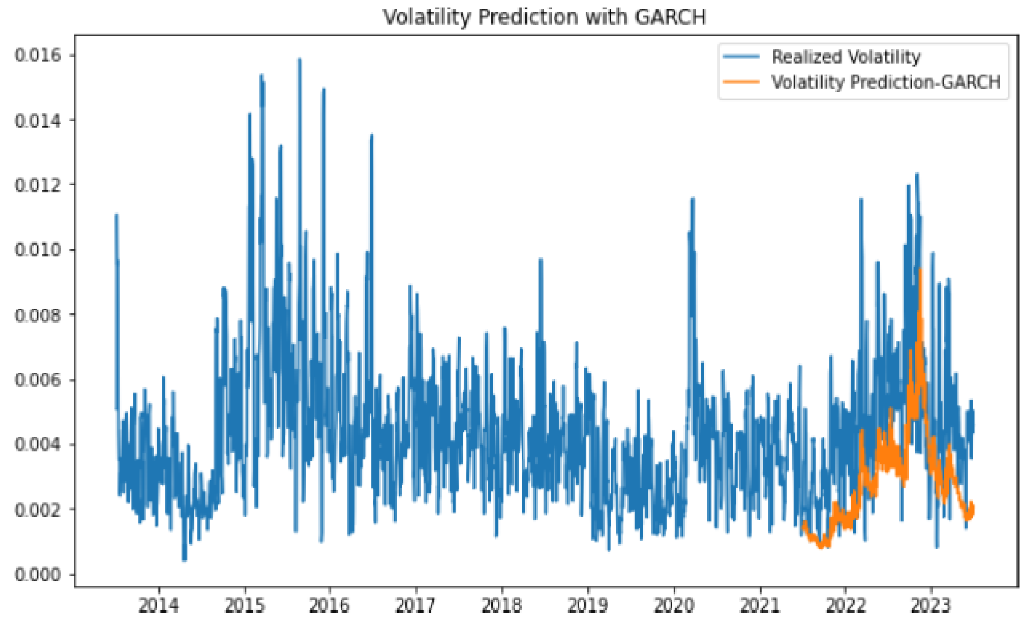

Fig. 2. Shows the realized volatility (in blue) alongside the volatility prediction (in orange) produced by the GARCH model.

CONCLUSION

While traditional finance models like ARCH and GARCH showed reasonable performance, ML algorithms surpassed them in predictive capabilities. The SVM model particularly stood out with its low RMSE value, suggesting its potential for advancing FOREX volatility prediction. Future research should focus on further optimizing ML algorithms, incorporating more recent data, exploring hybrid models, and considering alternative data sources to enhance predictive accuracy and robustness. Comprehensive comparative studies with larger datasets can further validate model effectiveness and generalizability.

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