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INTEGRATING THE STOCHASTIC VOLATILITY MODEL WITH ARTIFICIAL INTELLIGENCE (TRANSFORMER MODEL) FOR ANALYZING AND FORECASTING THE VOLATILITY OF S&P 500 INDEX STOCK PRICES

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ABSTRACT

This study aimed to develop a hybrid model combining the Stochastic Volatility (SV) model with Artificial Intelligence (Transformer Model) to analyze and predict stock price volatility, applied to the S&P500 index during the period from January 3, 2001 to November 30, 2024. The objective was to enhance the accuracy of financial returns predictions by integrating the conditional volatility outputs from the SV model into the Transformer model. Both models were evaluated using time-series data and performance metrics, including MSE, RMSE, and MAE, to measure prediction accuracy. The implementation was carried out in Python leveraging its relevant libraries.
The results demonstrated that the hybrid model outperformed the simple Transformer model, as performance metrics values showed a significant decrease. This indicates that incorporating SV outputs as an additional source of information improved the Transformer model's ability to capture temporal patterns, thereby reducing significant predictions errors.

KEYWORDS

Stock Price Volatility, Daily Returns, Stochastic Volatility Model, Transformer Model, S&P500 Index

CITATION

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I. Introduction

Financial markets witness increasing fluctuations alongside the global economic, political, and financial developments, and under the economic challenges imposed by various global events on financial markets, investors have been subjected to enormous pressures due to the phenomenon of price fluctuations, which significantly affected financial markets and imposed major challenges, thus requiring modern tools and techniques to analyze and forecast these fluctuations with the aim of improving investment performance and risk management. In this context, multiple traditional financial models appeared, such as the GARCH models, and Stochastic Volatility (SV) models, which possess the ability to study the temporal behavior of asset prices. However, thanks to the digital revolution, artificial intelligence has provided multiple techniques and advanced capabilities that allow for a deeper understanding of volatility patterns, most notably Attention Models, Artificial Neural Networks, and Transformer Models (Vaswani et al., 2017).

Despite the advances in financial market analysis techniques, there remain gaps in accurately understanding and predicting market fluctuations, which highlights the need to integrate traditional models with modern AI techniques for a more comprehensive and effective analysis of these fluctuations. Therefore, this study proposes the integration of Stochastic Volatility models with Transformer models, given that the SV model is effective in characterizing volatility dynamics, while modern deep learning models, such as the Transformer, demonstrate high efficiency in learning complex temporal patterns.

From here arises the study's main problem, posed as the following question: ***How effective is the integration of Stochastic Volatility models with Transformer models in analyzing and predicting the fluctuations of S&P500 index prices?***

Based on this question, the following sub-questions can be formulated:

- How accurate is the Transformer model in predicting financial returns and S&P500 price volatility?
- How does integrating the outputs of the Stochastic Volatility model with the Transformer model affect predictions?
- Which model is more efficient and accurate: the simple model or the hybrid model?

Study Objectives

Given the difficulty of making investment decisions in the stock market, especially under exceptional circumstances such as financial crises, this study aims to analyze and predict the fluctuations of S&P500 index stock prices, due to their importance in providing an understanding of significant volatility, which can help investors make better investment decisions and reduce financial risks during crises. This is achieved through proposing a hybrid model that combines the SV statistical model with a modern AI model, namely the Transformer, to improve the performance of analyzing and forecasting S&P500 index fluctuations, as well as comparing the performance between the hybrid model and the simple Transformer model.

Importance of the Study

This study acquires its importance through:

- The importance of integrating a traditional statistical model with a modern one to achieve better performance in analyzing and forecasting financial market volatilities.
- This research provides a practical framework for financial data analysis that combines traditional statistical models with modern artificial intelligence models.
- It contributes to improving the accuracy of financial forecasting, thereby enhancing decision-making based on data.
- Reaching results that assist in guiding traders' decisions in the stock markets through using a model that delivers precise predictions and understanding of huge volatilities.

Scope of the Study

The study focused on the stock prices of the S&P500 index, considering it the main and most important indicator in global financial markets. It relied on closing prices and daily returns for the period from January 3, 2001, until November 30, 2024.

Study Methodology

The descriptive method was used in presenting information regarding stock price volatilities and the models employed in the applied study, which relied on the Stochastic Volatility (SV) statistical model and one of the modern artificial intelligence models, namely the Transformer Model (TM), with the application carried out using the Python program.

II. : Theoretical Study

This section presents some theoretical concepts related to the study.

1- **Definition of Stock Price Volatility**

Stock price volatilities refer to the extent of change in the price of a stock. The larger and more frequent the price movement, the higher the degree of volatility. Statistically, volatility is the standard deviation of stock returns over a specific period, and in most cases, the higher the volatility, the higher the risk (Bhowmik & Wang, 2020).

Hence, volatility expresses the extent of stock price movement. If the stock price changes significantly, rising to the highest level and then falling to the lowest level or moving irregularly, this stock is considered highly volatile. In contrast, stocks that maintain relative stability in their prices are classified as low-volatility stocks. Stocks with high volatility are characterized by higher risks, but they may achieve higher returns in exchange for these risks. Therefore, investors who are risk-tolerant rely on various tools and measures to analyze these volatilities to evaluate past price changes and predict future movements, which helps them in choosing suitable investment strategies.

2- **Stochastic Volatility Model (SV)**

The Stochastic Volatility (SV) model is a traditional statistical model that appeared for the first time in the economic and financial literature in the late 1980s. The studies of Clark (1973) and Taylor (1982) were among the earliest works that proposed this model. The concept developed the idea that market volatilities are not constant over time but change randomly and show clustering properties. This concept further evolved thanks to the significant contributions of Johnson and Shanno (1987) and also Wiggins (1987). The most famous paper in this field is by Hull and White (1987), who developed the stochastic volatility model with leverage effects (Neil Shephard, 2003, p. 07).

The stochastic volatility model is widely used in financial market analysis to estimate conditional volatilities in time series. It is considered an effective tool to understand daily volatility dynamics, as it aims to describe the dynamic behavior of volatilities over time. It assumes that the volatilities themselves follow a stochastic process rather than being fixed or predetermined, and it can capture financial data characteristics such as volatility clustering (Andersen & Benzoni, 2008, p. 04).

3- **Transformer Model (TM)**

The Transformer algorithm was born in the famous paper entitled “Attention is All You Need” in December 2017, written by members of the Google Brain team and researchers from Google Research. It outperformed previous advanced models in natural language processing and data analysis, being faster in training compared to previous architectures and achieving higher evaluation results (Denis Rothman, 2021, p. 01-02).

The Transformer model is a deep learning model that relies on the Self-Attention mechanism, sometimes referred to as internal attention. It is an architecture that avoids recurrence and works alongside artificial neural networks. It is used to analyze sequential data such as texts and time series and is considered one of the most important developments in modern artificial intelligence. The model works by transferring or moving information across time points in the data to identify important patterns and relationships, instead of processing data point by point. The Transformer processes data in parallel using the Multi-Head Attention mechanism. It is commonly used for natural language processing, time series analysis, classification, and prediction (Vaswani et al., 2017).

III. : Applied Study

This section provides an explanation of the steps of the applied study and how to implement the simple model, which represents the Transformer model, and the hybrid model, which works on integrating the Stochastic Volatility model with the Transformer model. This means using the outputs of the Stochastic Volatility as inputs for the Transformer model and evaluating the performance between the simple model and the hybrid model.

1- **Population and Sample of the Study**

The study population represents the financial markets, while the study sample relied on daily data of the stock prices and returns of the S&P500 index for the study period extending from January 03, 2001, until November 30, 2024, with the data obtained from the website (Investing, 2024).

2- **Description and Analysis of the Behavior of S&P500 Stock Prices**

In this section, the descriptive statistical indicators for the S&P500 stock prices were calculated, represented by the mean, standard deviation, maximum value, minimum value, in addition to various percentages as shown in the table:

Table 1. Statistical Description of S&P500 Stock Prices

	S&P500
count	8733
mean	2127.026
std	1242.115
min	676.53
25%	1191.1
50%	1519.79
75%	2786.24
max	6032.38

Source: Outputs of Python program.

From Table (01), it is observed that the average price of S&P500 stocks reached $2127.026, reflecting the long-term upward trend of the market, while the maximum value reached $6032.38 and the minimum value $676.53. This vast difference between the values confirms that there were severe volatilities in the index stock prices during the study period. Meanwhile, the standard deviation value was 1242.115, which reflects the large variation in prices, as the relatively high value indicates the existence of significant volatilities in the index prices during the studied period, confirming the volatile nature of the financial market.

3- **Study of the Development of S&P500 Prices and Returns**

To illustrate the behavior of S&P500 stocks, the price development curve and the daily returns curve are presented, as shown in the following figure:

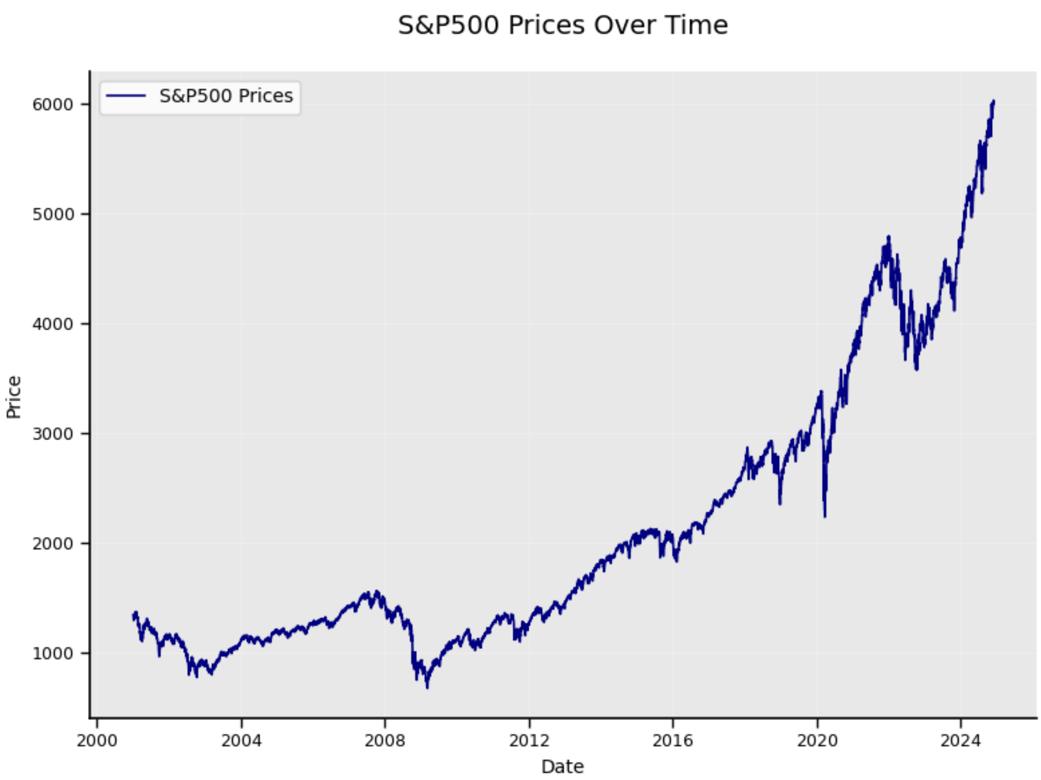

Fig. 1. Study of the Development of S&P500 Stock Prices
Source: Outputs of Python program.

The curve represents the movements of S&P500 prices over time during the study period from 2001 until 2024, showing continuous price changes with large fluctuations in some periods. The curve indicates a long-term upward trend, reflecting that the index experienced sustainable growth over the past two decades. A sharp decline in prices is also observed during the 2008-2009 period due to the global financial crisis. Afterwards, the index gradually recovered and then experienced rapid growth, especially after 2016, where the curve shows an acceleration in the upward trend, until 2020 where severe volatility appeared with a sharp increase in prices, which may reflect the impact of the COVID-19 pandemic and the economic stimulus that followed. In general, the curve reflects market dynamics during the study period, the interaction of prices with economic events, and the significant impact of global crises on financial markets, with an upward trend highlighting the strength of the S&P500 over time.

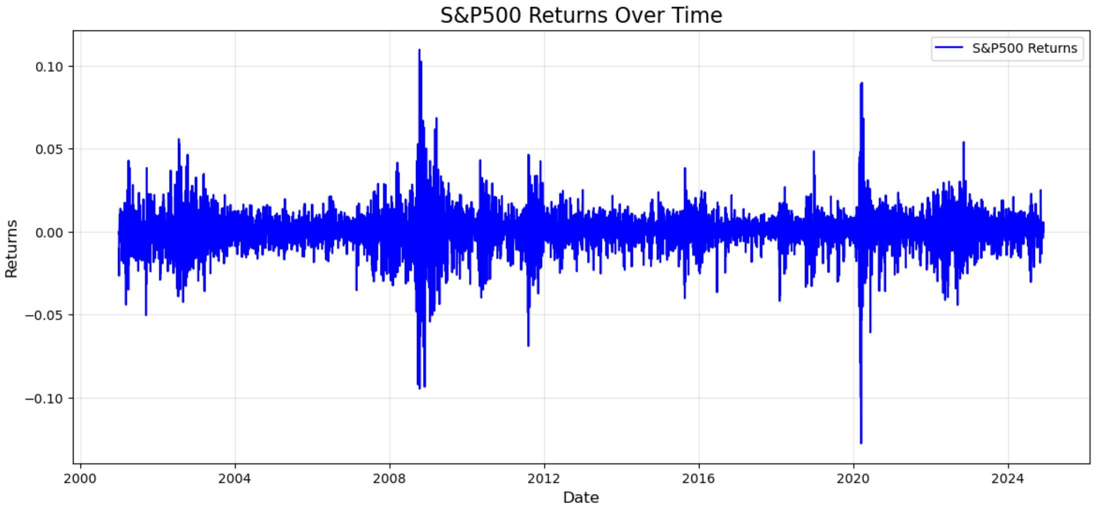

Fig. 2. *Study of the Development of S&P500 Stock Returns*
Source: Outputs of Python program.

The curve represents the development of daily returns of the S&P500 index, based on the logarithmic differences of prices during the study period. A significant increase in volatility is observed during financial crises, such as the 2008 crisis, which witnessed severe fluctuations in returns with high positive and negative values indicating significant market turmoil, and the 2020 crisis represented by the COVID-19 pandemic, which also showed increased volatility again. After recovering from financial crises, returns tend to relative stability with less severe fluctuations. In general, this curve confirms the importance of using specialized models to analyze these data due to their irregularity and the existence of periods with severe volatility.

4- **Forecasting Using the Simple Transformer Model**

The TensorFlow library and the Keras library were used to build and implement the simple Transformer model, where only daily returns are used as inputs to learn temporal patterns and predict the daily returns for the model. To implement it, the following steps were followed:

a- Data Splitting

For the model to train and reach optimal values for input weights, the study data must first be divided into three main groups: the training set, the validation set, and the test set. The following table illustrates the division:

Table 2. Distribution of Data for Groups Used in the Transformer Model

Group	View Rate	Number of Views.
Training	80%	6985
Validation	10%	874
Testing	10%	873
Total	100%	8732

Source: Outputs of Python program.

It is noted from the table that the total data used is 8,732 observations, randomly classified. The training sample included 80% of the data, equivalent to 6,985, while both the validation and test sets included 10% each, equivalent to 874 observations for the validation set, and 873 observations for the test set.

b- Data Processing

At this stage, the data are normalized, where the time series values are constrained within the range (-1,1) or (0,-1), using the StandardScaler class from the sklearn.preprocessing library.

c- Transformer Model Architecture

The model is a Transformer-based Regression Model designed to process sequential or temporal data and predict a numerical value based on patterns present in the data. The model starts with an Input Layer that takes data in three-dimensional form: the first dimension represents the number of samples (here we have one sample), the second dimension is the sequence length, which is 8,732, and the third dimension is the number of features, where only one feature is used, which is the historical returns of the S&P500 index. This is followed by a Transformer block consisting of a Multi-Head Attention layer with four heads, which learns temporal relationships among sequence elements, followed by the addition of a Skip Connection between the attention outputs and the original inputs. Then, a Layer Normalization is applied to improve value stability. The outputs then pass through a Feed-Forward Network with two layers: the first with 64 hidden units and a ReLU activation function, and the second reduces dimensions back to the original input shape, with the normalization and skip connection repeated.

The Transformer block outputs are flattened to be ready for Dense Layers: a layer with 64 units followed by a layer with 32 units, with ReLU activation to improve nonlinear representation of the data. The network ends with an Output Layer consisting of one unit to generate the target numerical value, which is the daily return of the S&P500 index.

The model is compiled using the Adaptive Moment Estimation (Adam) optimizer with a Mean Squared Error (MSE) loss function, and additional metrics Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used to evaluate performance. The model is trained using 30 Epochs, and the data are divided into batches of 32 samples each (batch_size=32).

d- Forecasting Results

The forecasting results using the simple Transformer model are illustrated in the following table:

Table 3. Performance Measurement Results for the Simple Transformer Model

Model	Test Loss(MSE)	RMSE	MAE
Simple Transformer	0.00011343	0.010650374	0.005421776

Source: Outputs of Python program.

The table shows the model's performance measured according to three metrics as follows:

- **Mean Squared Error (MSE)**: The mean squared error represents a measure to determine the deviation of predicted values from the actual values. The lower the value, the better the model. The calculated value in the model is 0.0001138, indicating that the errors between actual and predicted values are relatively small, which reflects good model performance.
- **Root Mean Squared Error (RMSE)**: The square root of the mean squared error is a measure of the root mean error between actual and predicted values. The lower the value, the better the model in forecasting. The calculated value is 0.01067, which is low relative to the studied data, indicating the model's ability to achieve good predictive accuracy.
- **Mean Absolute Error (MAE)**: The mean absolute error measures the average absolute difference between actual and predicted values, focusing on how much the forecasts deviate from the true values. The lower the value, the more accurate the model. The calculated value is 0.005421776, showing that the absolute deviation of the forecasts is very low, reinforcing the model's reliability in estimating volatilities.

Since the values of MSE, RMSE, and MAE are relatively low, it shows that the simple Transformer model has learned temporal patterns well, indicating that the model provided good performance in delivering accurate predictions.

5- Forecasting Using the Hybrid Model (Integration of Stochastic Volatility and Transformer Models)

To build and implement a hybrid model combining the SV and TM models, the conditional volatilities calculated using the SV model are used with the daily returns as inputs to learn temporal patterns and predict the daily returns of the hybrid model. The following steps were followed to apply the model:

a- Calculating Conditional Volatilities Using the Stochastic Volatility Model

To calculate conditional volatilities, or the daily fluctuation level (Conditional Volatility) of daily returns using the SV model, the NumPyro library was employed. The number of steps required to implement the model was 1,000, with 2,000 samples used for estimation, and 4 chains running in parallel. The conditional volatility results are shown in the following figure:

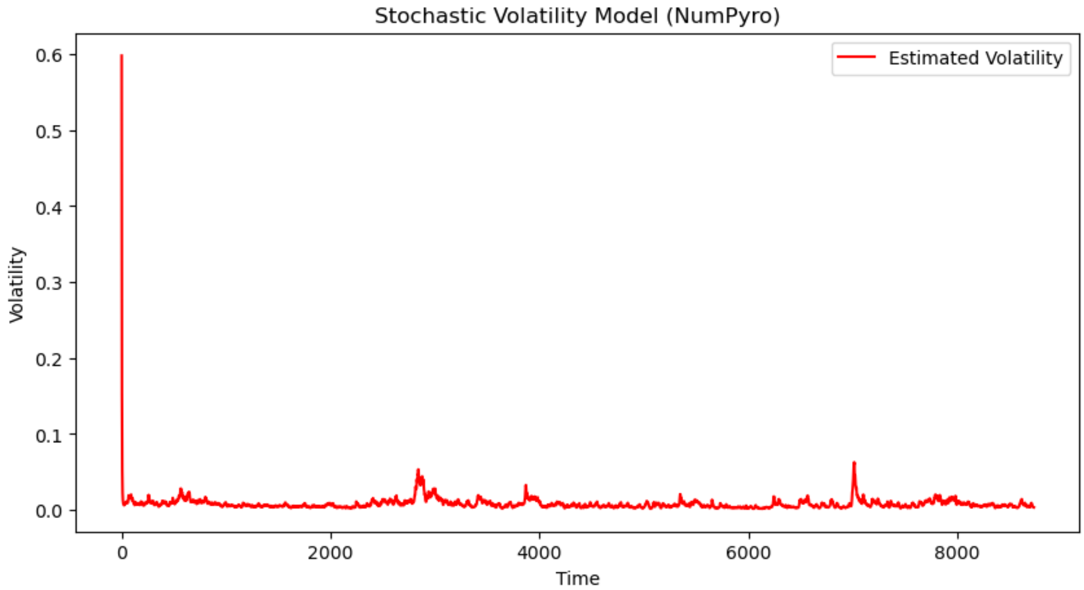

Fig. 3. *Conditional Volatilities Using the Stochastic Volatility Model*
Source: Outputs of Python program.

The curve represents the estimated level of conditional volatilities, i.e., an indicator of the degree of fluctuation of returns at each point in time (here, days). The curve shows high volatility at the beginning, indicating a shock or unusual fluctuation at the start of the time series. After the initial shock, a rapid decrease in volatility is observed, stabilizing at low levels over time, explaining the gradual decline in fluctuations. Small, scattered peaks appear in different time regions, indicating unexpected events or market changes. In long periods between these peaks, volatility remains near zero, indicating relative stability. High volatilities may result from significant financial or economic events affecting the market sharply, such as the 2008 global financial crisis and the 2020 COVID-19 pandemic. These peaks indicate uncertainty or temporary market changes. Hence, the curve reflects the dynamic nature of financial volatilities for the S&P500 index. The SV model proved efficient in capturing these dynamics by representing volatility on returns, demonstrating good ability to describe volatility clustering and random changes over time (Neil Shephard, 2003, p. 07; Andersen & Benzoni, 2008, p. 04).

b- Integrating the Stochastic Volatility Model with the Transformer Model

The hybrid model, which combines the SV model with the Transformer, was built using the same steps employed in building the simple Transformer model regarding data splitting, processing, and model architecture. The difference lies in the inputs of the hybrid model, which rely on combining the power of the SV model in analyzing volatility dynamics with the Transformer's ability to learn complex temporal patterns and long-term relationships. Information extracted from conditional volatilities was used as a starting point to improve forecasts. Therefore, the hybrid model inputs are: the daily returns of the S&P500 index and the conditional volatilities calculated using the SV model.

To evaluate the model, the same previous metrics were used, and the results are presented in the following table:

Table 4. Performance Measurement Results for the Hybrid Model

Model	Test Loss(MSE)	RMSE	MAE
Hybrid Model	9.36 E-05	0.009676604	0.005305552

Source: Outputs of Python program.

From the table, we notice:

- **MSE**: The calculated value was 9.3637e-05. This low value reflects the model's ability to reduce errors.
- **RMSE**: The calculated value is 0.009676. The low value enhances the model's predictive accuracy.
- **MAE**: The calculated value was 0.005305. Since it is also low, this indicates that the model delivers accurate predictions in general.

The low values of the metrics shown in the table reflect high model accuracy in forecasting volatilities. The model learns patterns from the data well, and balanced performance across training, validation, and test data indicates good generalizability. Hence, the model is very suitable for financial markets, as high accuracy in estimating volatilities is crucial for risk management decisions, making it an effective model for financial market analysis.

6- Performance Comparison Between the Simple Transformer Model and the Hybrid Model

The performance metrics of the two models are summarized in the following table:

Table 5. Performance Metrics for Each Model

Model	Test Loss(MSE)	RMSE	MAE
Simple Transformer	0.00011343	0.01065	0.005422
Hybrid Model	9.36 E-05	0.009677	0.005306

Source: Outputs of Python program.

- **MSE (Loss)**: decreased from 0.0001134 in the simple model to 9.3637e-05 in the hybrid model, indicating that the hybrid model delivers more accurate predictions.
- **RMSE**: decreased from 0.01065 to 0.009676, an improvement of about 9%, indicating that the hybrid model better handles large errors.
- **MAE**: decreased from 0.00542 to 0.005305, indicating that the hybrid model is more reliable in predicting volatilities.

Comparing the simple AI-based model with the hybrid Transformer model, which combines traditional methods and AI models, we notice that MSE, RMSE, and MAE are lower in the hybrid model. This means the model predictions are much closer to the actual values than the simple model, achieving better performance due to its ability to capture complex temporal patterns and nonlinear relationships. This indicates that the hybrid model benefited from the SV outputs as an additional feature, which helped improve performance (Bhowmik & Wang, 2020; Denis Rothman, 2021, p. 01-02; Vaswani et al., 2017).

IV. Conclusion

Price volatility within financial markets, particularly stock prices, has become currently one of the most critical areas of investment. This requires providing sufficient analysis and forecasting to make investment decisions based on a correct and scientific methodology, considering it as the most important factor for investors to reduce the degree of risk associated with such volatilities. Analytical and forecasting models have varied between traditional models and artificial intelligence techniques. Accordingly, this study aimed to analyze and forecast the volatility of S&P500 index stock prices relying on a hybrid model combining traditional models represented by the Stochastic Volatility (SV) model and artificial intelligence applications represented by the Transformer (TM) model, and to compare it with a simple Transformer model. The hybrid model, which integrates SV outputs with Transformer layers, proved its high efficiency in forecasting volatilities with greater accuracy and flexibility compared to the simple model, making it a powerful tool for financial market analysis and risk prediction. This demonstrates the importance of combining traditional models with modern artificial intelligence techniques (Bhowmik & Wang, 2020; Denis Rothman, 2021, p. 01-02).

Study Results

The study reached the following results:

- The hybrid model showed remarkable superiority over the simple model in reducing errors and improving forecasts.
- The hybrid model provides a practical framework that combines the advantages of both traditional and modern models.
- Integrating conditional volatilities with original returns significantly improved forecasting accuracy.
- SV model outputs added information about market dynamics; this feature helped the Transformer model better recognize temporal patterns, leading to improved predictive accuracy (Neil Shephard, 2003, p. 07; Andersen & Benzoni, 2008, p. 04).

Recommendations

Based on the obtained results, the study recommends the following:

- Broader applications of the hybrid model, such as testing it on other financial markets to verify its generalizability.
- Integrating additional indicators, such as economic indices or external factors, to improve forecasting accuracy.
- Exploring other models or using other deep learning techniques to handle the data.
- Combining other traditional models with different techniques for financial data analysis.

Using the hybrid model to forecast volatilities in high-risk assets to improve risk management strategies.

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