Identifying the Machine Learning Model that Most Accurately Predicts S&P 500 Volatility Using United States of America Economic Indicators

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The S&P 500 index which comprises 500 of the largest publicly traded companies in the United States (US) is widely recognized for its fluctuating behavior. Stock volatility is a measure of how much and how quickly a stocks price (or a market index such as the S&P 500) moves up and down over time. Accurately forecasting the fluctuations in S&P 500 volatility is crucial for investors seeking to maximize returns and businesses that rely on such predictions for strategic financial planning and operations. Traditionally, this task is approached using sophisticated statistical models which often experience limited accuracy and inefficiency when capturing complex and nonlinear patterns in financial time series data. Advancements in machine learning have opened the door to developing Artificial Intelligence (AI) models that can predict stock volatility with improved accuracy and effectiveness. There has been limited research that utilizes machine learning to study the relationships between economic indicators and stock volatility; this area remains underexplored. This study employs a comparison of various forecasting models to identify the most accurate machine learning model for predicting S&P 500 volatility based on US economic indicators which were chosen because of their proven significance in representing macroeconomic conditions and their potential impact on S&P 500 volatility. More specifically, this research evaluated Neural Networks: Long Short-Term Memory (LSTM) (a type of Recurrent Neural Networks (RNN)) and Feedforward Neural Networks (FNN), traditional supervised machine learning models: Linear Regression, Lasso Regression, Decision Trees, and Random Forests, statistical models: Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and AutoRegressive Integrated Moving Average (ARIMA), and baseline model: mean forecast method, where the statistical and baseline models were used to show whether the most accurate machine learning method provided higher accuracy. The predictive accuracy, measured by Root Mean Square Error (RMSE), of each model was assessed to identify the most effective one. The hypothesis states that LSTM would outperform the other models since it is the most suitable for problems related to time series data. The results confirm this as LSTM achieved the lowest RMSE, indicating its comparatively strong capability in predicting S&P 500 volatility using US economic indicators.

Introduction

Accurately and efficiently predicting S&P 500 volatility is essential for individuals and organizations seeking to minimize investment risks [1,2]. Before the adoption of machine learning in finance, forecasting methods primarily relied on complex mathematical and statistical models including Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and Autoregressive Conditional Heteroskedasticity (ARCH) models [3]. These approaches often lack accuracy and are computationally inefficient because they rely on past errors to estimate volatility and can struggle when data exhibits strong persistence in variability, a common characteristic of financial time series data [4–6]. Previous research has highlighted the superior accuracy of machine learning models [7,8]. For instance, one study comparing Neural Networks and statistical models such as GARCH and Autoregressive Moving Average (ARMA) [9] finds that statistical models are not only less accurate but also more complex and difficult to optimize compared to machine learning approaches [10]. Given the strong influence of economic conditions on stock market behavior, incorporating economic indicators into predictive models has become increasingly important [11,12]. Therefore, the objective of this research is to determine the most accurate machine learning model for predicting S&P 500 volatility using US economic indicators.

Several recent studies have aimed to determine the most effective machine learning model for forecasting S&P 500 volatility and price movements, using either US economic indicators or technical indicators data [13–15]. One research finds that a hybrid Deep Convolutional Neural Network (DCNN) outperforms a standard Convolutional Neural Network (CNN) in this task [13]. Another analysis comparing Baseline Linear Regression, Feedforward Neural Networks (FNN), Decision Trees, and Random Forests concludes that Random Forest provides the highest predictive accuracy among the models tested [14]. Similarly, additional research evaluating models such as Logistic Regression, Linear Regression, Random Forest, Bagging Regression, Gradient Boosting Regression, Ridge Regression, and

Lasso Regression also identifies Random Forest as the most effective[15]. Despite these contributions, there is still a lack of studies directly comparing Neural Networks, traditional supervised machine learning models, statistical models, and baseline models. This gap motivates the present study which compares Long-Short Term Memory (LSTM) (a type of Recurrent Neural Networks (RNN)), FNN, Linear Regression, Lasso Regression, Decision Trees, Random Forests, GARCH, AutoRegressive Integrated Moving Average (ARIMA) (a type of ARMA), and mean forecast model to identify the machine learning model that can most accurately predict stock volatility based on US economic indicators. The statistical and baseline models were employed to evaluate whether the most accurate machine learning method demonstrated higher accuracy compared to non-machine learning models. The predictive accuracy of each technique was assessed using Root Mean Square Error (RMSE), with the machine learning models prediction fit graphs serving as supplementary illustrations. The LSTM model is included in this comparison due to its strength in modeling sequential data, making it particularly well-suited for time series forecasting tasks such as stock volatility prediction[16,17].

Methodology

In this research, the input features include seven economic indicators: US monthly inflation rate[18], US monthly unemployment rate[19], US monthly West Texas Intermediate (WTI) crude oil price[20], US monthly Industrial Production Index (IPI)[21], US monthly personal saving rate (PSAVERT)[22], US quarterly Gross Domestic Product (GDP)[23], and US monthly 3-month Treasury Bills rate (TB3MS)[24]. These seven indicators were selected because they broadly represent the main drivers of economic activities, covering growth, inflation, employment, consumer behavior, financial markets, and monetary policy[14,25]. Months are also one of the features since incorporating temporal information is considered good practice when working with time series data[16]. The target variable is the monthly volatility of the S&P 500 index, calculated as the standard deviation of its daily returns over each month[26]. The dataset consists of 421 samples, each containing the eight features above and the one target variable. A visualization of the economic indicators is presented in Figure 1.

The original dataset was split sequentially into three subsets: 64% for training, 16% for validation, and 20% for testing. Following this train-validation-test split, a look-back window was applied to each subset, transforming the data into overlapping sequences of fixed length where each input sample was composed of a sequence of consecutive observations of features, determined by the specified look-back window, and the next data point in the target series. This transformation enabled the model to capture the temporal dependencies within the economic indicators. After this preprocessing step, all three datasets were standardized using a scaling method before being fed into the machine learning models.

The first machine learning model evaluated in this study was LSTM[27]. It was trained, validated, and tested on training, validation, and test sets, respectively. During training, overfitting was observed. To mitigate this issue, hyperparameters — the look-back window, learning rate, batch size, number of layers, and dropout rate — were tuned, and subsequently, cross-validation and data augmentation which adds noise to the expanded datasets were utilized. In the search for an optimal setup, grid search was applied, and the combination yielding a validation loss curve with the steepest and most consistent downward trend was chosen. The best results were achieved by expanding the training set to 4000 samples with a sigma of 0.09, combined with a hyperparameter configuration consisting of a look-back window of 17, a batch size of 8, three layers, and a learning rate of 0.01. However, this setup only modestly reduced overfitting. In order to better assess the accuracy level of each machine learning model, both the original and augmented datasets were used for training and comparison.

Table 1 presents the hyperparameter ranges used in the LSTM grid search, while Table 2 details the data augmentation ranges used in the LSTM grid search.

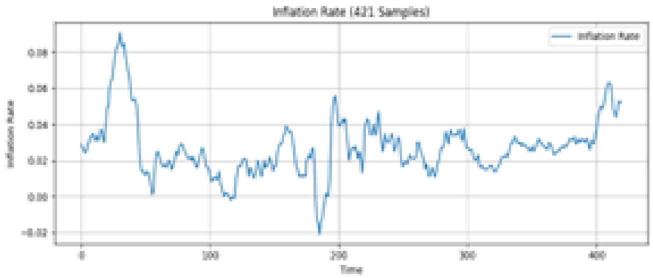
Table 1 Hyperparameter ranges used in the LSTM grid search. This table shows the ranges of the five hyperparameters tuned.

Look back window	Learning rate	Batch size	Number of layers	Dropout number
11 - 20	0.01 - 0.1	8 - 16	1 - 3	0.2 - 0.4

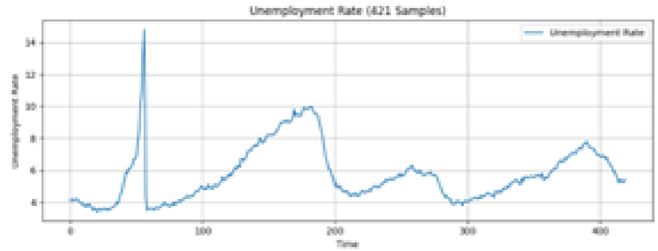
Table 2 Data augmentation ranges used in the LSTM grid search. This table presents the ranges of the data augmentation settings. Sigma represents the standard deviation of the Gaussian noise added to the original data.

Number of training samples	Number of validation samples	Sigma value
2000 - 64000	No augmented validation set - 16000	0.09 - 0.2

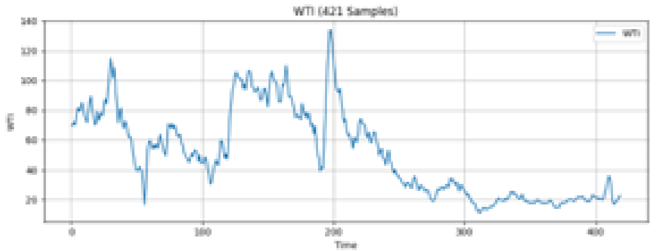
Other than LSTM, FNN[28,29], Linear Regression[30], Lasso Regression[31], Decision Trees[32,33], Random Forest[34,35], GARCH[3], and ARIMA[36] were also employed. The last model utilized was the mean forecast model which was intended to show whether the LSTM model provided higher accuracy than the baseline method. Hyperparameter tuning was conducted for the Decision Tree model across max depth, min samples split, min samples leaf, and random state, and for the Random Forest model across max depth and random state. The Decision Tree model achieved the most accurate results using a max depth of 5, a min samples split of 10, a min samples leaf of 5, and a random state of 42. The Random Forest model obtained the most accurate results using a max depth of 2 and a random state of 0. Data augmentation was not applied to the GARCH, ARIMA, and mean forecast



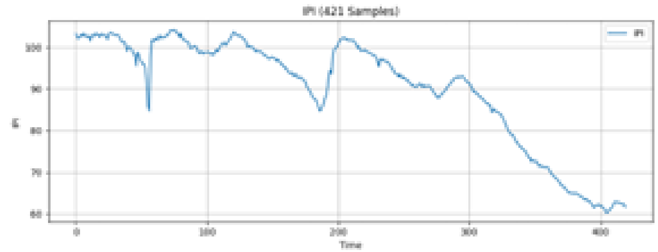
(a) US monthly inflation rate from January 1990 to December 2024.



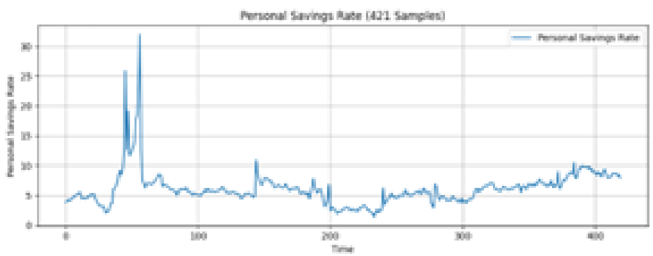
(b) US monthly unemployment rate from January 1990 to December 2024.



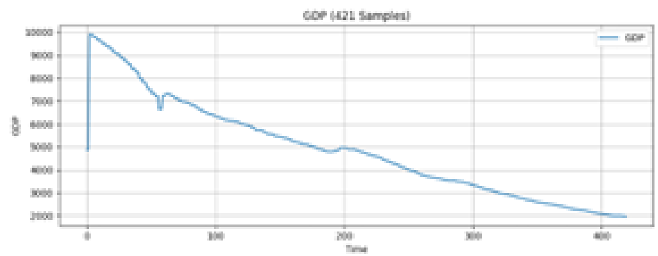
(c) US monthly WTI from January 1990 to December 2024.



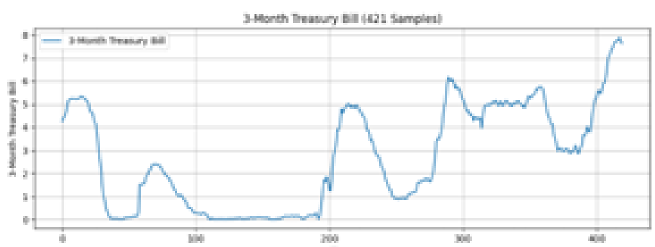
(d) US monthly IPI from January 1990 to December 2024.



(e) US monthly PSAVERT from January 1990 to December 2024.



(f) US monthly GDP from January 1990 to December 2024.



(g) US monthly TB3MS from January 1990 to December 2024.

Fig. 1 A visualization of the economic indicators.

models since they don't rely on artificially generated data in the same way as machine learning models do.

The predictive accuracy of each model was assessed using test RMSE, with the machine learning models prediction fit graphs serving as supplementary illustrations, and then compared across models to evaluate their relative effectiveness.

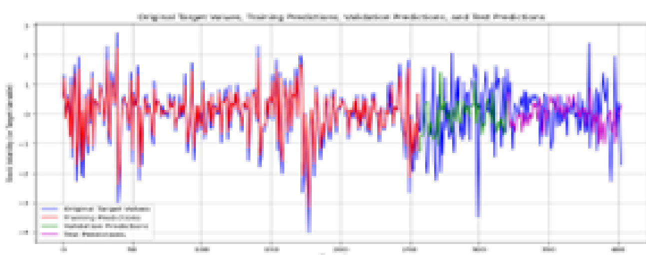
Results

After hyperparameter tuning, cross validation, and data augmentation, the signs of overfitting exhibited by the LSTM model were modestly mitigated by augmenting the training data to 4000 samples using a sigma of 0.09, with a batch size of 8, three layers, a learning rate of 0.01, and a look-back window of 17.

The LSTM, FNN, and traditional supervised machine learning models were trained on both the 421 samples and the 4000 training samples, whereas the statistical and mean forecast models were trained on the 421 samples only. Tables 3 and 4 present the RMSE and R^2 values for the LSTM model. Table 5 provides the RMSE of the FNN, the traditional supervised machine learning models, the statistical models, and the mean forecast approach. Table 6 summarizes a comparison of the test RMSE of all models in this research. Figures 2 and 3 show the prediction fit graphs and the train and validation loss curves for the LSTM model. Figure 4 illustrates the prediction fit graphs for the traditional supervised machine learning models. The prediction fit graphs of the FNN model are omitted, as they reduce to two straight lines without variation, underscoring that the FNN model underperformed relative to both the LSTM and the traditional supervised machine learning models.

Table 3 RMSE and R^2 scores of the LSTM model with 421 samples. This table presents the RMSE and R^2 scores of the LSTM model, using a dataset of 421 samples in total.

Train RMSE	Validation RMSE	Validation R^2	Test RMSE	Test R^2
0.215	1.318	-0.291	0.92	-0.49



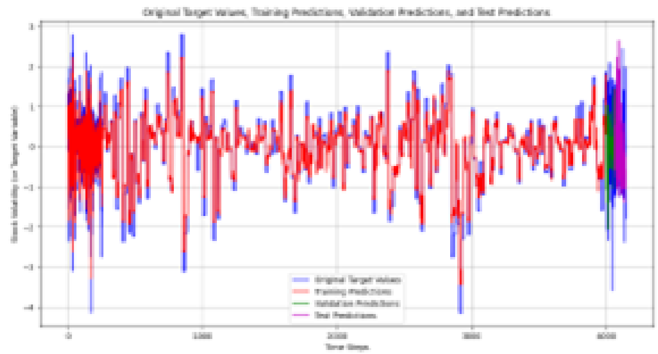
(a) Original target values vs predicted target values for the LSTM model (421 samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.

(b) Train and validation loss curves for the LSTM model (421 samples). This graph shows the training and the validation loss curves, using a dataset of 421 samples in total.

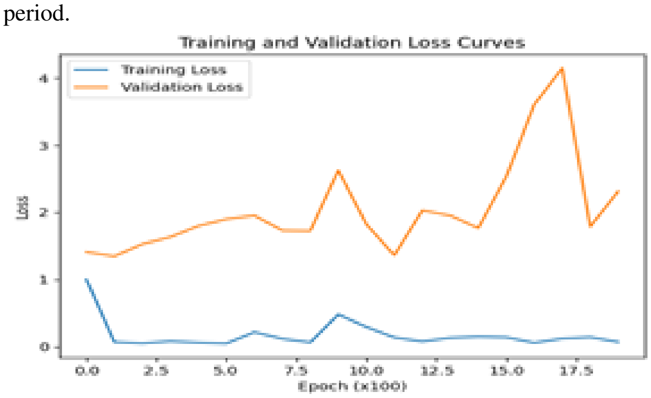
Fig. 2 Prediction fit graphs and the train and validation loss curves for the LSTM model.

Table 4 RMSE and R^2 scores of the LSTM model with 4000 training samples. This table presents the RMSE and R^2 scores of the LSTM model, using a training dataset of 4000 training samples and a 0.09 sigma value.

Train RMSE	Validation RMSE	Validation R^2	Test RMSE	Test R^2
0.259	1.521	-0.647	1.059	-0.893



(a) Original target values vs predicted target values for the LSTM model (4000 training samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.

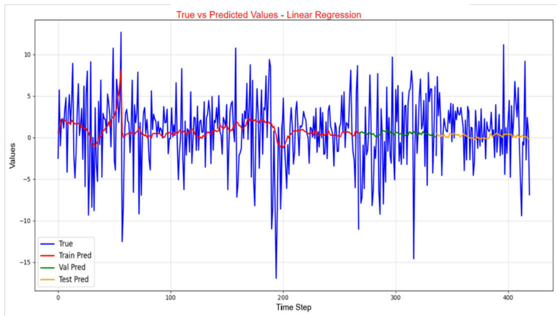


(b) Train and validation loss curves for the LSTM model (4000 training samples). This graph shows the training and the validation loss curves, using 4000 training samples and a sigma value of 0.09.

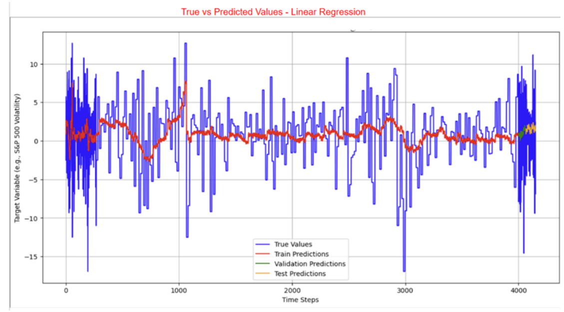
Fig. 3 Prediction fit graphs and the train and validation loss curves for the LSTM model.

Discussion

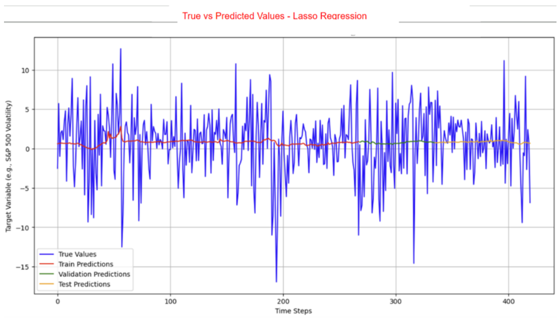
Based on the test RMSE comparison of the LSTM, the FNN, the traditional supervised machine learning models, the GARCH model, the ARIMA model, and the mean forecast method, it can be concluded that the LSTM model consistently provides higher predictive accuracy than the others, regardless of the data augmentation, which supports the original hypothesis. With



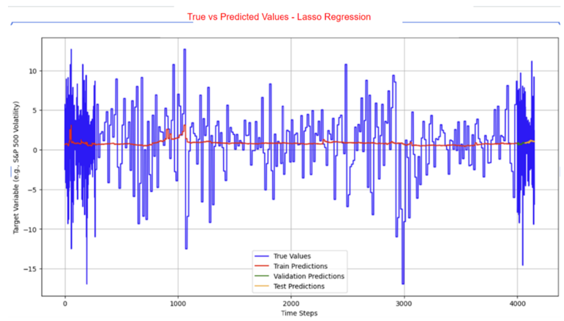
(a) Original target values vs predicted target values for the Linear Regression model (421 samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.



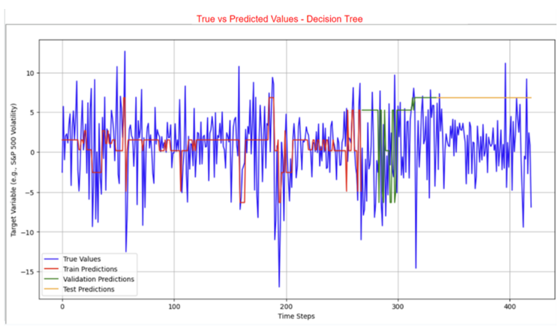
(b) Original Target Values vs Predicted Target Values for the Linear Regression model (4000 training samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.



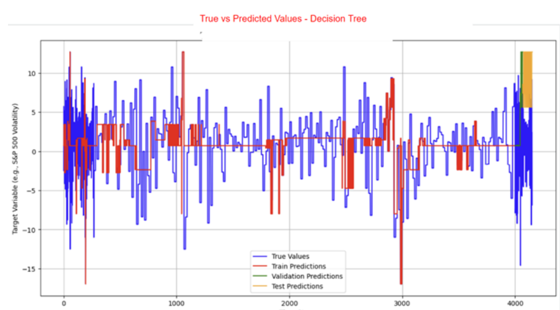
(c) Original target values vs predicted target values for the Lasso Regression model (421 samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.



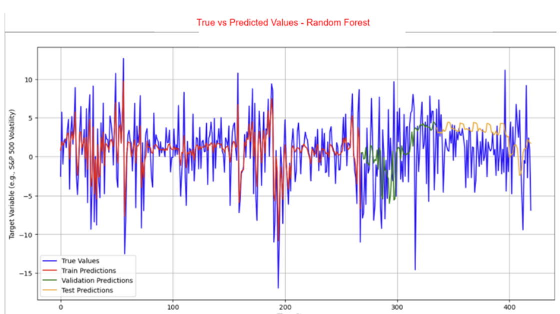
(d) Original target values vs predicted target values for the Lasso Regression model (4000 training samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.



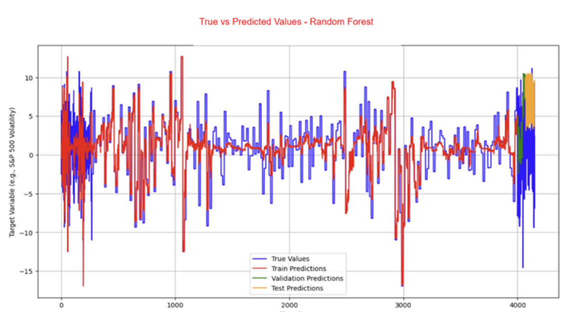
(e) Original target values vs predicted target values for the Decision Tree model (421 samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.



(f) Original target values vs predicted target values for the Decision Tree model (4000 training samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.



(g) Original target values vs predicted target values for the Random Forest model (421 samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.



(h) Original target values vs predicted target values for the Random Forest model (4000 training samples). This graph displays the original target values (blue) compared to the training predictions (red), the validation predictions (green), and the test predictions (purple) across the entire period.

Fig. 4 Prediction fit graphs for the traditional supervised machine learning models.

Table 5 RMSE of the FNN, the traditional supervised machine learning models, the statistical models, and the mean forecast model with 421 samples and 4000 training samples. The table summarizes the train RMSE, validation RMSE, and test RMSE for all models using a dataset of 421 samples and a training set of 4000 samples.

Model	Train RMSE	Validation RMSE	Test RMSE
FNN (421 samples)	4.000	5.000	5.000
FNN (4000 training samples)	4.000	5.000	5.000
Linear Regression (421 samples)	4.135	5.076	3.484
Linear Regression (4000 training samples)	4.076	5.087	3.453
Lasso Regression (421 samples)	4.238	5.117	7.002
Lasso Regression (4000 training samples)	4.196	5.122	4.086
Decision Tree (421 samples)	3.737	7.347	6.739
Decision Tree (4000 training samples)	3.527	6.578	8.981
Random Forest (421 samples)	2.409	5.385	3.369
Random Forest (4000 training samples)	2.084	6.495	3.433
GARCH (421 samples)	1.013	1.825	1.124
ARIMA (421 samples)	1.509	1.601	1.760
Mean Forecast (421 samples)	4.360	5.061	3.297

Table 6 Test RMSE of the LSTM, the FNN, the traditional supervised machine learning models, the statistical models, and the mean forecast method with 421 samples and 4000 training samples. This table summarizes the test RMSE achieved by all models using a dataset of 421 samples and a training set of 4000 samples.

Model Type	Model	Test RMSE From 421 Samples	Test RMSE From 4000 Training Samples
Neural Networks	LSTM	0.920	1.059
	FNN	5.000	5.000
Traditional Supervised Machine Learning Models	Linear Regression	3.484	3.453
	Lasso Regression	7.002	4.086
	Decision Tree	6.739	8.981
	Random Forest	3.369	3.433
Statistical Models	GARCH	1.124	N/A
	ARIMA	1.760	N/A
Baseline Model	Mean Forecast	3.297	N/A

421 samples, the FNN model achieved a test RMSE of 5.000 which is higher than the LSTM models test RMSE of 0.920. The LSTM model also outperforms the traditional supervised machine learning models whose test RMSE ranged from 3.369 to 7.002. Among the statistical models, the GARCH model recorded a test RMSE of 1.124, while the ARIMA model obtained 1.760, proving that the statistical models perform worse than the LSTM model. The LSTM model also proves to be more effective than the mean forecast model which achieved a test RMSE of 3.297. After augmenting the training set to 4000 samples, the LSTM model reported a slightly higher test RMSE of 1.059 while the FNN model still obtained a test RMSE of 5.000. In comparison, the traditional supervised machine learning models showed test RMSE values between 3.433 and 8.981. Overall, regardless of data augmentation, the LSTM model consistently demonstrates better predictive accuracy compared to all other models evaluated in this study. Among the traditional supervised machine learning models, the Random Forest model achieved the highest predictive accuracy, with the lowest test RMSE compared to the other traditional machine learning models. This finding is consistent with the conclusions of the previous studies [14,15]. These outcomes are further supported by the graphical results presented earlier. Both statistical models showcase higher accuracy than the traditional machine learning approaches, though they remain less accurate than the LSTM model. The LSTM model faced the issues of overfitting and negative R^2. R^2 measures the proportion of variance in the target variable explained by the model. A positive R^2 indicates that some proportion of the variance in the target variable can be explained by the model. The negative R^2 values of -0.490 and -0.893 for the 421 samples and 4000 training samples models respectively suggest that the LSTM model is less effective at explaining variance than the mean forecast method. One key source of error in this research that likely contributed to the LSTM model's overfitting and negative R^2 is the presence of noises. As shown in Figure 1 in the Methodology section, while each feature exhibits potential trends, they are also filled with numerous small fluctuations that dont contribute to the overall trend of the data. These fluctuations, also known as noises, might cause the model to expand capacity on learning irrelevant patterns, ultimately increasing the risk of overfitting and negative R^2. Another key source of error is that some of the economic indicators used in this study have limited relevance to S&P 500 volatility [37]. Including less informative features can lead the model to learn unwanted patterns, resulting in overfitting and negative R^2. A feature importance analysis which was not conducted prior to model training indicates that WTI, Inflation Rate, IPI, 3M Treasury Bill, Personal Savings Rate, Unemployment Rate, Month, and GDP have relative importance scores of 0.1661, 0.1568, 0.1484, 0.124, 0.1237, 0.1082, 0.0893, and 0.0833, respectively. These results demonstrate that WTI, Inflation Rate, and IPI are the three most influential predictors of volatility. They are followed by 3M Treasury Bill, Personal Savings Rate, Unemployment Rate, month, and GDP which have relatively lower importance, suggesting that they play a smaller role in the models predictions. A third reason is that S&P 500 volatility is influenced by a mix of complex factors, including human behaviors, economic conditions, and global events, many of which were not considered in this study [38]. One limitation of this study is the frequency and the volume of the data used. Stock volatility changes rapidly — often on a second-by-second basis — while this study relies on monthly volatility data, which may reduce the predictive accuracy [39]. Moreover, the real-world dataset used for analysis in this study is relatively small, limiting the models exposure to fluctuating market conditions and rare events. This constraint limits the predictive accuracy [40].

In future research, performing ensemble methods and feature selection using models including Random Forest or Lasso coefficients prior to model training might reduce data noise and feature redundancy, enhancing predictive accuracy. Additionally, more informative features beyond traditional economic indicators can be considered. For example, variables capturing human behavior such as investor sentiment, social media activity, and trading psychology as well as global events including geopolitical tensions, natural disasters, or unexpected policy changes may provide extra explanatory power[41]. Accuracy might also be improved by integrating monthly economic indicators with high-frequency stock volatility data, which at the same time expands the volume of real-world dataset. Incorporating higher-frequency data, such as daily volatility, can provide more granular insights but would introduce challenges including increased noise, higher computational requirements, and the need for more sophisticated models to handle the larger and more volatile dataset. Additionally, exploring a broader range of models could enhance the generalizability of the findings.

Conclusion

Stock volatility, a key indicator of market behavior, provides valuable insights for both investors and companies. This study was therefore driven by the goal of identifying the most effective machine learning model for predicting S&P 500 volatility using US economic indicators data. To accomplish this, the LSTM, the FNN, the traditional supervised machine learning models, the GARCH model, the ARIMA model, and the mean forecast model were implemented and evaluated. Their performances were compared to determine the most accurate approach. Judged by the test RMSE values, the LSTM model outperforms the other models in achieving this objective. Beyond minimizing investment risks, accurate LSTM-based forecasts can help businesses anticipate market fluctuations, optimize strategic planning, and make more informed operational and financial decisions. Future research could benefit from conducting ensemble methods and feature importance tests before training models, including factors beyond traditional economic indicators, incorporating higher-resolution data, and exploring a wider range of machine learning models.

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