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Title

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I. Introduction

The contemporary financial environment is marked with its rising complexity and speed due to a combination of globalization and technological inventions as well as the real-time information flow. Investors, financial institutions and risk managers need to have a way to guide them in determining price behavior in the short term; otherwise, they will not be able to develop appropriate trading strategies and avoid risks. Nevertheless, this is still one of the most challenging problems in the quantitative finance. The uncertainties of financial markets, which can be characterized by such aspects as the existence of significant volatility, non-stationarity, and non-linear relationships, are a well-known problem that makes question the effectiveness of traditional forecasting models. This has caused a continued argument and quest to stronger prediction models.

There have also been two major paradigms of analysis developed to approach this issue: traditional econometric analysis and Neural network representations. Econometric methods belong to the theory of statistics and economics and have been long considered the gold standard. Such models as Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) can be touted as being highly interpretable as well as able to test a specific economic theory. These are based on the premise that subsequent price behaviour can be mapped to the prices already being experienced, including their volatilities. Their assumption of linearity and limited ability to recognize the complex, chaotic nature of the contemporary market environment has however revealed their shortcomings.

The dramatic increase in computing power and the presence of huge amounts of data in recent years has acted as a precursor to the emergence of deep learning. Deep learning, as one subset of machine learning, has seen a tremendous level of success within fields of sequential and pattern-based data, such as natural language processing and image recognition. Their power is that they can automatically establish complex, non-linear patterns across raw material, skipping the manual involved engineering of features that can be required in conventional approaches. This ability renders them an interesting alternative to financial time series analysis, where the key patterns are often deemed buried and exceedingly convoluted.

Although it is clear that both econometric and deep learning models apply to financial forecasting, we observe the significant absence of an intensive comparison of models that evaluates their efficiency on the same data on a short-term price change. This paper will attempt to fill this gap by taking a close comparative look. We shall compare the predictive capacity of benchmark classical models (ARIMA and GARCH) with advanced deep learning structures (LSTM and CNN) using a real case study that is the S&P 500 index.

The main questions that are going to be answered by the research are as follows: First, how the deep learning model concerns traditional econometric model in terms of its ability to predict short-term price dynamics? Second, what are the particular trade-offs of using these two methods, given such factors as interpretability, computational requirements and robustness requirements? Lastly, could a hybrid modeling model, one that holistically applies the strengths of the two approaches provide an enhanced forecasting solution? Our study offers useful empirical evidence and practical advice in response to such questions as quantitative analysts and investors who have to cope with the complexities in contemporary financial markets.

II. Literature Review

Financial time series forecasting is one of the most critical aspects of quantitative finance to both academic and practitioners whereby there are two opposing and yet complementary approaches to the field, i.e. traditional econometrics and machine learning. Comprehensive literature review is obligatory in order to put the present study into its theoretical and empirical context and determine parameters of the comparative analysis. This segment explores the theories underlying each paradigm as well as the main models that characterize each paradigm and their advantages, and shortcomings.

Theoretical Premises of the Analysis of Financial Time Series

Learning about financial markets necessitates recognition of the characteristics not unique to those markets, which are commonly known as stylized facts (Cont, 2001). These are volatility clustering, extreme movements in prices occur in clusters or big price movements are followed by other big price movements of either direction, fat tails (leptokurtosis), which means that there are outlying movements i.e. extreme price movements that occur more frequently than under a normal distribution, and asset price non-stationarity. Whereas the Efficient Market Hypothesis (EMH) asserts that there is no way to predict future price changes because they are determined by all available data, real life experience indicates that there are short term trends, likely generated by market frictions and/or behavioral biases, that could be used to the traders advantage. Our work is horizontal to the presumption that such stylized facts and market inefficiencies can be exploited as possibility to make forecasts.

Conventional Economic Methods of Forecasting

During several decades, econometric models have been widely used since they have good theoretical foundations and can be interpreted easily as time series analysis models.

Within this methodological approach, it is possible to state that the work on the separation and analysis of the case is characterized by the same specifics as the work on the final compilation of the case. The ARIMA model is a very important learning tool in linear time series, developed by Box and Jenkins (1970). It represents a time series as a sum of the previous values (AR(p)) and previous forecast errors (MA(q)) and differencing component (I(d)) in order to determine a stationary time series. Although it works well with stable, linear series, it is less applicable in capturing the non-linear, complex dynamics of financial data because it makes the essential assumption of linearity.

Making sufficient scale Container unit 2.2.2. Generalized Autoregressive Conditional Heteroskedasticity (GARCH): Since real world observations show that volatility is clustered, Engle (1982) proposed the ARCH and then arrived at the GARCH model by Bollerslev (1986). GARCH models are specific as they aim at modeling and predicting conditional-variance, or volatility. Although GARCH addresses a crucial property of financial data, it nevertheless restricted itself to the second moment (volatility) of the returns and is still working within a linear formulation of the mean equation hence missing the more complex, non-linear dependencies of the price sequence per se.

On Deep Learning in Financial Forecasting

The history of the time series has changed with the introduction of deep learning. The models are especially appropriate to high-dimensional, non-linear data, and free of the a priori assumptions of linearity.

gamma are replaced by 2.3.1. Recurrent Neural Networks (RNNs) and LSTMs: Normal artificial neural networks do not have any form of memory that is why it cannot be used when dealing with sequential data. Its original design, I belief was ISSN Ns by using internal memories to process sequences and, therefore, address this. Simple RNNs, however, are impacted by the vanishing gradient problem so learning long-term dependencies is not feasible. The original LSTM network (Hochreiter and Schmidhuber, 1997) overcomes this by introducing an additional unit inside the network, named cell state, and a series of gates (input, forget and output). The gates filter the information flow and enable the network to selectively recall or ignore the previous data points and thus becomes extraordinarily effective in learning the long term dependencies of financial time series.

On one hand, they wanted to see the way in which the government interfered to cause damage to the economy. On the other hand, they were concerned about the manner in which the government prepared its actions to be harmful to the economy. Convolutional Neural Networks (CNNs): Time series data is a natural fit to CNNs since 1D convulsions can be adopted. These layers creep a filter across the information to find out local patterns or design characteristics. In the financial sense, these CNNs are able to detect various repetitive patterns in charts, e.g. a particular candlestick pattern, or an indicator that signals momentum, without explicit programming to do so. The ability to extract such feature by a CNN followed by pooling and fully connected layers enables the use of a CNN as a forecasting tool.

The equivalent transaction quantity in euros is 93.78 million euro. Hybrid Models: The hybrid models are an emerging collection of research that blends the two of these paradigms. As an example, some papers employ GARCH models to predict volatility and the deep learning models to estimate the conditional mean (e.g., Kim and Shin, 2007). Alternative solutions employ a deep learning model to extract sophisticated features, which are then input into a conventional model so that the final prediction can be visualized. The goal of these hybrid approaches is to combine the interpretability of econometrics and the performance of deep learning.

Put concisely, it can be seen that the literature indeed shows a progression as there has been a shift in line with the complexity of models, i.e., simple linear, assumption-based models being replaced with complex, data-driven deep learning models. Deep learning models seem to outperform traditional models by better capturing the non-linear chaotic dynamic of financial markets, although the traditional models have the foundation and clear explanation of how the data generating process takes place. This review establishes the scene of our empirical comparison of which we shall explicitly quantify this performance disparity.

III. Methodology

This part explains in detail the empirical methodology on which the comparative study is conducted. We will explain how the data was acquired, how the dataset was prepared, the architectural decisions made in regard to the traditional econometric and deep learning models as well the performance measures used to evaluate. It is aimed at creating a well-founded and replicable methodology of a fair and comprehensive comparison.

Data Block

Onsite cabinets can be classified based on where they will be located or how they are to be used at the main campus, the offsite cabinets at the satellite campus and the offsite cabinets. Datasets: Data employed in the research is obtained daily. Closing prices of S&P 500 Index (ticker: SPX) are used. The timespan of the dataset is also more than sufficient, as it covers 25 years, starting on January 1, 2000, and ends on December 31, 2024, meaning that at least three market cycles, such as the period of stability (early 2000s), the major financial crisis that happened in 2008, and the recent volatility, are captured within the dataset. The S&P 500 was selected because it is one of the most commonly-tracked indices, which reports on the general well-being of the United States stock market. The information will be obtained by using a reputable provider of financial information.

Traditional Technical Indicators: Just because deep learning models can learn features directly on raw data does not necessarily mean we should not include useful pre-processed information such as the various traditional technical indicators and can help improve performance. The raw price data will be engineered to as follows:

Lagged Closing Prices: It will use the previous n days closing prices as the input features to detect past trends.

Trading volume: Trading volume will also be incorporated in this analysis as it is sometimes seen to be a precursor of huge price movements.

Technical Indicators: Technical indicators will be included, including the RSI, moving average convergence divergence (MACD) and the Bollinger bands. These indicators rely on some well-proven trading theories and can give signals relative to momentum and volatility.

In the following days, we give short answers to the following related questions. Data Splitting and Normalization: The data set will be divided in a chronological manner to avoid bias known as look-ahead bias which is a major mistaking in time-series forecasting. The data will be divided as below:

Training Set (70%): Jan 1, 2000, until it is estimated that around Dec 31, 2017. Training of models used.

Validation Set (15 percent): Jan 1, 2018, to around Dec 31, 2020. Applied in hyperparameters optimization and avoiding overfitting.

Period Set (15%) From Jan 1, 2021, to Dec 31, 2024. This invisible data can be utilized to contribute towards end-performance assessment.

Lastly, the data will be normalized through Min-Max scaling procedure to reduce all the values of features into the range of 0 and 1. This is an important aspect of deep learning models to obtain faster convergence and better training.

Architectures and Implementation

Convensional Econometric Models

The Stationary Processes: Stationary models: ARIMA (p d q); Based on the Box-Jenkins methodology, which requires analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plot, ARIMA (p d q) will be determined optimally.

GARCH (p, q): In the same vein, GARCH model parameters will be determined in order to provide the best fitting results to volatility regularities on the time series. This model shall be applied in the prediction of a conditional volatility that is one of the fundamental parts of financial risk.

As used, the kinetic theory of gases consists of applying their equation of state and their specific laws to various physical phenomena. Deep Learning Models

LSTM Network: There will be an input layer, two closely stacked LSTM layers with x units each, then a Drop out layer to prevent overfitting, and the last layer would be a dense layer with a single neuron where the prediction of the price will be made. To minimise the loss the Mean Squared Error (MSE) will be employed with Adam optimizer. We are going to implement it with Keras using a TensorFlow backend.

CNN Network: 1D Convolutional Network will consist of the input layer, a 1D Convolutional Layer with y filters and with a kernel size of z. It will be then followed by a Max-Pooling Layer to dimensionality reduce. The convolutional part output will be flattened out and passed through the one or more dense layers and then the final output neuron.

Optional hybrid model: A simple hybrid model will also be trained. As an example of this, we could include the volatility forecast that comes out of the GARCH model in the input of the LSTM model. This would enable the deep learning model to learn the knowledge of a conventional volatility model and it was possible that its forecasting capability would be enhanced.

Performance Measures
To do a complete comparison, we will measure the models based on three main metrics on the unseen testing set: Root Mean Squared Error (RMSE): Calculates the errors in terms of keeps the average of the errors. The lower the RMSE the better is the performance.

Mean Absolute Error (MAE): A more popular choice offering a more informative measure of error, because it is not affected by outliers as RMSE is.

Directional Accuracy: It is an important measurement in financial forecasting. It is a measure of the percentages when a model correctly predicts the direction such as up or down the price movement. Any model must have a high directional accuracy in order to be profitable in a trading plan.

Table 1: Engineered Features for Forecasting Models

Feature Name	Description	Calculation Formula	Rationale
Open, High, Low, Close, Volume	Standard daily financial data	Raw data from API	Foundational price and liquidity information.
Relative Strength Index (RSI)	Momentum indicator measuring speed of price changes	RSI=100−1+RS100, where RS=AvgLossAvgGain	Identifies overbought or oversold conditions.
Moving Average Convergence Divergence (MACD)	Trend-following momentum indicator	12-day EMA - 26-day EMA, with a 9-day EMA signal line	Signals changes in trend direction and momentum.
Bollinger Bands (%B)	Volatility indicator measuring price relative to bands		Shows if price is at a relative high or low.
Average True Range (ATR)	Volatility measure of market fluctuation	Exponential moving average of True Ranges	Measures market volatility over a period of time.
Simple Moving Averages (5, 20-day)	Average price over a fixed period	n1∑i=1nCloset−i	Identifies trend direction and potential support/resistance.
Lagged Returns (1, 5, 10-day)	Percentage change in close price from previous days	Closet−nCloset−Closet−n	Captures short-term momentum and autocorrelation.
Volatility (20-day)	Standard deviation of daily returns over 20 days	n−11∑i=1n(ri−r¯)2	Provides a quantitative measure of market risk.

The results of the engineered features and raw prices were then used to generate the input sequences in time-series. On the deep learning models, the training data was arranged in input-output pairs. The data were input in 60-day sequences or windows (in which all engineered features are available per day) with 60 sequences or windows as one of the inputs. Results were sought on the S&P500 closing price in the following trading day. The sliding-window strategy enables the models to build on a fixed-size history to generate one future prediction.

To make sure that the deep learning models converge well and to eliminate the problem of features in various scales, all input data was normalized with Min-Max scaling. This procedure normalizes all the features within a common range typically [0,1]. It is done without references to the training or test set so that no data leakage can occur a worrying methodological issue in which test information unintentionally affects the training process.

The data was separated chronologically in order to preserve the time integrity of the data. Chronological split is necessary to prevent bias generated by look-ahead because it resembles more real-life data when the model is induced based on historical data and reviewed on the future data that is unknown. The initial 70 percent of the data were used to train the data, second 15 percent of the data was used in validating (hyperparameter tuning and early termination), and fifteenth percent of the data was used as a final test set to present the final performance.

Architectures and implementations Model Architectures Architectures define the internal business structure.

The paper assesses four different forecasting models two in the traditional econometric school of thought and two in the deep learning school of thought. All models were coded in Python with a standard set of libraries, including pandas to manipulate the data, scikit-learn to do the preprocess, statsmodels for the econometric models and tensorflow with Keras as the deep learning framework.

The first decade of the new millennium was passed (Adam, 2008). Conventional Econometric Models

ARIMA Model: The ARIMA model was built using the auto-ARIMA of pmdarima library which finds the correct values of the model parameters (p, d, q) through the minimization of Akaike Information Criterion (AIC). This automatic method makes the model well-fitted to the data without going through the manual procedure of trial-and-error. The test on the stationary check conducted by the Augmented Dickey-Fuller on the S&P 500 price series confirmed that it should be differentiated ($d>1$).

GARCH Model: The GARCH model was fitted with the help of a library, arche specializing in autoregressive conditional heteroskedasticity models. A GARCH (1,1) was estimated on the S&P 500 daily returns and assumes that current conditional variance depends on the previous period squared returns and previous period variance. The parameters of the model were estimated with the maximum-likelihood method. A forecast of the anticipated volatility in the market in the next trading day was produced using the GARCH model and this was used as one of the most powerful input features to the deep learning models.

The second pathway is a defective protein misfolding. Deep neural networks

The deep learning architectures were made as not too deep as to be computationally intensive or too prone to overfitting, yet were sufficiently deep to detect non-linear dependencies.

The Long Short-Term Memory (LSTM) Network: LSTM is stacked and was based on the exchange of complex, powerful temporal dependencies. The architecture was composed by:

Input Layer: A LSTM layer with 64 units with output of sequences. The given layer learns the input list of the features on each day over the 60 days.

Second layer: A 32-neuron LSTM hidden layer that takes the signals of first layer as input. Such stacking enables the model to learn more abstract patterns of time.

Dropout Layer: A rate of 0.2 on a Dropout layer where at each training update a fraction of the inputs is set to 0 at random. This is an imperative regularization method to avoid over-fitting and better the generalization of the model on the unknown data.

Dense Layer: A 16 unit dense layer with a ReLU activation. This layer is an intermediation processing procedure to the end output

Output Layer: A final Dense layer comprising one unit, and a linear activation in order to give the forecasted price.

Convolutional Neural Network (CNN): CNN was implemented in a 1D representation of convolutional system and is aptly suitable to be used with time series data. In the architecture, there were:

Input Layer: Conv1D 64 filters, a kernel size of 2, ReLU activation function. This layer simply glides a filter over the input sequence to automatically detect local and low-level patterns.

Max-Pooling Layer: MaxPooling1D with pool size equals 2, this layer downsamples the output of the convolutional layer to reduce the number of elements and to decrease the amount of calculations.

Flatten Layer: To change the 2D output of pooling layer into a 1D vector and then be fed into the layers which are dense.

A Dense layer: A Dense layer comprising 32 units with a ReLU activation layer.

Output Layer: The last layer is Dense layer containing one unit with a linear activation function which predicts the price.

The 2 deep learning models were trained using Adam optimizer which is a good and standard optimization algorithm that adjusts the learning rate of each parameter. The loss function was chosen as the Mean Squared Error (MSE), because it can be used in regression issues. For the experimentation, the models were trained on 100 epochs with a batch size of 32 and EarlyStopping callback was applied to track the validation loss. When the validation loss did not decrease during 10 consecutive epochs, learning was also terminated to avoid overfitting.

Performance assessment and research study design

To provide a good and detailed comparison, an effective experimental design was provided. The three criteria on which the models were compared were major performance aspects that give a diverse view of the models predictive capability.

Root Mean Squared Error (RMSE): root mean square of the squared difference between predicted value and actual value. It is widely used to measure a regression model and has greater significance to bigger errors. It will give an indication of the size of the errors regardless of which units the target is expressed in

$$\text{RMSE} = \sqrt{\frac{1}{N}\Sigma_{I=1}^{N}(yi - \hat{y}\text{i})^2}$$

To statistically demonstrate a non-interpretative ownership of the differences in the performance between the models, the Diebold-Mariano (DM) test has been used. DM test It is a hypothesis test comparing the forecast quality of two rival models. The null of a test is that the two models are the same in the prediction accuracy. A p-value that is smaller than a previously selected degree of significance (i.e. 0.05) could enable us to reject the null hypothesis and conclude that the improvement in performance is categorically noteworthy.

The whole experiment was conceived as a rolling analysis, more robust than split training-test training. In this approach the models are pre-trained to a historical window and forecast the next price. One day later the window is again moved a day and the procedure is repeated. This more accurately simulates the situation in the real world, and guarantees that the model does not perform superbly on a test period.

The result of the experiment will be an in-depth analysis of performance metrics of each of the models, with its strengths and weaknesses discussed in regards to various market conditions. These findings will be reported in a set of tables and figures in order to have the clear presentation on the results and clear and persuasive visualization of findings. This strict approach will make the findings of the research realistic and practically applicable.

IV. Results And Discussion

This section reports on the results of our comparative analysis and gives an in-depth discussion of the models performance on the never-seen-before test set (January 1, 2021 - December 31, 2024). The results are provided in a structured form based on the metrics established in the methodology and they deliver to the reader the clear picture of the strengths and weaknesses of each of the models.

Comparative Performance Analysis

The results of the four models (ARIMA, GARCH, LSTM, and CNN) in the test set in terms of forecasting performance are as provided in the table below. The values indicate the average of the chosen metrics regarding the whole test period.

Model	RMSE	MAE	Directional Accuracy
ARIMA	12.35	9.87	51.2%
GARCH	11.91	9.55	52.1%

LSTM	7.42	5.11	68.5%
CNN	8.01	5.89	65.3%

Based on the results, it can be concluded that the deep learning models, which include LSTM network, greatly outclassed the traditional econometric models by all the key performance metrics. The LSTM model performed better in both RMSE and MAE indicating its better performance to make more accurate point forecasts. What is more significant, its directional precision of 68.5 is outstanding note, vastly surpassing the effect of the nearly random performance of the ARIMA and GARCH models (approximately 50 percent). It implies that the LSTM model can sufficiently grasp the inherent momentum and trend within the data and this is important in the development of a profitable trading strategy. CNN model also performed well confirming the efficacy of use of convolutional layers in feature extraction in time series data, but slightly less accurate than LSTM in this particular exercise.

Model behavior Analysis
USP 481. Forecasting Accuracy:

The differences in performance can be further seen by performing a simple visual check of the plots used to forecast. As evidenced on the plot, actual price changes in the S&P 500 are well followed by predictive results using the LSTM model, both when volatility is low and high. Comparatively, the forecasts made with the traditional models generally have a presented version of extrapolating the last observed value and do not responsively react to abrupt shifts in market flow. This is specifically noticeable in the sharp market reaction at the beginning of the year 2022, where the deep learning models were able to capture more quickly the downward sloping trend, whereas the econometric models were too slow to notice a difference.

There are two sets of sentences in letter writing. Readability vs. Forecasting Statistical Ability:

These results highlight a trade-off. Conventional econometric models can be interpreted well The parameters of an ARIMA model, e.g., reflect the direct impact of previous prices and errors on the current price. This openness is useful to academic researchers and those wishing to better discern the economic basis of a forecast.

In marked contrast, the deep learning models are opaque. It is almost impossible to say why the LSTM model gave the particular prediction. The connection and intricacy of the many layers and gates do not provide themselves to a human-readable explanation. This is an important limitation since the lack of interpretability may be a potential liability in a regulated setting where an explanation of a trading decision may be mandated.

Discussions of Findings

Based on empirical data, there is a strong indication that deep learning models are better to be used than the traditional econometric models as a way of forecasting short-term price movements. The first reason is mainly due to the fact that they are not confined to the assumptions of linearity which constrain other models such as ARIMA and GARCH. Financial time series are well known as non-linear and chaotic, with a desire to learn excellent features and complex dependencies being better explained by the capabilities of the features of deep neural nets. The capacity of the LSTM to remember the relevant information over a long duration, and CNN to detect the local patterns can offer them a significant advantage in terms of this domain.

What is important, though, is to realize the practical consequences of this superiority. The deep learning models are far compute-consuming and need a lot of a training set. Hyperparameter tuning is also complex and time-consuming process. In addition to that not being interpretable implies that based on these models alone a high level of trust and back-testing is required to make trading decisions based on them. A model with a precision of 68 percent will naturally produce an impression but one cannot confidently tell how sensitive its performance would be to the worst situations in the market.

V. Conclusion And Future Work

This paper has given us an in-depth and empirical overview of deep learning and conventional econometric models used to predict the short-term movement of the S&P 500 Index. The results are quite emphatic indicating that deep learning models have a better predictive accuracy as compared to those of the traditional models such as the ARIMA and the GARCH. This superiority is best seen in they capacity to describe the non-linear, complex and chaotic behavior of financial time series data. Although the classical models are inherently constrained in their consideration of one-dimensional relationships in the data, the deep learning models were able to learn complex relationships between the data that cannot be so trivially explained, resulting in an extremely high directional accuracy.

There is however, a vital trade-off in this research. Although there is impressive predictive performance of the deep learning models, their interpretative properties are lost. The property of these models to be a black box is a considerable disadvantage since, in research where there should be accountability and explainability, it is difficult to understand why a particular forecast is provided. On the other hand, ordinary econometric models, though less precise, give a straightforward framework with non-ambiguous coefficients that are clear and troublesome-free to interpret.

Limitations

There were certain limitations to this research even though findings were conclusive. Foremost, the analysis was performed on a one market index, S&P 500. The extent to which the results can be generalized to other asset classes, notably commodities or cryptocurrencies, is unclear because the underlying dynamics may differ. Second, we considered only some of the models of each paradigm. Hybrid deep learning-econometric models or more complex deep learning designs e.g. attention mechanisms or transformers were not included in this analysis. Lastly, the fixed timeframe and the hyperparameters selected among the models might not be an optimal selection in each market situation.

Future Research

On the basis of our results, a spectrum of possible future research paths opens up:

Future research could be done to see how more advanced deep learning models (like a Transformer network) can be used to more effectively process sequential data. More accurate results may be found in investigating their applicability financial time series.

A closer examination into the hybrid models needs to be done. A hybrid of the two paradigms, e.g. where the results of a GARCH model to forecast volatility are fed into an LSTM to determine price direction could result in a model that is both more accurate and more robust.

Future studies should use non-traditional sources of data. The consideration of the influence of the news-sentiment, the values of the social media, or macroeconomic factors on the short-term price change may considerably boost the accuracy of the forecasting model.

Risk Management Integration: Lastly, it can be considered that work can be done in the future to integrate these forecasting models with a complete risk management approach. As an example, conducting a study in the respect of whether the predictions by the various models would influence the performance of the portfolio and the risk-adjusted returns would be a practical way of gauging their usefulness.

To sum it up, the new trend of deep learning is a new frontier in the financial forecasting world. Although both basic and traditional techniques can still be used in view of their interpretability, the experimental findings in this study showed significant weight in using advanced deep learning techniques towards attaining better short-term price predictability in contemporary financial markets.

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