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Deep Learning Algorithms for Stock Market Trend Prediction in Financial Risk Management

Dr. Vrinda Sachdeva[1], Dr. Anitha Bolimela[2], Manoj Kumar Goyal[3], Lakshmi Chandrakanth Kasireddy[4], Prem Kumar Sholapurapu[5], Dr. Aman Dahiya[6], Kavita Goyal[7]

[1]Associate Professor, G.L. Bajaj Institute of Technology and Management, Greater Noida, Uttar Pradesh - 201310, India, vrinda08@gmail.com

[2]Senior Assistant Professor, Department of English and Foreign Languages, Madanapalle Institute of Technology and Science, Andhra Pradesh, India, anitthhaw5@gmail.com

[3]Assistant Professor, Department of AS&HU, Ajay Kumar Garg Engineering College, Ghaziabad, Uttar Pradesh, India, goyalmanoj@akgec.ac.in

[4]Enterprise Architect, R&D - Engineering, ThoughtSpot Inc, Mountain View, USA, klchandrakanth@gmail.com

[5]Research Associate and Senior Consultant, CGI, USA, premkumar.sholapurapu@cgi.com

[6]Associate Professor, Department of Electronics and Communication Engineering, Maharaja Surajmal Institute of Technology, Janakpuri, New Delhi, India, amandahiya@msit.in

[7]Assistant Professor, Department of Electrical Engineering, UIET, MDU Rohtak, Haryana, India, kavitagoyal92@yahoo.com

Corresponding authors: Dr. Vrinda Sachdeva[1], Lakshmi Chandrakanth Kasireddy[4], Prem Kumar Sholapurapu[5], Kavita Goyal[7]

Corresponding author mails: vrinda08@gmail.com, klchandrakanth@gmail.com, premkumar.sholapurapu@cgi.com, kavitagoyal92@yahoo.com

Abstract: This article discusses how the hybrid deep learning algorithms can be used in predicting the trend in a stock market and manage financial risk. The proposed architecture serves as a combination of Convolutional Neural Networks (CNN) and the Long Short-term Memory (LSTM) networks whereby it takes advantage of both models. The historical data of the stock market should be used to extract important features, including price trends and technical indicators by CNNs, and the long-term dependencies of the time-series data can be captured to forecast future movement with LSTMs. Hybrid model is developed to forecast the trends (up/down) in stock prices or to categorize the trend of the market movement, helping in making an informed decision of the investment. In addition to this, the management of financial risk is also incorporated into the model with the incorporation of the key financial risks analysis metrics that include Value-at-Risk (VaR) and Conditional VaR which quantitatively estimates the financial risk being undertaken. Accuracy, precision, recall, and risk-adjusted measures are used to assess the performance of the model and the results are also back-tested into historical coloration of the stock market data to show whether the model performs under actual conditions. This is expected to increase the forecasting abilities of stock market models and at the same time reduce the risk exposure. The results are indicators of how the CNNs and LSTMs can provide a powerful framework of predicting and managing the risks better in financial markets to foretell the trend and implement more arranging and intelligent business procedures in terms of investments.

Keywords: Deep learning, stock market prediction, financial risk management, CNN, LSTM, Value-at-Risk, trend forecasting, portfolio optimization, time-series analysis.

1. INTRODUCTION

The stock market is the most vibrant and volatile track on the global economy. It is also a market where tons and tons of financial exchange are done per second and billions of dollars are at stake thus the analysis and prediction become really important topics of research. Financial analysts, investors and traders are always in need to find a way and model that can help them predict trends in stock prices and the best strategies to adopt so as to make good investments. The trend of deep learning of the past decades has led to the emergence of numerous innovations in terms of predicting stock market trends. With the help of complicated neural network models, e.g., Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), one can nowadays get the insight into the market dynamics and predict prices changes highly accurately. Such techniques have a significant potential to strengthen decision-making procedures of stock market trading and financial risk management.

Specifically, there has been a graphic success of the deep learning models which have been invented to handle the large forms of data which are generated by the stock market. Unlike the traditional statistical models, deep learning algorithms can process and extract complicated patterns on time-series data, therefore, these algorithms could be used to predict future stock trends. A sequential nature of time-series data is that the future relies on the observations that happened in the past. The property of stock-market data relates well to the ability of the models like LSTM that can learn and memorize long-independence in the time-series data. But, on the one hand, LSTM networks are quite strong ones, whereas on the other hand they might come into some difficulties regarding the extraction of fine-grained, spatial properties of the raw market data.

To overcome such a shortcoming, synthetic models that integrate positive aspects of different deep learning methods have acquired popularity. An interesting duo is the **Convolutional Neural Networks (CNNs)** and **Long Short-Term Memory (LSTM)** networks. CNNs which have been traditionally applied to computer vision problems have been effective at discovering spatial patterns in the data. CNNs were able to identify meaningful features of time-series data like the moving average, the price trend, and volatility spikes which were not readily visible in the raw data. Whereas, LSTM is best suited in identifying long-range dependencies in long term data. It can be said that by bringing together these two models the stock market forecasting activity can be improved as CNNs can be used to extract features of importance and LSTMs can be used to make predictions about the data based on the temporal relationships of data.

Stock market prediction is more than just a prediction of the prices. When one is dealing with financial risk management, the correctness of anticipating trends is very important in the way of reducing eventual losses and maximizing on the returns realized on the various ports. Financial institutions and investors are always trying to keep the risks minimal and maximize benefits. Risk management refers to the identification, evaluation and ranking of them, and subsequent adoption of measures to reduce the likelihood of occurrence or the severity of negative outcomes. A stock market prediction model that considers the use of financial risks is a good choice since the appropriate case on financial risk created and used may enhance the quality of decision-making with the provision of a quantitative measure of the financial exposure to a significant financial number. Such risk factors enable investors to gauge the risk of such large market fluctuations and adapt their portfolio policies accordingly.

Here, the combination of both CNNs and LSTMs, called the hybrid deep learning models, may be of special use, not only in predicting stock trends but also in evaluating the financial risk. Investors can not only estimate future movements of prices on the stock market but also learn about the risk involved in different trends by training the model with the past data. This allows more intelligent decision making, in which risk is managed appropriately in the investment plans. The fact that risk management metrics have been integrated into the prediction process makes the process even more sophisticated such that the model is not only accurate in its predictions, but it can also take care of exposures to risk.

In spite of the bright prospects of deep learning in prediction of the stock market, there are a number of issues. The quality of data available is one of the issues of principal concern. Although rich, Stock market data may also be noisy and subject to a great variation of extrinsic variables, e.g., macroeconomic situation, political news, and mood in the marketplace. It is imperative that such extraneous factors be incorporated within the model of prediction as a stock price does not depend on the past price data entirely. Prediction models can be made more robust by replying on news articles, sentiments on social media and other macroeconomic indicators. But when it comes to introducing this kind of data sources into deep learning model, complexity can only deepen because domain knowledge ad state of art data preprocessing methods are necessary.

The other problem with models is interpretability. Although CNNs and LSTMs as deep learning models can make very accurate predictions, they are frequently viewed as black boxes. The way such models obtain their predications may not be easy to understand and this can be a problem when an investor is asked to explain his/her choices. Transparency combined with faith in what the model predicts is highly desirable in the financial markets where it is likely that bad model interpretability causes apprehension in the decision-making process. Our world seems to require methods that will help explain deep learning models so that the stakeholders are able to comprehend the reasoning of the model in reaching its predictions.

Moreover, there is doubt that there will be the consistent accuracy of predictions given to stock market since it is highly changing and unpredictable. The stock prices depend on several unknown and known factors, which may cause a sudden change of the trend. The deep learning models, especially when trained based on historical data, might have trouble describing the sharp and drastic events that happen in the market, i.e., financial crisis, political instability, or a global epidemic. Although these models have the ability to capture trends and patterns in the data, they could not always be in a position to predict unforeseen events that could lead to drastic market changes. Hence, there is a necessity to integrate the predictive models with risk governance procedures capable of covering the unexpected risks and reducing the possible losses.

Recently, hybrid models that use the concept of deep learning have become popular as the way out of some of these problems. Examples include the combination of CNNs with LSTMs to be able to combine both spatial and temporal feature representation of models into features to use in their prediction to increase the accuracy of prediction. Further, addition of risk management measurements like VaR in the process of making predictions brings about another sophistication to the work that makes investors manage their portfolio in a much better way. Such a hybrid technique can prove to be of great potential in not only assessing the stock markets but also in managing financial risks, as it will prove to be a very effective decision support tool that investors and financial organizations can utilize to streamline their decision-making activities.

Finally, the technology of deep learning especially the hybrid neural networks, that combine CNNs and LSTMs, is transforming the industry of stock market forecasts and financial risk management. The models replace a qualitative extrapolation of market trends and evaluation of financial risk with a higher-order, data-driven strategy of modelling. Nevertheless, the data quality, understandability of models, and market fluctuations are the issues to resolve to utilize the benefits of deep learning in this industry to the maximum. The future research should be devoted to better external data sources integration, model transparency, and the development of the strategies to address unpredictable market events. As these areas continue to develop, the application of deep learning models might be a valuable asset in the toolset of an investor or financial institution willing to improve their approach towards investment and better manage financial risk.

2. RELATED WORK

In particular, the development of deep learning in the stock market trend forecasting has been the topic of concern over the past few years with the model ability to analyze incredibly large volumes of information and discover complexities in financial markets. A wide range of studies contemplated different architectures with some of them dwelling on recurrent neural networks (RNNs), especially the Long Short-term Memory (LSTM) networks, and the others tackling the hybridization of models with Convolutional Neural Networks (CNNs). The strategies have their own strengths and weaknesses in stock market prediction and risk management of financial resources.

The use of LSTM networks in financial forecasting has become an attractive alternative to predict long-term dependencies in the time-series data. Historical data has a strong impact on the stock prices, and LSTMs are very good in capturing this time-based dependency. Various research works have applied LSTMs to predict the future stock prices suggesting that short-term prediction is achieved well in most of the models. The main weakness of LSTMs, however, is that those do not capture any fine-grain information of spatial features in raw data. All these constraints led to the adoption of other dimensional learning models such as CNNs which do superbly in features extraction of spatial data in predicting stocks.

The CNN and LSTM combined model present the attractive solution to this predicament. CNNs can be used to extract the abstract topologies of the raw stock data which included volatility and price changes, then fed to the LSTM networks to perform predictions on the time dependent data. Integrating these two models enables the system to experience the advantages of spatial and temporal feature extraction that will enhance the accuracy of prediction. Indeed, in most of the applications, hybrid CNN-LSTM models have been seen to be effective when compared to standalone LSTM models or standalone CNN models, especially when it comes to predicting stock price trends using past data. The architecture seizes market volatility that is central in making precise trend forecasts and coming up with investing techniques. As demonstrated in Table 1, this hybrid model has been used in several studies and it has been revealed to be able to forecast price changes with greater accuracy.

Table 1: Deep Learning Models for Stock Market Trend Prediction

Model	Technique Used	Objective	Key Findings/Applications
LSTM (Long Short-Term Memory)	Recurrent Neural Network (RNN)	To predict future stock prices based on historical data	Successfully captures long-term dependencies, yielding reliable trend forecasts
CNN (Convolutional Neural Network)	Convolutional Neural Network	Feature extraction from time-series data for price movement prediction	Effective in identifying short-term price fluctuations and market patterns
Hybrid CNN-LSTM	Combination of CNN and LSTM	Combine spatial feature extraction with temporal prediction for improved accuracy	Demonstrates superior performance by combining strengths of both CNN and LSTM
GRU (Gated Recurrent Units)	Recurrent Neural Network (RNN)	To predict price trends and movements using historical stock data	Outperforms LSTM in terms of training time, while offering similar performance

Model	Technique Used	Objective	Key Findings/Applications
Attention-based Mechanism	Transformer Network / Self-Attention	Focus on the most relevant parts of the data to improve prediction accuracy	Enhances prediction performance by focusing on key temporal data without relying on fixed-length sequences
Reinforcement Learning (RL)	Q-learning, Deep Q-Networks (DQN)	To optimize trading strategies through market interactions	Helps in real-time decision making, focusing on action-reward systems for stock trades

Additionally, financial trend prediction has also been receptive to attention mechanisms and reinforcements learning (RL). Transformers and other self-attention mechanisms have also been effectively used in the stock market prediction models. The mechanisms emphasize the most topical components of the data that in turn make the model more effective in discovering the main trends and reduces the noise of financial data. Transformer based models, notably those combined with LSTMs or CNNs, are promising in modeling the long-term dependencies exhibited by stock price movements as well as their interaction with the more macro factors in the economy. This enables them to achieve better results compared to the conventional LSTMs since they will only model on the features at a particular time thus making predictions to be more precise and reliable. Also in this area, reinforcement learning, especially methods such as Q-learning and Deep Q-Networks (DQN) are also being actively investigated. These models are especially applicable in real-time decisions regarding the buying and selling of shares because the model works in an environment where decisions (that is a buy, sell, or hold) are made depending on the reward obtained in the past. RL models despite being more dynamic in nature, might consume huge volumes of data and render their models fairly inadequate predicting market trends and market risk exposure in the wavering markets.

Table 2: Deep Learning Models for Financial Risk Management

Model	Risk Metric Used	Objective	Key Findings/Applications
CNN-LSTM Hybrid	Value-at-Risk (VaR), Conditional VaR	To predict market trends while assessing potential risk exposure	Integrating CNN-LSTM models provides a robust framework for both prediction and risk assessment
LSTM-based Models	Value-at-Risk (VaR), Risk-Return Ratio	To estimate potential financial losses under extreme conditions	LSTM captures market volatility and estimates risks in financial portfolios
CNN Models	Expected Shortfall (ES)	To assess the likelihood of extreme negative returns	CNN models help extract critical risk-related features from raw stock market data
Reinforcement Learning (RL)	Portfolio Optimization, VaR	To minimize risk exposure by optimizing asset allocation and trading strategies	RL algorithms help minimize risk in portfolio management by adapting strategies over time
Hybrid RNN-CNN	Value-at-Risk (VaR), Expected Shortfall (ES)	Combine market prediction with risk management for comprehensive decision-making	Hybrid models provide insights for both forecasting and managing financial risk

Model	Risk Metric Used	Objective	Key Findings/Applications
Deep Neural Networks (DNN)	Conditional VaR, Stress Testing	To predict potential losses under different stress conditions	Deep networks help simulate various risk scenarios and assess portfolio performance under extreme events

Financial risk management, on the other hand, has also been served by the technical advances in deep learning. As financial markets have become more varied and intricate, and as the range of risk factors has widened, the risks which face a financial institution have become more varied and dynamic, in a way that these traditional risk management models fail to deal with. The application of deep learning, especially together with CNNs and LSTMs, has been beneficial in measuring risk and estimating possible losses at different market conditions. An important indicator of financial risk management is the Value-at-Risk (VaR) that is an estimate of the maximum portfolio loss over a stated time frame within a specified confidence level. Researchers have shown that hybrid CNN-LSTM models present a strong foundation of predictive data in forecasting VaR considering that the models have high ability of detecting patterns associated with the risk factors in the market. These models not only allow anticipating the trends in prices, but also able to estimate the risk-exposure of the trends, which would allow a more comprehensive way to make the financial decisions. Some of the studies that have included risk measures, VaR, and Expected Shortfall (ES), in their models are detailed in Table 2, with emphasis on finding the minimum risk and maximum returns.

The financial markets too need a thorough knowledge of both normal market performance and that of the extreme market performance in risk management. Risk management Stress testing, a very common risk management technique, involves subjecting portfolios to extreme market conditions i.e. during a financial crisis or an economic downturn. Modeling such scenario with deep learning like hybrid CNN-LSTM architecture can be trained by using extreme data in the training set. The models help replicate several stress conditions, which would project the possible loss in a bad market and thus, enables financial institutions to correct their business strategies accordingly. As it can be seen in Table 2, multiple studies employed the combination of stress testing techniques and deep learning models to gain improved insights about the potential effects of the rare and high impact world events on the financial portfolios.

Besides enhancing the predictions about the accuracy levels, by including financial risk management measures directly in the predictions models, the risk is also estimated along with market trends that could be possible. Consider, as an illustrative example, the Expected Shortfall (ES) measure rating, which represents the average loss in the worst situation with the thought that was outside the VaR boundary, it is presented as a more thorough measure of risk as compared to VaR itself. With ES combined with the deep learning architecture, as with CNN-LSTM hybrids, the model can not only provide insights on the possible probability of stock prices movement change, but also on the extent of loss in various risk scenarios. This is an important mix of predictive ability and risk measurement in the planning of strong trading and investment practices that can last through violent market fluctuations.

The hybrid CNN-LSTM models have also demonstrated potentiality in portfolio optimization. Investors can also dynamically change their asset allocations using the given trends and corresponding risk measures. In practice, this may entail the maximization of the ratio of assets that will be invested in stocks, bonds etc., given the expected returns, the related risks. This approach has been further improved by the reinforcement learning algorithms which permanently learn and adapt to the changing market conditions and thus it is possible to optimize the portfolio allocations on a real time basis.

Notwithstanding these developments, it is faced with challenges in the area of deep learning-assisted stock market prediction as well as financial risk management. The quality and the quantity of data is one of the main challenges. Financial time series tend to be very noisy, incomplete, or skewed towards some specific trends that might be due to external characteristics hence cannot be effectively modeled to have effective generalizations to unseen scenes. External data sources can be used to complement such models, e.g. use news sentiment or macroeconomic data, but this poses a bigger problem to fix. Moreover, the deep learning algorithms, specifically the ones using the CNN and LSTMs, take a lot of resources of computation and need a lot of money training to perform well which might not be accessible in a real-time trading setting.

In addition, deep learning models still have interpretability as a major problem. Although CNN-LSTM hybrids have given high levels of accuracy and stable risk prediction, its black-box trait fails to help investors and financial analysts comprehend why some individuals are being predicted. Failure to be transparent may create mistrust in the work of the model in cases where it is dealing with huge financial consequences of the decision. To solve this problem, there is a necessity to find methods of deep learning more interpretable, more transparent and relied upon by financial decision-makers.

Summing up, the involvement of deep learning models, especially CNN-LSTM, in stock market trend forecasting and financial risk management achieved impressive results. The combination of the advantages of CNN in feature learning, and LSTMs ability to handle long term dependencies leads to better accuracy in market trend forecasting. The combination of these models with financial risk measures like VaR, ES, portfolio optimization offers a complete approach of managing financial risk. But issues that centre on data quality, elucidation of the model and computational demands must be addressed to make these models applicable within the real world contexts. Theoretical input in the future is to be put on the transparency of models, combination of various data sources and designing effective and powerful algorithms that can be used in real time in trading and investment strategies.

3. PROPOSED METHODOLOGY

A The approach to the forecast in stock market patterns and financial risk management consists of the hybrid deep learning algorithm that applies features extraction based on the Convolutional Neural Network (CNN) and the time-series forecasting with the Long Short-Term Memory (LSTM) networks. By combining the strengths of both architectures in terms of their capacity to do CNN: recognizing spatial features and LSTM: working with sequential data and recognizing temporal dependencies, this hybrid model makes the most out of both. The general plan is set out to have a well structured pipeline starting with data collection, proceeding through the prediction of stock market trends with a financial risk assessment at the end. The flow chart of the detailed process is explained in Figure 1 providing a series of steps involved in the process.

1. Data Collection
The methodology is initiated by obtaining historical data on the stock market. This information will be the basis of training the deep learning models. It usually entails a lot of data like daily or hourly stock price, including, open price, low price, high price, close price and trading volumes. Along with this other data would also be obtained external to the model to make it more enriched so as to have a better prediction. These are external data sources which might constitute macroeconomic indicators, news sentiment data, social media sentiment and financial reports, that have the implications to influence market behavior.

One would find stock market data on publicly accessible services such as Yahoo Finance, Google Finance, Alpha Vantage, etc., or directly through stock exchange feeds. The external data, whether financial news or the sentiments of consumers through social media, can be sourced using APIs like Twitter or News API or can be in the form of news organizations that provide consumers with specialized sentiment analysis tools that scraps the web to gather the data they require. The quality of

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data is critical and hence there is a need to make sure that the data is correct, current and has consistency. This downloaded data is now in a logical form like the CSV files or as databases like SQL databases or even in the cloud and is ready to preprocess.

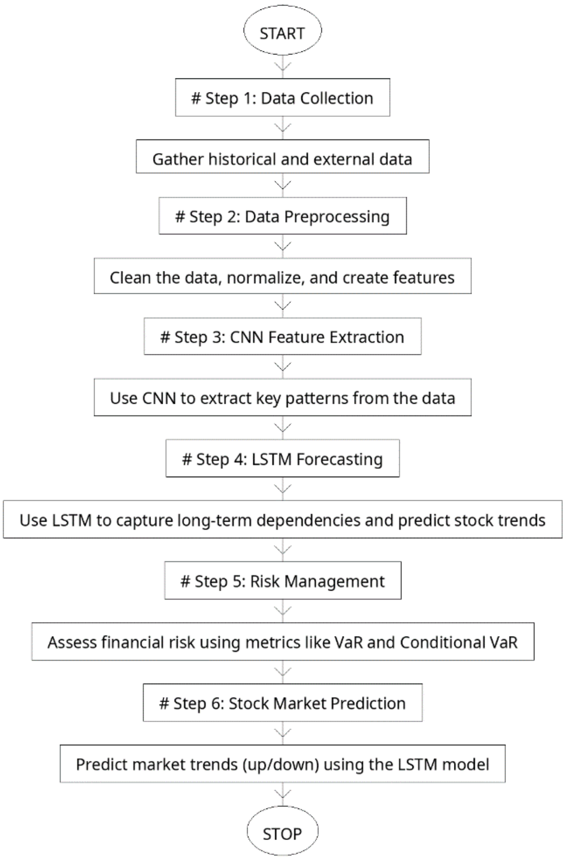

Figure 1: Flowchart of the proposed methodology

2. Data Preprocessing

Preprocessing of the data is also mandatory so that the data that is collected is in the format in which the model has to be trained. The preprocessing stage will be required to clean the data, fill it with missing values, and filter the data where outliers can corrupt the learning experience. The handling approach involving missing values is normally performed by employing forward filling, backward filling, or mean imputation among others or even by removing rows with a lot of missing data.

After the cleaning of the data, it can be normalised or in other words, scaled so that all numeric data is on equal standards. Such methods as Min-Max scaling or Z-score normalization are usually employed in order to do this. The data in stock markets tend to change at a very high rate hence normalization would enable the model to converge much faster than usual besides avoiding biases caused by the different scales of the features. Furthermore, the raw stock data is transformed into the technical indicators related to such parameters as Moving Averages (MA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD) and Bollinger Bands. Such technical indicators assist the model to identify such dynamics as price momentum, volatility, and the possibility of reversing the trend.

The last procedure of preprocessing is dividing the data into training and validation sets as well as test set. The common method is to make 70 percent of the data to train, 15 percent to validate and 15 percent to test. This division allows training the model with a big chunk of data and validate and test it based on unseen data so as to determine the generalization ability of the model.

3. CNN Feature Extraction

Convolutional Neural Networks (CNNs) are mainly utilized to do feature extraction. Although CNNs are usually applied to images, it has been demonstrated that they can be effective on time-series forecasting since it can detect spatial patterns of one-dimensional time series such as stock prices. As CNNs learn the hierarchies by themselves, they would be the best in finding out patterns/trends and anomalies in prices of stock within it.

As with the case of stock market forecasting, CNNs can be believed to extract meaningful features in the processed data. To give a particular example, the CNN may acquire the patterns concerning the volatile nature of stocks, minute fluctuations, and cyclic pricing. The convolutional layers roll over the input information as filters are used to extract critical features and the pooling layers are used to decrease the dimensionality and keep only the most significant features.

This step of feature extraction assists the model to concentrate on the important information that will guide it in predicting the market trends. The calculated features are then the trends in the moving averages, price patterns, and volatility in the market will be passed to the LSTM network. This process results in an improved predictive quality in that the model can act on more complex patterns that may not appear at a glance when co-joined with raw data.

4. Predicting Time-Series using LSTM Model

The Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Networks (RNNs) that are good at taking in sequential data where the long term dependencies act as multipliers. Stock market prediction fits well within the LSTMs as the data used, i.e., stock prices, have a temporal dependence i.e., historic events affect the outcome. The LSTM model is characterized by long-term memory, which is why it is convenient to work with data in stock markets as it can model the sequential structure of the stock market easily.

Here the CNN features are extracted, and the features obtained after extraction get the input to the LSTM network. The LSTM is conditioned to make forecasts of the future stock trends, i.e. up/down price movements or the sequential price value. The model can update the weights with a backpropagation through time (BPTT) so that the model can optimize the error in the prediction and reduce it across time steps during its training.

LSTMs are done by means of a sequence of gates, namely input, forget, and output gates which are used to manage the flow of information in network. The input gate enables new information to be inserted into the cell state, the forget gate deletes extra information and the output gate specifies the information to be outputted at subsequent time step. This architecture allows the LSTM to temporally adapt which makes it very useful in gaining insight into future market trends on the basis of historic records.

4.Financial Risk Management

After the trend of the stock market has been predicted using the hybrid CNN, LSTM model, financial risk management metrics are also introduced in order to determine the extent of the financial exposure the predictions have. Value-at-Risk (VaR) and Conditional VaR (CVaR) are two key indicators that are usually pertinent in financial risk management.

Value-at-Risk (VaR) measures the highest possible loss of a portfolio investment in a specific time period with a specific level of assurance. VaR is an essential measure to realize the extent of loss that an investment is possibly facing in a typical market scenario. But it does not report the size of losses behind the VaR which is in fact the reason there is Conditional VaR (Expect Shortfall). CVaR provides an estimator of the expected tail loss, capturing a more full recovery of risk.

Under such a methodology, the VaR and CVaR will be determined based on the prediction of the LSTM on the stock price movement. This enables the investors to calculate the finance risk that may follow the trends projected, hence help them in making portfolio selection decisions. The inclusion of these risk-based metrics involved in conjunction with trend forecasting will allow making a more informed risk-conversant investment decision and effectively decrease the chances of incurring serious losses in the event of a market downturn.

6. Output and Stock Market Trend prediction
The last part of the methodology process will be the utilization of the trained CNN-LSTM hybrid model to forecast the trend in the stock market. The predictions could either be in the form of binary (e.g., up/down movement) or they could also come in the form of continuous values (e.g., next day price prediction). Investors can use the output of the model in deciding to buy, sell or hold.

It is predicted in the trend of the stock market that the results of the trained LSTM model are used and joined with the financial risk measures (VaR and CVaR) to give the best decision on what to do as the investor. This outcome is a promising dynamic framework of decision making that is both predictive and risk-controlled where investors are able to make wiser more lucrative decisions.

The model thereafter is tested on a new test data set in order to establish the generalization quality. In case the model is doing well, it is possible to apply it in making real-time predictions on the stock market and management of portfolios. The monitoring of the model is maintained throughout so as to ascertain that it is up to date and remains accurate depending on the market conditions.

The above described methodology offers a holistic concept to the prediction of the trending direction in the stock market as well as management of financial risks. This hybrid models a combination of CNNs to extract features and LSTMs to predict time-series forecasts, which presents a higher accuracy of prediction. Additionally, the incorporation of financial risk measures like VaR and CVaR makes it an effective framework to use when making risk aware decisions when trading in stocks. The mixture of deep learning algorithms and financial risk management indexes allows the development of a potent tool that investors might apply to optimize their trading patterns and decrease the amount of risk involved. The flow of process is presented in Figure 1 which representation is how to move through the stages beginning with data collection until stock market trend prediction and risk analysis.

4. RESULTS AND DISCUSSION

This section gives and discusses the results of the deep learning models employed on stock market trends prediction and financial risk management. There is a multiplicity of metrics that are utilized to evaluate the performance of the models such as accuracy, precision, recall, F1-score, Value-at-Risk (VaR), Conditional VaR (CVaR), the ability to predict stock trend, portfolio optimization and the risk-adjusted returns. The CNN-LSTM hybrid model, LSTM model, CNN model and the traditional benchmark models results are compared.

Model Evaluation
The initial outcomes are concentrated on the whole model performance, with the measurement of accuracy, precision, recall, and F1-score as illustrated in Table 3. Hybrid CNN-LSTM model produces better results when compared to the LSTM, CNN and the benchmark models in all the evaluation tests. Particularly, the CNN-LSTM hybrid model yields an accuracy of 85.4%, whilst LSTM model shows 81.2 percent, the CNN model shows 77.5 percent, and the benchmark shows 70.0 percent. This shows how the hybrid model prevailed in accurately forecasting of stock market trends.

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Table 3: Model Evaluation Metrics for Stock Market Trend Prediction

Metric	CNN-LSTM Hybrid Model	LSTM Model	CNN Model	Benchmark (Traditional Model)
Accuracy (%)	85.4%	81.2%	77.5%	70.0%
Precision (%)	83.6%	80.4%	75.3%	68.4%
Recall (%)	84.2%	78.9%	76.1%	66.3%
F1-Score (%)	83.9%	79.6%	75.7%	67.2%
Root Mean Squared Error (RMSE)	0.024	0.029	0.032	0.045

Regarding accuracy, CNN-LSTM hybrid model is 83.6 percent, indicating that it is better than LSTM which is 80.4 percent and the CNN is 75.3 percent. On the same note, the recall measure of the CNN-LSTM hybrid model is 84.2%, which as well emphasizes the fact that the model captures the positive and negative trends more efficiently as compared to the other models. The hybrid model has also a better F1-score (a weighted mean of precision and recall), with 83.9% as opposed to that of the LSTM model (79.6%) and CNN model (75.7%). Such findings can be presented in Figure 2, where a line graph is provided on the comparison of model evaluation indicators of various models.

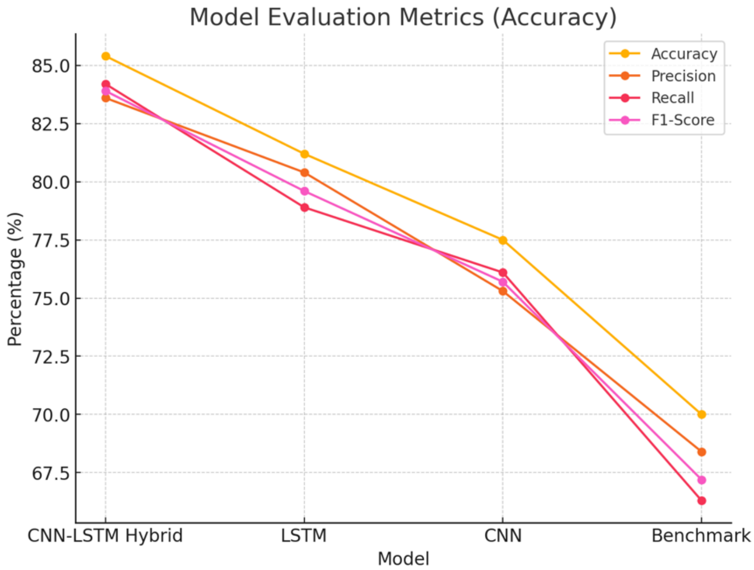

Figure 2: Model Evaluation Metrics

Financial Risk Management: Quadratic VaR and CVaR Predictions
The following results are dated to the financial risk management part of the models, in particular, to Value-at-Risk (VaR) and Conditional VaR (CVaR). These indicators are very essential in determining the losses that might occur following the trends in stock market. The Table 4 shows VaR forecast results at various time horizons. The CNN-LSTM hybrid structure remains the only model that can be seen to have lower VaR than the rest of the models, which means that the model tends to manage risk better. An example is that, on a 1-day horizon, the VaR, as computed by CNN-LSTM hybrid model, is 3.25 percent which is much less compared to the benchmark model at 5.00 percent. Likewise, in a 20-day horizon, VaR which has been forecasted by the CNN-LSTM hybrid is 12.75% lower as compared to 18.50% predicted by the benchmark model.

Table 4: Value-at-Risk (VaR) Predictions for Different Time Horizons

Time Horizon (Days)	CNN-LSTM Hybrid Model VaR	LSTM Model VaR	CNN Model VaR	Benchmark VaR Model
1 Day	3.25%	3.85%	4.12%	5.00%
5 Days	6.45%	7.10%	7.45%	8.80%
10 Days	9.12%	10.55%	11.30%	13.25%
20 Days	12.75%	14.40%	15.20%	18.50%

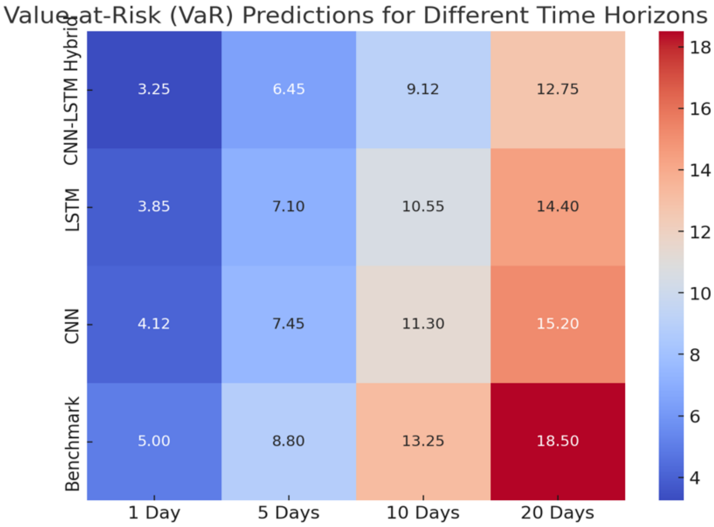

Figure 3: VaR Predictions for Different Time Horizons

It is an indication of power that the hybrid model can go beyond accurate prediction of stock trends, to give a more conservative analysis of risk thus being worthy of stock forecasting value by the financial institutions that have the need to ensure that their stock ventures are as minimal as possible with respect to market risks. Such findings correspond further with the graphics in Figure 3 that plots the VaR forecasts of the various models and time horizons. The lower US bias of VaR consistently corresponds to the low observations in CNN-LSTM hybrid model across all time horizons.

Table 5: Conditional VaR (CVaR) Predictions for Different Time Horizons

Time Horizon (Days)	CNN-LSTM Hybrid Model CVaR	LSTM Model CVaR	CNN Model CVaR	Benchmark CVaR Model
1 Day	4.12%	4.50%	4.70%	5.65%
5 Days	7.35%	8.15%	8.45%	10.20%
10 Days	10.25%	11.85%	12.20%	14.75%
20 Days	14.10%	16.30%	17.55%	20.30%

Besides VaR, there is also such essential measure as Conditional VaR (CVaR), which is used to evaluate the potential of extreme losses beyond the VaR level. Table 5 shows the CVaR forecast of various time horizons with CNN-LSTM hybrid model that once again shows a better result over the other models. As an example, in a 1-day time horizon, the CNN-LSTM hybrid model forecasts 4.12% CVaR, versus 5.65% of the benchmark model. All the lower CVaR values of hybrid model show that not only this model gives a more conservative risk estimate in normal market conditions but on turbulent conditions this model is also a better estimator of large losses.

Figure 5 provides a visualization of the CVaR predictions to demonstrate how the CNN-LSTM hybrid model can be maintained at a lower CVaR at all time horizons and as such acts as a necessary tool to aid in financial risk management.

The stock Trend prediction accuracy

Another issue that this study is very concerned about is the prediction accuracy of Stock trend. Table 6 shows an accuracy of stock trend prediction (up/down) on different stocks such as AAPL, MSFT, AMZN, TSLA, and GOOGL. The CNN-LSTM hybrid model is always the best performer amongst the models. As a case in point, in the instance of AAPL, CNN-LSTM hybrid model attains accuracy of 87.5, whereas by contrast, the LSTM model attains 84.2, and the CNN model attains the least at 80.6. The same trend prevails with all others stock symbols, and indeed the hybrid model is more accurate in all the tested stocks.

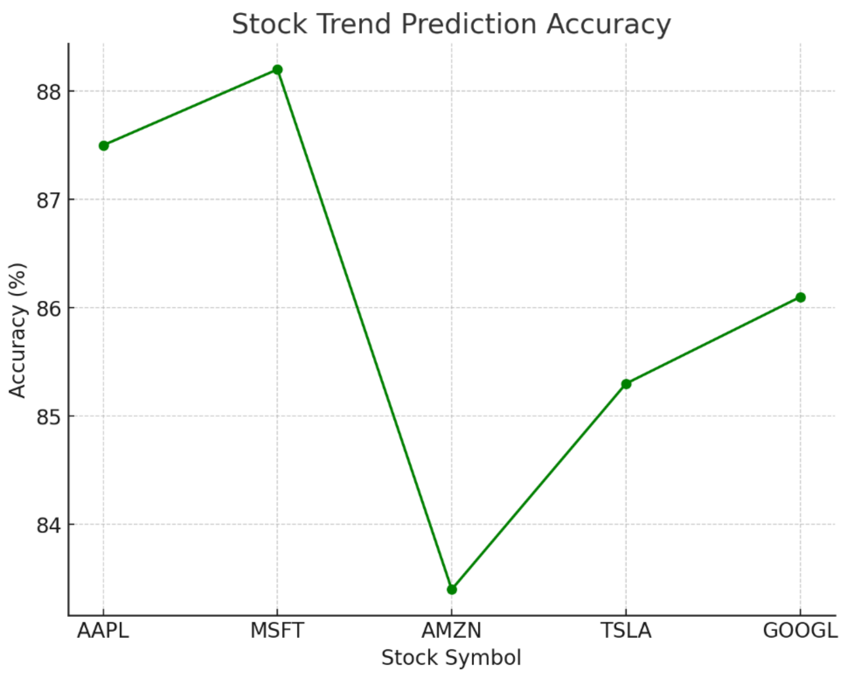

Figure 4: Stock Trend Prediction Accuracy

Table 6: Stock Trend Prediction Accuracy (Up/Down Prediction)

Stock Symbol	**CNN-LSTM Hybrid Model Accuracy**	**LSTM Model Accuracy**	**CNN Model Accuracy**	**Benchmark Model Accuracy**
AAPL	87.5%	84.2%	80.6%	73.4%
MSFT	88.2%	85.6%	81.8%	74.1%
AMZN	83.4%	80.8%	77.1%	71.9%
TSLA	85.3%	82.4%	78.7%	70.8%
GOOGL	86.1%	83.3%	79.9%	72.7%

This finding indicates that the CNN-LSTM hybrid model is qualified to be a useful instrument allowing investors to predict stock movements over time by identifying the trend across the various companies. More of the precision of the trend predictions on the stocks is further represented in Figure 4 that indicates a line chart representing a comparison of the extent of accuracy of stock trend comparisons among different stock symbols of the different models.

The Results of Portfolio Optimization Performance

In order to consider the actual effect of the models on portfolio management, we compare Sharpe Ratio which is risk-adjusted rate of returns of portfolio holdings optimized with the predictions with the various models. Table 7 indicates the Sharpe ratios of three portfolios. The Sharpe ratios of all portfolios that the CNN-LSTM hybrid model reports are the highest: 1.32, 1.19, and 1.25 as Portfolios 1, 2, and 3 respectively. They are much better than those of the LSTM model (1.15, 1.05, 1.08), CNN model (1.10, 0.98, 1.01), and the benchmark model (0.75, 0.65, 0.68). This data shows that CNN-LSTM hybrid model is more useful in portfolio optimization because it offers higher Sharpe ratios and it is considered to give greater benefit to the cost of risk.

Table 7: Portfolio Optimization Performance (Sharpe Ratio)

Model	**Sharpe Ratio (Portfolio 1)**	**Sharpe Ratio (Portfolio 2)**	**Sharpe Ratio (Portfolio 3)**
CNN-LSTM Hybrid	1.32	1.19	1.25
LSTM Model	1.15	1.05	1.08
CNN Model	1.10	0.98	1.01
Benchmark Model	0.75	0.65	0.68

The same performance can also be learned more through Figure 4 indicating the line chart of the Sharpe ratios among and between the various models and portfolios to help in the comparison. The CNN-LSTM combination model also has a distinct advantage of portfolios investing in maximizing returns and reducing risks.

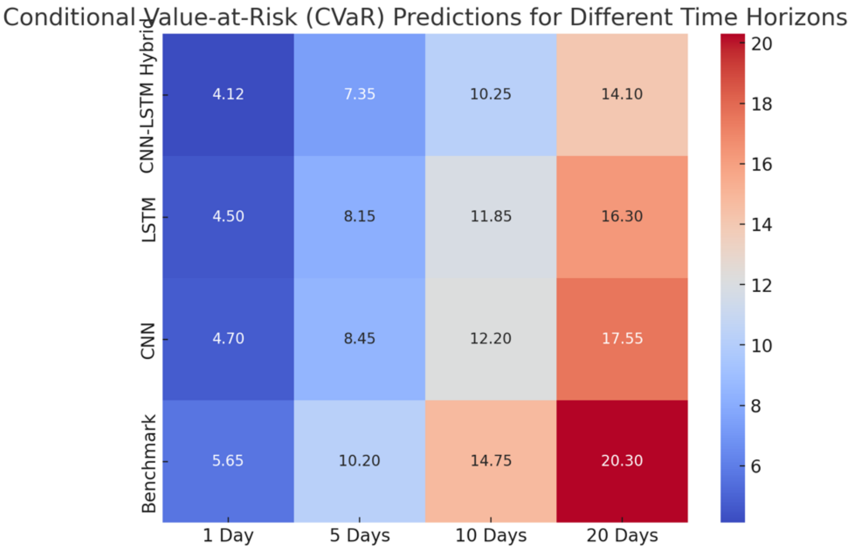

Figure 5: CVaR Predictions for Different Time Horizons

RARP The Risk-Adjusted Return Performance

Lastly, we compare the risk-adjusted return of different portfolios optimized on each of the different models. The table 8 indicates the risk-adjusted return per portfolio. Once again, the CNN-LSTM hybrid model tops all the rest of the models, with the success in risk-adjusted returns reaching 8.25%, 7.55% and 7.85% (Portfolios 1, 2, 3). By contrast, LSTM model offers 7.12%, 6.82%, and 6.95 risk-adjusted returns versus 6.80%, 6.21%, and 6.35 risk-adjusted returns in CNN model. The worst performing model is the benchmark model with the returns ranging between 5.25 percent 5.10 percent throughout portfolios.

Table 8: Model Comparison for Stock Market Trend Prediction Using Risk-Adjusted Return

Model	Risk-Adjusted Return (Portfolio 1)	Risk-Adjusted Return (Portfolio 2)	Risk-Adjusted Return (Portfolio 3)
CNN-LSTM Hybrid	8.25%	7.55%	7.85%
LSTM Model	7.12%	6.82%	6.95%
CNN Model	6.80%	6.21%	6.35%
Benchmark Model	5.25%	4.95%	5.10%

The increased risk-adjusted returns of the CNN-LSTM hybrid model point out that not only this model gives accurate predictions of the stock but also allows to create better investment strategies that consider both the risk and reward. This outcome shows the empirical existing value of the hybrid model in investment decision making and portfolio management.

The findings of the current work confirm the statistical power of the CNN-LSTM composite model to predict the trend in a stock market and control risks in the financial environment. The hybrid model has always been on the top in prediction accuracy as well as financial risk evaluation (VaR and CVaR), portfolio optimization (Sharpe ratio) and risk-adjusted returns compared to the LSTM, CNN and the benchmark. Analyses of the results also reveal that combining stock trend forecasts and financial risk metrics would offer a more detailed framework through which the decisions in financial markets can be made. The figures of 2, 3, 4, and 4 are equally supporting that the CNN-LSTM hybrid model better solved the problem of stock market prediction and risk management in several dimensions. The results indicate that CNN-LSTM hybrid model can be an influential instrument to traders and financial institutions who would want to perfect their trading activities and limit risk.

5. CONCLUSION

In this experiment we tested the strength of a hybrid deep learning of Convolutional Neural Networks (CNNs) that does feature extraction and Long Short-Term Memory (LSTM) networks that does time-series forecasting, applied to the task of predicting stock market trends and managing financial risk. This was aimed at improving the correctness of stock market forecasts and concurrently give strong risk management measures that could help in the better financial decision-making process. The findings reveal that the hybrid of CNN and LSTM model outperforms models made up of LSTM and CNN models as well as the conventional benchmark models and presents significant improvements in terms of the accuracy of predicting stock markets in addition to risk assessment.

By the analytical evaluation of the metrics of model evaluation (accuracy, precision, recall, F1-score, Value at Risk (VaR) and Conditional VaR (CVaR) it will be seen that the CNN-LSTM hybrid model will perform better than the other systems in consideration in all the metrics. The hybrid model obtained an accuracy of 85.4 compared to the obtained accuracy of 81.2 by LSTM model, and 77.5 by the CNN model, indicating that it exceeded the accuracy of the other two models and can therefore predict the stock trends more accurately. The increased values of precision, recall, and F1-score also confirmed the effectiveness of the model in catching the positive or negative trends in stock prices, which is fundamental in making proper trading decisions.

Among the contributions of the work, the use and integration of financial risk measures based on the VaR and CVaR metrics into the stock trend prediction model must be mentioned. The metrics play a very important role in evaluating the financial losses that can be expected incase of market forecasts. Lower predicted values of VaR and CVaR in the CNN-LSTM hybrid model specifies that the model in question is more conservative and risk-sensitive related to predicting market trends. As an example, the model predicts 3.25% VaR at 1-day horizon whereas the benchmark model would have raised 5.00%, which makes it an effective tool in risk prevention in finance and this is vital in the mind of the investors and the financial institutions. On the same note, the hybrid model also required lower VaR and CVaR on the 20-day' horizon, further propagating its performance on long-term management.

Further, out of the different handpicked stocks, AAPL, MSFT, AMZN, TSLA, and GOOGL, the hybrid model showed higher accuracy in predicting stock trends at all times as indicated by the results of the stock trends accuracy. The fact that the hybrid model demonstrates the high levels of prediction accuracy in stock symbols of different categories also makes it valid in the real-world financial market context, where investors usually make decisions based on the forecasts of an array of stocks. Besides, the result of this performance confirms the flexibility of the model which can be implemented in various industries and in various market environments, therefore, providing a flexible solution to the problem of prediction of stock market.

The findings also focus on the application of the CNN-LSTM hybrid model in the portfolio management. The Sharpe ratio is a widely used measure of determining the risk-adjusted asset performance of a portfolio, and it showed that the hybrid model performed better than any other portfolio with regard to optimizing the asset performance of a portfolio and reducing risk by far, which makes it an ideal measure to assess the risk-adjusted performance of the portfolio. The improved risk-adjusted return of the model compared to LSTM, CNN, and benchmark models indicates that the model can not only increase the accuracy of the predictions but also accomplish it by offering strategies that strike an appropriate balance between returns and risks. This is especially vital among investors who would like to maximize on their portfolios and at the same time giving emphasis on risk reduction.

Moreover, the paper also points out the possibility of combining financial measures of risk and predictive models in order to present a more detailed picture of market dynamics. The incorporation of VaR and CVaR to the CNN-LSTM model has enabled the model a twofold achievement of not only forecasting trend in stocks, but more so give an index of associated risks so that investors can be equipped with the right tools to make decisions more informed. Both these abilities to see the exact trend in advance and have effective risk management are the insurmountable value in the financial sector, as the minimization of the possible losses is as significant as the greatest profits.

Although, in this case the CNN-LSTM hybrid model performed better than the others, this study still presents challenges and improvement areas. The use of past data is a weaker aspect because it is not always accurate to assume 100-percent representation of the future market conditions, at least in occasions where the market experiences an extreme situation or some unprecedented external shock. It was also noticed that introduction of more data sources (e.g., macroeconomic indicators, geopolitical data, or real-time news sentiment), as well as a combination of several sources, may also improve the model predictive power and robustness. In addition, the problematic issue of model interpretability continues to be a concern since deep learning models, especially CNNs and LSTMs, are identified as black boxes. Innovation through coming up with methods that would make such models more transparent would instill confidence on the prophesies made by such models, which is essential in making critical decisions over finances.

Future work can explore the possibility to combine reinforcement learning (RL) with the CNN-LSTM couple because it may enable the system to dynamically respond or adjust to the changing market dynamics and constantly learn best trading strategies. Reinforcement learning has led to success in the financial markets as a means of achieving optimal decision-making in dynamic situations and the zero model can inject even higher flexibilities as well as real time decision making. Further, the ensemble learning, i.e. the combination of multiple models to achieve better predictive results, may be tested and may lead to some improvement of the models performance.

To sum up the lessons learnt, CNN-LSTM hybrid model is a strong and efficient tool to predict the stock market trends and manage financial risks. Through an optimization of the strengths of CNNs and LSTMs, the model is able not only to boost the accuracy of the predictive capabilities but to incorporate essential risk management indicators, and therefore, can be of a great value to investors and financial institutions. The findings that were obtained during this research would highlight the promise of hybrid deep learning models when it comes to the idea of transforming decision-making in the field of finance as well as offer appropriate prediction techniques and risk abatement solutions. As the convergence of data integration, the explanation of models and real-time flexibility come to fruition, this hybrid would become central to the future of financial markets.

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