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A Novel Approach of Stock Price Forecast Using Deep Learning Practices

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Abstract: The intricate dynamics of stock market data present an ongoing challenge for accurate forecasting, underscoring the need for advanced predictive models. This research paper explores the application of deep learning techniques, specifically focusing on LSTM, to enhance the prediction of complex stock market movements. By delving into historical data, this study aims to develop a robust predictive model capable of capturing intricate patterns and trends, thus providing valuable insights for investors, traders, and financial analysts. Recognizing the critical role of accurate predictions in financial decision-making, the research emphasizes the potential impact of leveraging deep learning in the stock market domain. The study underscores the importance of staying ahead in an ever-changing market landscape, where the ability to anticipate market movements is crucial. To address this, the research adopts the LSTM technique, a specialized recurrent neural network architecture known for its efficacy in handling sequential data and capturing long-term dependencies. This approach is expected to contribute significantly to advancing the precision and efficiency of stock market predictions, empowering stakeholders with valuable tools for navigating the complexities of financial markets.

Keywords: *Stock Market Prediction, Deep Learning Techniques, LSTM, Financial Decision-Making*

1. Introduction

The world of finance is a complex and dynamic ecosystem where numerous factors influence the ebbs and flows of the stock market. Investors, traders, and financial analysts continually seek effective tools and methodologies to navigate this intricate landscape and make informed decisions. In recent years, the application of deep learning techniques has emerged as a promising avenue for enhancing the prediction of stock market data. Stock market prediction has long been a pursuit that amalgamates historical data, statistical models, and, more recently, advanced machine learning algorithms. The volatility and unpredictability inherent in financial markets pose challenges for traditional forecasting methods. Recognizing the limitations of conventional approaches, the research community has increasingly turned to unlock new dimensions in predictive modeling. The significance of accurate stock market predictions cannot be overstated. Investors and financial professionals rely on timely and precise forecasts to allocate resources, manage risks, and optimize returns. The rapid evolution of technology and the availability of vast amounts of financial data have paved the way for innovative approaches that leverage artificial intelligence to discern intricate patterns and trends. As financial markets become more interconnected and information-intensive, the demand for sophisticated predictive models intensifies.

In the pursuit of unraveling the complexities of stock market dynamics, this research focuses on the development of a predictive model grounded in deep learning principles. The study aims to harness the power of neural networks to decipher patterns within historical stock market data, facilitating the anticipation of future market movements. By employing advanced machine learning techniques, the research endeavors to provide stakeholders with a tool that goes beyond traditional forecasting methods, offering a nuanced understanding of the ever-changing financial landscape. Modern stock markets have their roots in 1602 when the Dutch East India Company began trading in Amsterdam. It wasn't until 1607 that the first offshoots were exchanged; profit distribution among shareholders occurred years later. Initially, the buying and selling was limited to this one corporation. One location where shares can be traded, sold, and dispersed is a stock market.

Large companies are able to raise their assets from shareholders through this network. However, a flood of capital enters the stock market following stock issuance,

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which boosts the composition of business assets through increased investment vigilance and, in turn, aids the expansion of the product economy. Whereas, by facilitating the transfer of stocks, money is distributed and investment development is effectively encouraged. Consequently, the stock market is widely considered a barometer of a nation's or region's economic and financial health. In particular, the stock market's purchasing and selling prices can show a relationship between supply and demand, which makes them a good indicator of stock value and quantity. Diverse factors, such as the economy, politics, and the market, as well as technological developments and investor mood, will combine to cause index values to fluctuate. As a result, stock values are constantly fluctuating, which increases the uncertainty around the indexes and provides room for potential interactions. Anxieties like these not only drain funds from shareholders' pockets, but they may also impede states' and enterprises' ability to grow financially. When it comes to stakeholder selections, including state financial stability, it is very critical to examine and predict indices in the right approach. If we can accurately predict the stock market's challenges, it will provide a strong basis for a country's financial industry to flourish. Investment returns for shareholders, as a result of methodological analysis and forecasting of the stock market, might contribute to the expansion of national financial resources. The inherent structure of unpredictability in indexes makes their forecasting a difficult issue in the realm of financial time series. In light of the worrying scenario, study in financial economics is crucial if investors are to maximize their profits, as shown in several corresponding research publications. While the details of LSTM will be elaborated upon later in the paper, its inclusion is significant in the context of handling sequential data and capturing long-term dependencies – attributes crucial for modeling the intricacies of stock market trends. As we delve into the intricacies of stock market prediction using deep learning, it is imperative to recognize the broader context within which this research unfolds. The fusion of finance and artificial intelligence represents a paradigm shift in how we approach complex problem-solving within the financial domain. By pushing the boundaries of traditional methods, this research aspires to contribute to a growing body of knowledge that seeks to empower market participants with cutting-edge tools for navigating the challenges and opportunities presented by the dynamic world of stock markets.

2. Literature Survey

1. In this [1] the authors demonstrated the effectiveness of their approach in handling the uncertainty inherent in stock price prediction. Through extensive experimentation, the model showcased robust performance, providing accurate predictions within specified intervals. The proposed method incorporates dual convolutional neural networks, contributing to improved feature extraction and pattern recognition in the context of interval-valued data. The results highlight the potential applicability of this approach in financial forecasting, offering a valuable tool for investors and analysts seeking more reliable predictions in the dynamic stock market environment.

2. In this [2] through empirical evaluation, the authors demonstrated the superior performance of their model in forecasting cryptocurrency trends at high frequencies. The attention mechanism played a crucial role in enabling the model to focus on key features, thereby improving its predictive accuracy. The findings suggest that the Attention-based CNN–LSTM model presents a promising solution for effectively analyzing and forecasting trends in the dynamic and volatile cryptocurrency market.

3. In this [3] the proposed TRNN model demonstrates notable efficiency in handling time-series data, showcasing its effectiveness in forecasting stock prices. Through comprehensive experimentation, the authors illustrated the model's capability to capture temporal dependencies within stock price movements, contributing to improved prediction accuracy. The efficiency gains of TRNN make it a promising tool for financial analysts and investors seeking reliable forecasts in the stock market. The study underscores the significance of tailored recurrent neural network architectures, such as TRNN, in addressing the complexities of time-series data inherent in stock price prediction.

4. In this [4] through the integration of multi-head self-attention mechanisms, the model effectively captures complex dependencies and relationships within the electricity price time series data. The CNN-based techniques contribute to feature extraction, enabling the model to discern relevant patterns in the data. The experimental results demonstrate the efficacy of the proposed framework, showcasing its ability to provide reliable and competitive electricity price forecasts. This research presents a valuable contribution to the field of electricity market forecasting, offering a robust methodology that combines self-attention and CNN approaches for improved prediction accuracy.

5. In this [5] the authors assessed the evolving landscape of demand and supply for NEV charging infrastructure in China. The CNN-LSTM prediction model demonstrated its utility in anticipating the future needs of this critical component of the new energy vehicle ecosystem. The findings provide valuable insights for policymakers and stakeholders involved in planning and developing sustainable charging infrastructure for the growing Chinese NEV market.

6. In this [6] the deep learning model processes the input data to generate initial predictions. Subsequently, the error compensation technique is applied in the second step to refine the predictions and mitigate potential inaccuracies. Through comprehensive evaluations, the authors demonstrated the effectiveness of their two-step framework in providing more reliable and precise. This

research contributes to the ongoing efforts to improve the efficiency of electricity price forecasting methods, especially in the context of short-term predictions crucial for energy market participants and decision-makers.

7. In this [7] the model integrates various deep learning techniques to enhance the accuracy of wave height predictions. Through the hybridization of these methods, the model demonstrated improved capabilities in capturing the complex patterns and dynamics of wave heights in the designated region. The utilization of deep learning in wave height prediction contributes to more effective assessments for potential wave energy generation. The results highlight the suitability of the hybrid deep learning approach for addressing the challenges associated with wave height prediction.

8. In this research, a Unified CNN-LSTM model was proposed by the authors for predicting keyhole status in Peripheral Arterial Waveform (PAW) based on spatial-temporal features providing a unified framework to effectively capture spatial and temporal characteristics in PAW data. Through comprehensive experimentation, the authors demonstrated the model's capability to predict keyhole status accurately, leveraging the synergies of CNN and LSTM architectures. The spatial-temporal features extracted by the unified model contribute to improved understanding and prediction of keyhole events in PAW, offering valuable insights for medical practitioners and researchers in the field of cardiovascular health monitoring. This research underscores the significance of combining spatial and temporal information for enhanced predictive accuracy in medical applications.

9. In this [9] the author created a synergistic framework to capture complex temporal dependencies and spatial features in the oil production data. Through extensive experimentation, the authors demonstrated the efficacy of their approach in providing accurate forecasts for Enhanced Oil Recovery systems. The CNN-GRU neural network's ability to effectively analyze both temporal and spatial aspects of the data contributes to improved prediction accuracy. The findings of this research offer valuable insights for the oil and gas industry, providing a promising methodology for enhancing forecasting capabilities in the context of Enhanced Oil Recovery.

10. In this [10] the model showcased improved predictive capabilities by effectively combining the feature extraction prowess of CNNs and the ability of bi-directional LSTMs to capture temporal dependencies in the stock market data. Through empirical evaluation, the authors demonstrated the efficacy of their approach in providing more accurate predictions of stock market indices. The integration of CNNs and bi-directional LSTMs presents a promising solution for investors and financial analysts seeking improved forecasting models in the dynamic and complex stock market environment.

11. In this [11] the authors demonstrated the model's effectiveness in predicting price movements deep learning framework contributes to a more comprehensive understanding of complex patterns in financial time series data. This approach represents a valuable contribution to the field of financial forecasting, offering a sophisticated model for investors and analysts to enhance their ability to predict price movements in various markets.

12. In this [12] the model combines the strengths of both recurrent and convolutional architectures, enabling it to capture temporal dependencies and extract relevant features from financial data. Through their research, the authors demonstrated the efficacy of the RCNN in predicting financial prices. The integrated approach allows the model to discern complex patterns in stock market data, enhancing its predictive capabilities providing insights into the potential of RCNNs for improving predictions of financial prices in stock markets.

13. In this [13] the research focused on leveraging the combined capabilities of CNNs and LSTMs to enhance the robustness of analyzing stock price time series data. Through their work, the authors demonstrated the effectiveness of their deep learning models in providing robust insights into stock price dynamics. The integration of CNNs and LSTMs allows the model to capture both spatial and temporal dependencies in the time series data, contributing to a more comprehensive analysis. This research contributes to the exploration of advanced deep learning techniques for improving the robustness of stock price time series analysis, offering valuable implications for investors and financial analysts.

14. In this study [14] the authors demonstrated the effectiveness of this approach in capturing the inherent frequency characteristics of stock price movements. The model showcased its capability to provide accurate forecasts by considering the decomposed frequency components. This methodology offers a novel perspective on stock price forecasting, emphasizing the importance of frequency analysis in predicting market dynamics. The research contributes to the field by introducing a unique combination of EMD and neural networks for improved forecasting accuracy in stock price prediction.

15. In this December 2017 study, the authors proposed a method for predicting stock prices using financial news, employing Recurrent Convolutional Neural Networks (RCNN). The research focused on integrating both recurrent and convolutional architectures to effectively analyze textual information from financial news and make stock price predictions. Through their work, the authors demonstrated the capability of RCNNs to capture temporal dependencies in news data and extract relevant features, contributing to improved stock price predictions leveraging the information embedded in financial news to enhance forecasting accuracy. The study provides insights into the potential of RCNNs for modeling the complex relationships between textual information and stock price

movements, offering a valuable contribution to the intersection of artificial intelligence and financial analysis.

3. Technical Issues

These are the three main technical challenges encountered when attempting to predict stock prices.

- There are a number of things that might affect stock values. Many things, including government policy, the state of the economy, and new innovations in certain industries, can affect the stock market, making it a complicated and unpredictable system. It is rather difficult to anticipate stock prices with any degree of accuracy when information is both incomplete and asymmetric.
- As a result, stock prices are not static. Because of the impact of many factors and their individual causes, stock prices exhibit non-stationary and non-linear features as time-series data. Consequently, it is imperative that the forecasting model excels in dealing with non-linear issues.
- The stock market is a place of pure chance. Emotional swings caused by forum discourse influence investors, who in turn affect their decision-making and, frequently, stock price movements. Stock price forecast accuracy is affected by data noise.

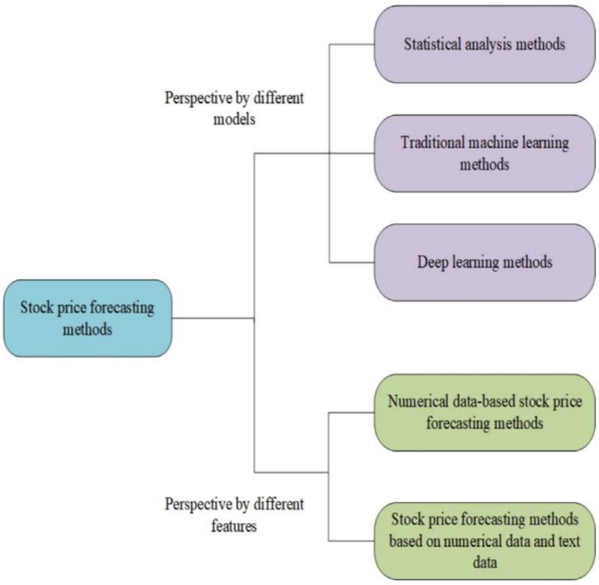

Fig 1: Forecasting stock prices using multiple models and features.

Platform for stock price forecasting

Because of the maturation of financial stock markets and the growth of research on stock price forecasting, academics have produced a multitude of platforms and tools for stock price forecasting. These platforms and tools have been developed in response to the aforementioned factors. A selection of the published systems that forecast stock prices are presented in Table 1 which may be found here.

Table 1: Dataset resources of stock price forecasting.

Data set introduction	Data Selection Period	Data source
SSE Composite Index	December 29, 1990 - May 18, 2018	wind database
Jakarta composite Index Daily Closing Price Data	January 2014 to December 2014	Yahoo Finance
NIKKEI225 P/E Ratio	February 22, 1985 to December 30, 2008	Undisclosed
AAPL Stock Price Data	May 2008 to May 2018	national association of securities dealers automated quotations
Trading data for 100 stocks on the NDAQ exchange	December 31, 2014 to December 31, 2019	Application Programming Interface (API service of Yahoo
total Maroc historical data	February 8, 2018 to May 17, 2018	the website of Casablanca stock exchang
Trading data, technical indicators and valuation indicators of CSI 300 Index	January 5, 2015 to December 31, 2019	Guotaian database and wind database
Closing price data and related messages for XOM, DELL, EBAY, IBM, KO	July 23, 2012 to July 19, 2013	Yahoo Finance, Yahoo finance message board
S&P data and publicly available financial news	October 2006 to November 2013	reuters and bloomberg
Alibaba Stock Data and Related News Information	September 19, 2014 to March 24, 2017	Thomson reuters databasegooseeker software
weakly data of DSE stock	January 1, 2016 to July 31, 2018	Dhaka stock exchange data archive
HSIAXnd S&P 500 Index Data	August 23, 1991 to August 23, 2017	Yahoo Finance
A number of indicators for Auto-desk (002227)	102 trading days in 2015	communication stock trading software
Shanghai Stock Exchange SSE Composite Index	November 30, 2009 to April 29, 2010	Undisclosed
BSE-30 and Nifty-100 weekly data	April 2011 to December 2016	Yahoo Finance

Technical requirements

The statistical foundation of technical indicators is the analytical approach that is based on stock trading data—this is the foundation of technical indicators. There are a number of variables that are included in the trading data. These variables include stock volatility, closing price, and turnover rate. By examining the pattern of price changes in the market, the primary objective of technical indicators is to provide traders with assistance in determining the most significant trends and the optimal periods to buy and sell stocks.

Table 2: Common technical indicators of stock price forecasting

Indicator Name	Type	Usage
MACD	Trend type	When MACD turns from negative to positive, buy; when MACD turns from positive to negative, sell.
EMV	Trend type	Buy when EMV crosses the 0 axis from bottom to top; sell when EMV crosses the 0 axis from top to bottom.
DMI	Trend type	Buy when +DI crosses up -DI; sell when +DI crosses down -DI.
KDJ	Overbought and oversold type	Buy when the KDJ forms a golden cross; sell when the KDJ forms a dead cross.
RSI	Overbought and oversold type	If the RSI breaks above the previous high platform, buy to rise; if the RSI falls below the previous low line, sell.
ROC	Overbought and oversold type	Buy when ROC breaks the centerline upwards; sell when ROC breaks the centerline downwards.
VR	Energy type	Buy when VR takes the value in the low price area; sell when VR takes the value in the alert area.
OBV	Volume type	Buy when the OBV line rises slowly; sell when the OBV line rises sharply.
BOLL	Path type	Sell when the price crosses the upper pressure line; buy when the price crosses the lower support line.

4. Methodology

An exceptional RNN version, LSTM an address the gradient explosion issue in long-term sequence prediction. These days, time-series prediction is where it's at. With an emphasis on credit indicators, this article details the process of projecting the finance companies. Next, in order to make use of the LSTM model for prediction, it executes risk prediction.

Furthermore, we incorporate CNN to enhance the LSTM model's training time and speed while decreasing the number of parameters. Prior to the data being fed into the LSTM model, the CNN is utilized for feature extraction. We then filter out indicators that are less relevant to the company's credit-risk prediction, simplify the data, create a CNN-LSTM model that combines the best features of both models, and lastly, we implement an attention mechanism. After being integrated into a CNN-LSTM-AM model, the attention mechanism may train autonomously, choose to enhance the CNN-LSTM model's prediction accuracy.

Various companies are done using a CNN-LSTM-AM model in this research. You can see the model's framework in Figure 1. Among CNN's many capabilities is the ability to extract local key features for use in feature processing. When it comes to long-sequence prediction, LSTM clearly outperforms RNN since it can leverage historical data to handle sequence difficulties. Thus, by merging CNN and LSTM, a new CNN-LSTM model is created. The attention mechanism is further integrated into the model to enhance its accuracy and efficiency.

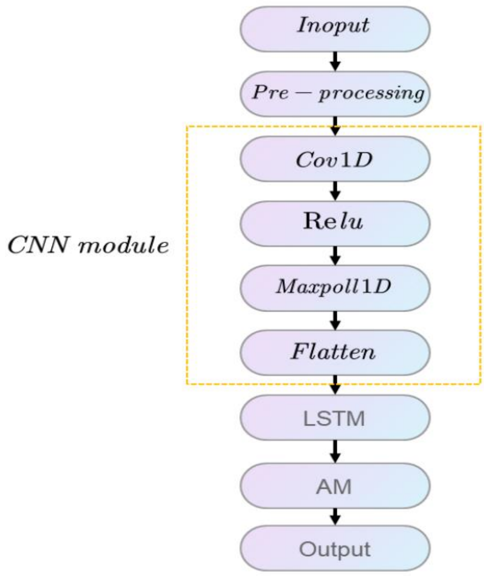

Fig 1. CNN-LSTM model.

CNN Model

One type of deep neural network that incorporates convolutional processing is the convolutional neural network, sometimes known as a CNN. Because of its one-of-a-kind architecture, it can lessen the likelihood of overfitting and free up more memory for the deep network—which finds similarities between input data and newly-created features in order to extract those features. Three basic components make up a convolutional neural network (CNN): convolutions, pooling, and full connections (FC). Feature extraction is carried out via convolutions and pooling, while classification recognition is done by FNN. Pictured in Figure 3 is the building.

For convolutional computation, various weights are applied. Typically, a more comprehensive feature extraction may be achieved by developing several convolutional kernels. Next, the pooling operation is employed for down sampling, which helps to decrease the model's complexity and parameters while also reducing computation. Thanks to its one-of-a-kind architecture, convolutional neural networks (CNNs) simplify and optimize data processing while simultaneously reducing computing effort.

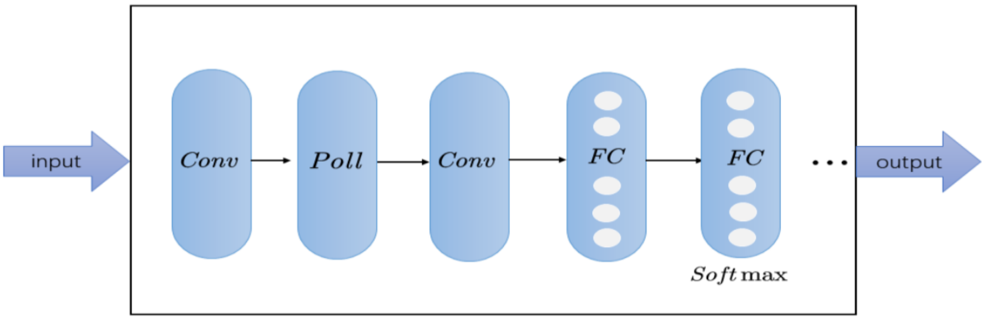

Fig 3. One-dimensional CNN

AM Model

AutoML (Automated Machine Learning) models have emerged as powerful tools in the field of predictive analytics, and one noteworthy example is the AutoML model (AM model). Leveraging advanced algorithms and optimization techniques, AM models exhibit impressive prediction capabilities. The key strength lies in their ability to efficiently navigate the complex landscape of model configurations, saving time and resources for data scientists and practitioners. AM models are designed to adapt to diverse datasets and problem domains, making them versatile solutions for a wide range of prediction tasks. Their automated approach enables users with varying levels of expertise to harness the power of machine learning without the need for extensive manual intervention. As a result, AM models have become instrumental in democratizing access to advanced predictive analytics, offering scalable and efficient solutions for organizations across different industries.

LSTM Model

The LSTM network is another name for the extended RNN. Information may flow freely in both directions because to the RNN's hidden layer. In this model, the input to the RNN is the state of the node before it, and the output is a reaction to both the input layer and the state of each hidden unit. Its performance in the inquiry is significantly less efficient than anticipated for the two reasons given below. Initially, RNNs may struggle to find the optimal might result in inadequate retrieval of the variational features of the data. The second issue is that when RNNs use gradient descent to process historical data, the gradient could show either an increasing expansion or a decreasing drop, a phenomenon known as gradient explosion. This strategy is motivated by the fact that RNNs retain a lot of unnecessary information due to their wide link topology, which does not filter. Therefore, when dealing with long-term data, the standard RNN is not the best option. Optimizing the RNN is achieved by substituting the RNN's hidden layer nodes with LSTM's expressive "gate" structure, which uses filtering and conversion of prior states and information, and unique memory cells (blocks). To ensure that the internal cell values don't grow infinitely, the forget gate contributes by deciding how much data from the prior cell state should be retained and how much should be discarded. Because of its design, the output gate may filter the updated state before sending just the filtered data out. The LSTM network's method is described by the following steps.

An expanded model founded on RNN is LSTM Traditional RNN models still have problems with long-distance dependency, including gradient disappearance and gradient explosion. Both gates are interdependent.

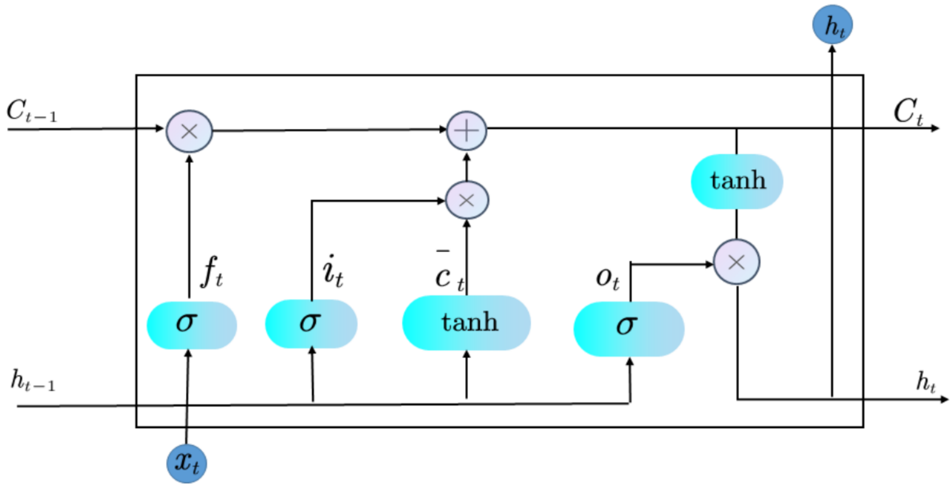

Fig 4: A schematic showing how an LSTM operates

In Figure 4, the following symbols are used: ft for forgetting, it for input, ot for output, Xt for current input, Ct−1, ht−1 for prior output and cell state, and Ct,t for current output and cell status. A novel gate system controls the input/output gates, forgetting gates, and cell states in the LSTM. To manage the memory units' long-term dependencies, the unit state is utilised.

5. Experimentation & Analysis

We compared the speed of the CNN-LSTM-AM model to that of the classic Logistic and KMV models after running the findings through the dataset. After that, we attain the processing speed for complicated scenarios. Here, we're comparing two models: Tree and SVM. Subsequently, our model is used to compute the accuracy level and compare it to other models using the same findings. Additionally, we compare the CNN-LSTM-AM model and we assess its accuracy on several datasets.s

In order to assess the predictive capacity of our models in a more visual way, we also analysed the computing effort of the different models, made images, and then found the other models' accuracy and error charts. Lastly, we investigate several models' area under the curve (AUC). In addition, we assess our models' strengths and limitations by testing their prediction power in other data sets.

Specifically, data loading consumes the bulk of overhead when the number of inference cases is low, whereas inference consumes the bulk of overhead when the number of inference instances is high. The other models clearly have a major impact on the CNN-LSTMAM model's inference speed. On the other hand, it appears that the equipment becomes hotter and the time cost goes higher when the number of inference instances goes greater.

Due to this, our model outperforms the more conventional logistic and KMV models in terms of cost-effectiveness.

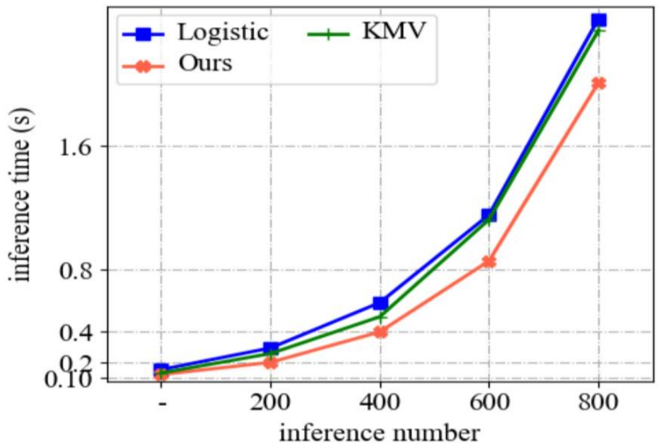

Fig 5: Different reasoning quantities are considered by the three theories.

Figure 6 shows the results of a speed comparison between the various models that were evaluated in difficult instances. Dealing with challenging case scenarios is of utmost importance in finance, and these facts are vital for corporate credit evaluation. The graphic clearly shows that our technique outperforms the new neural network model when dealing with difficult scenarios; this model is a crucial source of inspiration for future credit rating algorithms.

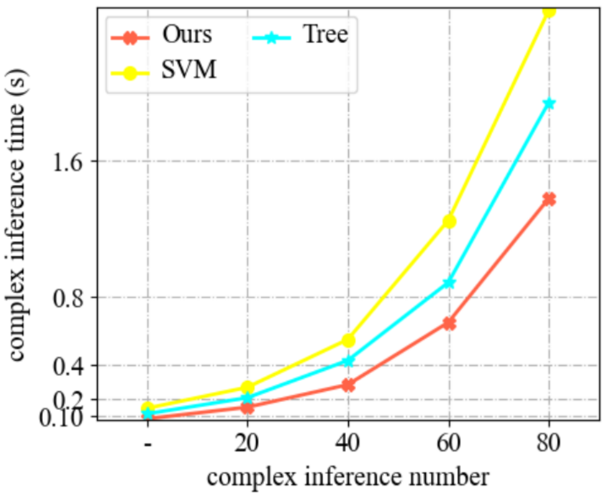

Fig 6: A graph showing how three alternative models handle complicated and distinct inference quantities in terms of how quickly they draw conclusions.

6. Results

By utilising the attention mechanism model, we are able to conduct deep learning and independently determine the weight ratio, thereby enhancing the efficiency of machine learning. This makes the LSTM operation process more user-friendly, and operations improve efficiency by targeting more critical influencing factors.

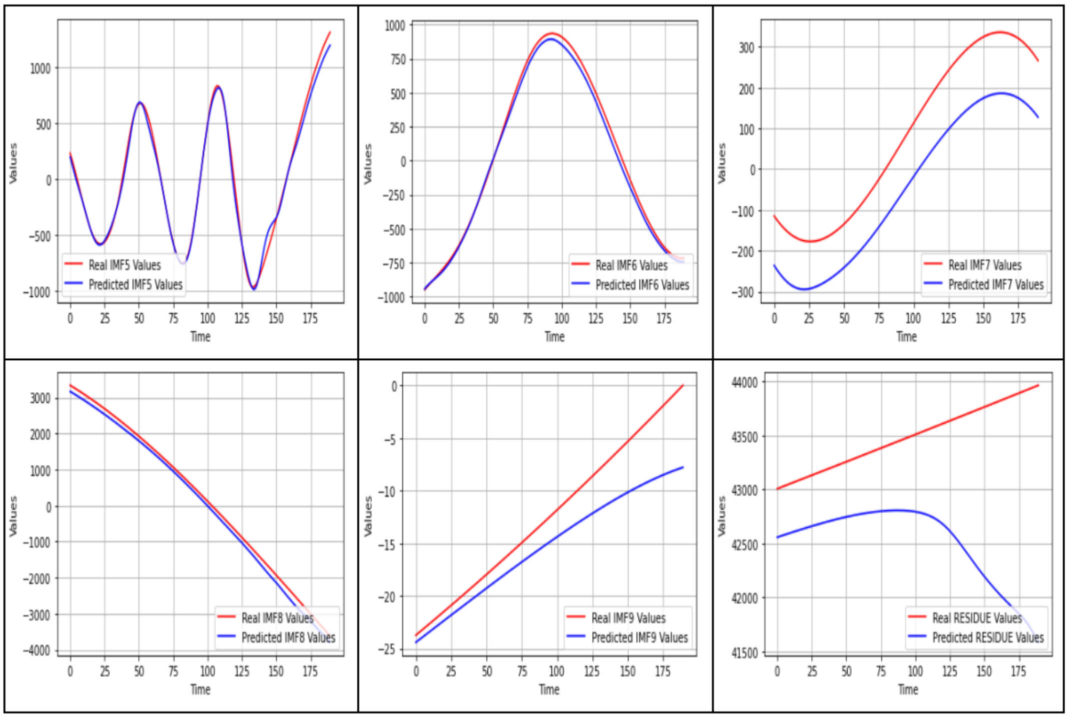

Fig 7: Expected outcomes of interdependent components

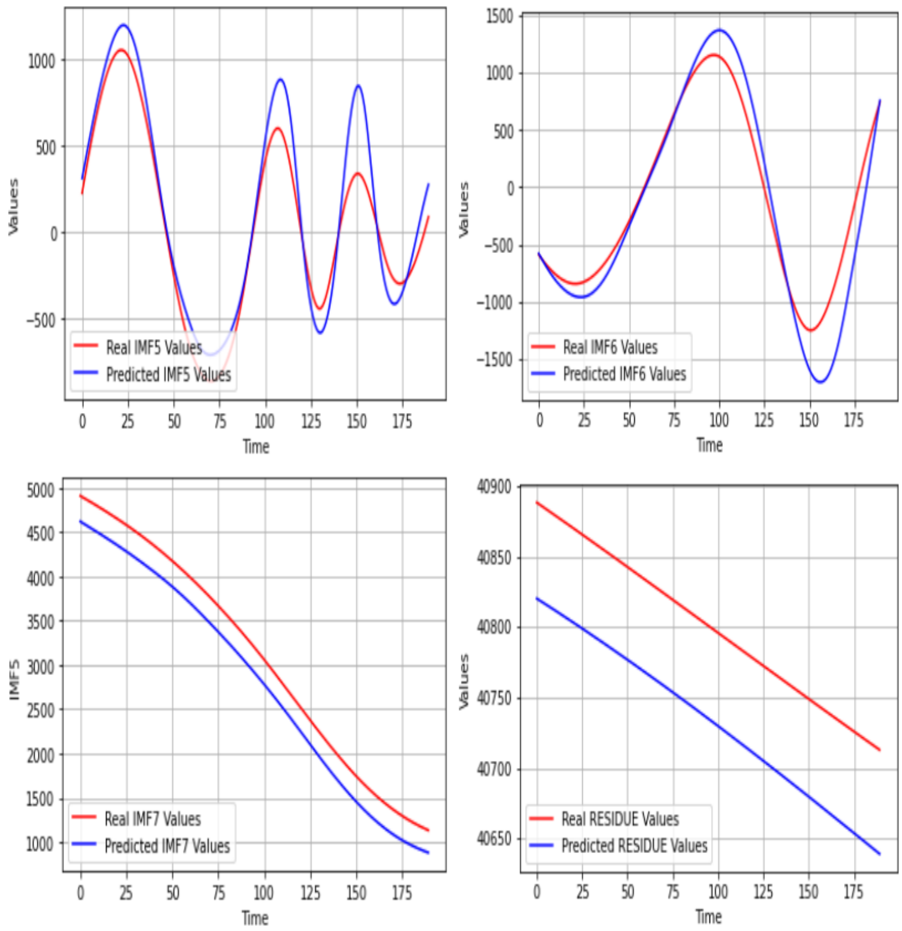

Fig 8: The LSTM model's predicted outcomes for associated subcomponents

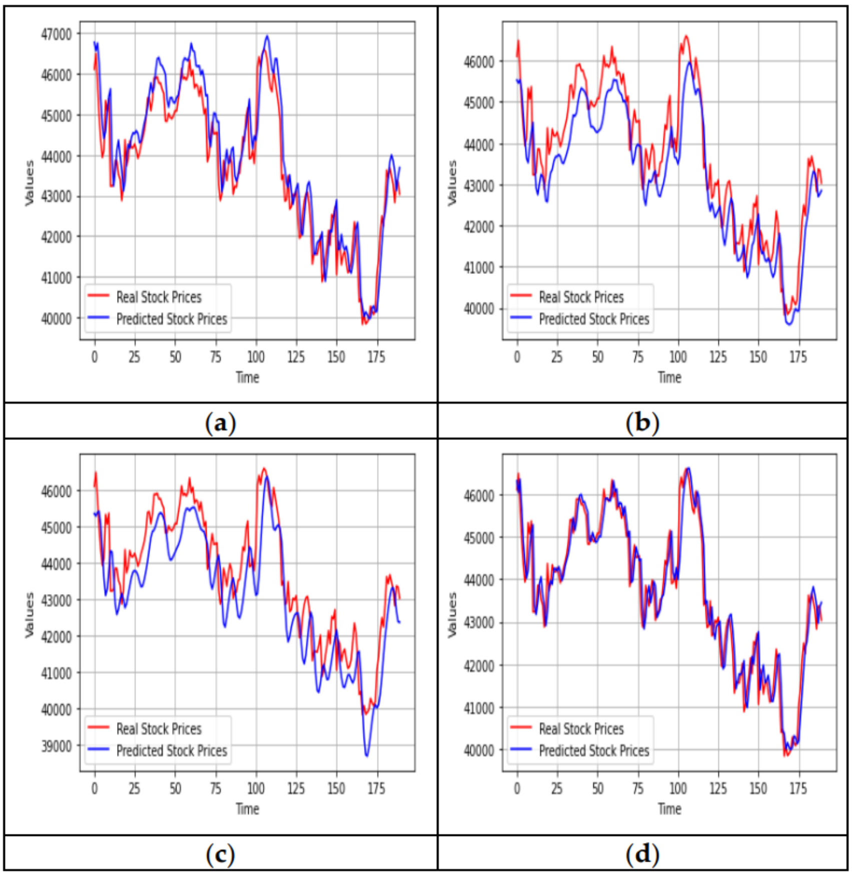

Fig 9: Prediction Results by comparison of different models

Figures 7–9 show the sub-series prediction results for the closing stock price of the KSE-100 index. Due to the large amplitude and frequency of the low correlated IMFs, the forecast accuracy with the actual stock price is rather low components, whereas the projected value is near to the actual value for the highly correlated IMFs, which include the one monotone residue that stands for the long-term trend of the index data. If the suggested updated EMD can eliminate the overshoot and undershoot issues, as well as the wiggle room at both ends when compared to the benchmark EMD, then the forecast accuracy will be much improved. See Figure 8 for a visual representation of the KSE-100 index's actual prediction results; this model outperformed both the conventional classical time series and non-hybrid machine learning approaches in terms of both accuracy and the pattern of stock price movements.

7. Conclusion

In conclusion, the integration of deep learning techniques, particularly the utilization of Long Short-Term Memory (LSTM), presents a promising avenue for enhancing the prediction of complex stock market data. The financial landscape's ever-evolving nature demands advanced tools capable of navigating intricate patterns and providing accurate forecasts. This research has underscored the significance of adopting deep learning methodologies to address the limitations of traditional stock market analysis. By exploring the intersection of deep learning and financial markets, this study has aimed to contribute to the growing body of knowledge surrounding predictive modeling. The incorporation of LSTM into the research framework reflects a strategic choice to leverage its ability to capture long-term dependencies, offering a nuanced understanding of sequential data inherent in stock market trends. This approach addresses the challenges associated with traditional methods, unlocking the potential for more accurate and timely predictions. The implications of this research extend beyond academia, with potential benefits for investors, traders, and financial analysts seeking reliable tools for decision-making in an increasingly complex market environment. As the field of deep learning continues to evolve, the findings of this study contribute valuable insights into the practical applications of LSTM and its role in advancing the accuracy and efficiency of stock market predictions. In the future, further exploration and refinement of deep learning techniques, including the ongoing development of LSTM models, will likely yield even more sophisticated predictive tools. The pursuit of these advancements remains crucial in empowering stakeholders to navigate the intricacies of financial markets, fostering a landscape where informed decision-making becomes not only attainable but also a key driver of success.

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