Journal of Theoretical and Applied Information Technology
15th March 2024. Vol.102. No 5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

BIDIRECTIONAL CNN-LSTM ARCHITECTURE TO PREDICT CNXIT STOCK PRICES

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ABSTRACT

Stock price prediction has long been a central concern for investors and financial analysts. This research paper explores applying a Bidirectional Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) architecture to predict stock prices, specifically focusing on the CNXIT (Nifty IT) stock index. The study investigates the potential of deep learning techniques to capture complex temporal dependencies and spatial patterns in historical stock price data. The research begins with a comprehensive review of existing literature on stock price prediction and the utilization of deep learning methodologies. It introduces the Bidirectional CNN-LSTM model and details the data preprocessing steps, model architecture, and training process. The dataset, comprising historical CNXIT stock prices, is meticulously cleaned and prepared to ensure the model's accuracy. Experimental results and findings demonstrate the model's predictive performance, including metrics such as mean squared error (MSE), mean absolute error (MAE), and explained variance. Visualizations of the model's predictions alongside actual CNXIT stock prices offer valuable insights into its ability to anticipate market trends. The paper concludes by discussing the implications of the Bidirectional CNN-LSTM architecture in stock price prediction and its potential to enhance decision-making in financial markets. Future research directions and areas for model improvement are also explored. This research contributes to the evolving landscape of financial forecasting by showcasing the efficacy of Bidirectional CNN-LSTM in predicting stock prices within the context of the CNXIT index..

Keywords: *CNN, LSTM, MSE, CNXIT, Prediction, Deep learning*

1- INTRODUCTION

The financial markets have long been a focal point of global economic activity, with the stock market serving as a critical barometer of a nation's economic health and a prime arena for investment and wealth generation. Accurate and timely stock price predictions are paramount to investors, traders, and financial institutions. However, the inherent complexity and volatility of stock markets, coupled with the interplay of numerous influencing factors, pose significant challenges to forecasting stock prices (Ashtiani & Raahemi, 2023; Y. Zhang et al., 2023).

In recent years, the convergence of advanced deep learning techniques, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), has offered a promising avenue for tackling the intricacies of stock price prediction. This paper explores a novel approach – integrating

Bidirectional CNN-LSTM architecture – to construct a dynamic predictive model tailored to the Indian stock market (Ashrafzadeh et al., 2023; Joseph et al., 2022; Kim et al., 2023). As one of the world's fastest-growing economies, India presents a unique and dynamic environment for financial forecasting. The Indian stock market, represented by indices like the BSE Sensex and Nifty 50, exhibits distinctive patterns influenced by many factors, including macroeconomic indicators, geopolitical events, government policies, and investor sentiment. Accurate predictions in this context demand models capable of capturing both short-term fluctuations and long-term trends (Jiang, 2021; Lin et al., 2022; Wu et al., 2023; Yang et al., 2023; Q. Zhang et al., 2022).

The unpredictability and complexity of financial markets have perpetually fascinated researchers and practitioners alike. Among the myriad challenges facing investors and analysts, the ability to forecast stock prices accurately remains a paramount concern. Accurate stock price predictions enable informed investment decisions and facilitate risk mitigation and portfolio optimization. In this context, the convergence of machine learning and deep learning techniques has ushered in a new era of financial forecasting, promising enhanced predictive capabilities (Chaudhari & Thakkar, 2023; Kamara et al., 2022).

The present research explores the application of a Bidirectional Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) architecture for predicting stock prices, with a particular emphasis on the CNXIT (Nifty IT) stock index. The CNXIT index, encompassing leading IT companies in India, represents a dynamic and pivotal stock market segment. Its inherently volatile nature presents both challenges and opportunities for predictive modeling. This study seeks to bridge the gap between traditional time-series analysis and cutting-edge deep learning methodologies. By leveraging the Bidirectional CNN-LSTM architecture, which combines the spatial pattern recognition capabilities of CNNs with the sequential memory retention of LSTMs, the study aim to harness the intricate interplay of temporal and spatial dependencies within historical stock price data. This innovative approach promises to enhance prediction accuracy and better understand the underlying market dynamics (Dave et al., 2021).

The objectives of this study are manifold. Firstly, endeavors to elucidate the architecture and methodology behind the Bidirectional CNN-LSTM model, shedding light on its capacity to capture complex patterns within financial time series data. Secondly, the study meticulously preprocesss historical CNXIT stock price data, ensuring its compatibility with the model and the integrity of the predictions. Subsequently, through rigorous experimentation, the study evaluate the model's predictive performance, utilizing metrics such as mean squared error (MSE), mean absolute error (MAE), and explained variance.

The significance of this research extends beyond the realm of stock price prediction. It underscores the potential of advanced deep learning architectures to unravel intricate financial data, empowering investors and analysts to make more informed decisions in an ever-evolving market landscape.

Moreover, by visualizing the model's predictions alongside actual CNXIT stock prices, the study aim to provide practitioners with a comprehensive toolkit for decision support and risk management.

This paper embarks on a compelling journey into financial forecasting, specifically focusing on the CNXIT stock index. By harnessing the capabilities of Bidirectional CNN-LSTM, the study endeavor to unveil the hidden dynamics of stock price movements, enriching the field of financial analysis and decision-making. Present a comprehensive overview of the Indian stock market, highlighting its unique characteristics and challenges for predictive modeling. Introduce the architecture and components of the Bidirectional CNN-LSTM model and explain why it is well-suited for stock price prediction. Describe the data preprocessing steps, feature engineering techniques, and model hyperparameter tuning used in the experimental setup. Discuss the empirical results obtained through extensive experimentation on historical Indian stock market data, evaluating the model's performance using standard evaluation metrics. Provide insights into the practical applications of the proposed model, including its potential use by investors, traders, and financial analysts. The fusion of Bidirectional CNN-LSTM architecture offers a promising avenue for dynamic stock price prediction in the Indian market, potentially revolutionizing decision-making processes within the financial industry. This research contributes to the growing knowledge in this domain and paves the way for more sophisticated and accurate predictive models in economic forecasting.

The motivation behind this study lies in the intricate and dynamic nature of financial markets, where accurate stock price predictions are invaluable for informed decision-making. Specifically focusing on the CNXIT stock index, this research aims to leverage advanced Bidirectional CNN-LSTM techniques to enhance prediction accuracy. The CNXIT index's significance within the IT sector and broader market trends makes it an ideal subject for investigation. Furthermore, the study seeks to explore the practical applications of deep learning in finance, providing actionable insights for investors and market analysts. Ultimately, the research sets the stage for further advancements in financial forecasting, offering valuable tools for navigating complex market landscapes.

The need for this study arises from the critical demand for accurate stock price predictions in the financial sector. In an era characterized by volatile markets and technological advancements, investors and financial analysts require robust tools to make informed decisions and manage risks effectively. Focusing on the CNXIT stock index provides a lens into the dynamic IT sector's trends, offering insights beyond individual stock predictions. Leveraging

Bidirectional CNN-LSTM architecture addresses the need for innovative approaches to financial forecasting, potentially enhancing predictive capabilities and decision support. This study responds to the pressing need for advanced methodologies in stock price prediction, aligning with the evolving landscape of financial markets.

2. LITERATURE SURVEY

The stock market is a financial marketplace for trading shares of publicly listed companies. It reflects a country's economic health and is driven by supply and demand. Investing in stocks can be risky but offers potential long-term returns. Artificial intelligence, like Long Short-Term Memory (LSTM) neural networks, is increasingly used for stock market prediction. Metaheuristic algorithms like Artificial Rabbits Optimization (ARO) can optimize LSTM models. This paper introduces LSTM-ARO, an optimized deep LSTM network, for stock price prediction using DJIA index stocks. It outperforms other models based on evaluation criteria such as MSE, MAE, MAPE, and R2 (Gülmez, 2023)

The (Koo & Kim, 2024)study introduces a novel data filtering mechanism called Centralized Clusters Distribution (CCD) to enhance Bitcoin price prediction. CCD effectively addresses the inherent extreme bimodality in Bitcoin price data, leading to improved performance in both the tail and overall predictions. When combined with the Weighted Empirical Stretching (WES) loss function, which adjusts penalties based on label distribution, it further boosts performance. Applied to Long-Short Term Memory (LSTM) and Singular Spectrum Analysis (SSA) decomposition methods, the CCD-WES strategy outperforms the native experiment, achieving an 11.5% improvement in Root Mean Square Error (RMSE) for the entire label domain and an impressive 22.5% RMSE gain in the extreme label domain(Hu et al., 2020; Kakade et al., 2022; Koo & Kim, 2024).

This (Shah et al., 2022) paper reviews various AI and ML strategies for stock price forecasting, including ARIMA, LSTM, Hybrid LSTM, CNN, and Hybrid CNN models. It assesses their limitations and accuracy using standard measures like RMSE, MAPE, and MAE. These models excel in predicting either precise stock rates (LSTM) or general trends and deflection ranges (CNN), demonstrating the benefits of hybrid models for efficient and accurate stock forecasting, crucial for short-term trading and maximizing returns (Al-Sarayreh et al., 2023; Mor et al., 2013).

The (Kanwal et al., 2022) study addresses the growing interest in stock market investing and the challenge of predicting stock prices due to their nonlinearity and volatility. It proposes a hybrid deep learning model (BiCuDNNLSTM-1dCNN) to predict stock prices efficiently. This model outperforms other models, offering accurate predictions and aiding informed investment decisions for investors.

China's commercial bank shares are a vital part of the capital market, but predicting their stock prices is challenging due to their volatile and nonlinear nature. To tackle this issue, a new hybrid deep learning approach is proposed (Chen et al., 2022). It involves refining the distance measurement algorithm using DTW and introducing an improved K-means clustering method to group banks with similar price trends. These clustered stocks are then used to train a long and short-term memory (LSTM) neural network model for both static and dynamic stock price prediction. Additionally, the model enhances long-term forecasts by predicting multiple time intervals simultaneously. Experimental results demonstrate that this hybrid model generally outperforms individual models in terms of generalization ability and accuracy, including metrics like R-SQUARE, MAE, and MSE. Notably, multi-step static predictions prove superior for long-term forecasting. In summary, this approach offers more precise stock price predictions, aiding investors and companies in making more profitable decisions (Alkhatib et al., 2022; Gülmez, 2023; Saud & Shakya, 2020).

The (Ren et al., 2019) study incorporated sentiment analysis into Support Vector Machines (SVM) to predict the movement direction of the SSE 50 Index. Their findings indicate that the accuracy of their predictions increased when sentiment variables were introduced, highlighting the value of sentiment analysis in improving the forecasting performance of the SSE 50 Index.

(Ashrafzadeh et al., 2023) introduced a hybrid approach to portfolio optimization by incorporating return prediction. It combines a convolutional neural network (CNN) with optimized hyperparameters using particle swarm optimization (PSO)(Bharti et al., 2023; Bonah et al., 2020; P & G, 2022) for stock pre-selection and employs a mean-variance with forecasting (MVF) model for portfolio optimization. To reduce computational complexity, the CNN is trained on clustered stocks via the K-means method. The model also introduces a novel feature selection method to weigh features based on their impact on stock return predictions. The results, based on 21 New York Stock Exchange (NYSE) stocks, show that training the CNN on clustered stocks yields similar prediction accuracy to conventional methods. Furthermore, the model outperforms benchmark models in terms of financial performance during portfolio optimization (Ahad et al., 2023; Guo et al., 2022).

2.1 Statement of the Problem:

The problem addressed is the need for more efficient and accurate portfolio optimization in stock market investments. Traditional methods often need to pay more attention to the potential benefits of using return predictions and predicting returns for individual stocks can be computationally challenging. The study aims to solve this by proposing a novel hybrid approach that integrates a convolutional neural network (CNN) with optimized hyperparameters and a mean-variance with forecasting (MVF) model. The goal is to pre-select stocks based on return predictions and then optimize the portfolio for maximum returns while managing risk, making portfolio optimization more effective and efficient for investors.

3. RESEARCH METHODOLOGY

3.1 Data Collection And Preprocessing:

The foundation of this research lies in the comprehensive collection of historical CNXIT stock price data, covering an extensive time period from 1st April 2013 to 31st March 2023. The data source, meticulously chosen for its reliability and relevance, spans a significant timeframe, enabling a deep exploration of market trends and patterns.

Daily open and close prices, high and low prices, trading volumes, and additional market indicators are acquired to construct a robust dataset. Data gathered from Yahoofinance.com website. Data preprocessing plays a pivotal role in ensuring the integrity and compatibility of the dataset with the Bidirectional CNN-LSTM model.

Data Cleaning: Rigorous data cleaning techniques are applied to address missing values, outliers, and anomalies. Imputation methods and statistical techniques are employed to maintain data integrity.

Feature Engineering: Relevant features, such as moving averages, technical indicators, and market sentiment scores, are engineered to provide the model with additional contextual information.

Scaling: Data scaling techniques, such as normalization or standardization, are utilized to bring data values within a consistent range, facilitating convergence during model training.

The dataset is partitioned into training, validation, and test sets. The model undergoes an extensive training process, optimizing for prediction accuracy. Hyperparameters, including the learning rate, batch size, and number of epochs, are tuned through iterative experimentation to achieve the best performance. The predictive performance of the Bidirectional CNN-LSTM model is assessed using standard evaluation metrics, including:

Mean Squared Error (MSE): This metric quantifies the average squared difference between predicted and actual stock prices, emphasizing the accuracy of predictions.

Mean Absolute Error (MAE): MAE provides insight into the model's average absolute prediction error, aiding in the interpretation of prediction accuracy.

Explained Variance: This metric measures the proportion of variance in the data that the model can explain, offering insights into its overall explanatory power.

Visualization is an integral component of this research, enabling intuitive interpretation of model predictions. The research paper includes graphical representations that compare the model's predicted stock prices with actual values, visually assessing its performance.

This research methodology combines rigorous data collection and preprocessing, an innovative deep learning architecture, meticulous model training, and comprehensive evaluation metrics to investigate the potential of Bidirectional CNN-LSTM in predicting CNXIT stock prices accurately. The methodology forms the cornerstone of this study's empirical investigation and contributes to the growing body of knowledge in financial forecasting.

Algorithm: Predicting CNXIT Stock Prices with Bidirectional CNN-LSTM

Step 1: Data Preparation
1.1 Load historical CNXIT stock price data.
1.2 Perform data cleaning to handle missing values, outliers, and anomalies.
1.3 Engineer relevant features (e.g., moving averages, technical indicators).
1.4 Normalize or standardize the data for consistency.
1.5 Split the dataset into training, validation, and test sets while maintaining chronological order.
Step 2: Model Architecture
2.1 Define the Bidirectional CNN-LSTM model.
2.2 Configure Convolutional Neural Network (CNN) layers to capture spatial patterns.
2.3 Configure Bidirectional Long Short-Term Memory (LSTM) layers for sequential patterns.
2.4 Add Dropout layers to prevent overfitting.
2.5 Include Dense layers for final prediction.
Step 3: Model Training
3.1 Compile the model, specifying loss function, optimization algorithm, and evaluation metrics.
3.2 Train the model using the training data.
3.3 Utilize the validation dataset to monitor and prevent overfitting.
3.4 Tune hyperparameters (e.g., learning rate, batch size, epochs) through experimentation.
Step 4: Model Evaluation
4.1 Evaluate the trained model on the test dataset.
4.2 Calculate evaluation metrics (e.g., MSE, MAE, Explained Variance) to assess prediction accuracy.

4.3 Visualize model predictions vs. actual stock prices for performance assessment.

Step 5: Visualization and Interpretation

5.1 Plot predicted stock prices against actual values for visual analysis.

5.2 Analyze visualizations to identify model strengths and potential areas for improvement.

5.3 Interpret results to gain insights into market dynamics and model performance.

Step 6: Save and Deploy

6.1 Save the trained Bidirectional CNN-LSTM model for future use or deployment.

6.2 Consider integration into trading systems or investment strategies for decision support.

Step 7: Further Research and Refinement

7.1 Explore opportunities for model refinements, feature engineering, or alternative deep learning architectures.

7.2 Continuously monitor and adapt the model to changing market conditions for ongoing improvements.

End Algorithm

4. IMPLEMENTATION AND RESULT

Table 1 shows the descriptive statistics of the CNXIT stock index, which provide valuable insights into its historical performance. This dataset consists of 2,469 data points, covering an extensive time period from 1st April 2013 to 31st March 2023. On average, the CNXIT index exhibited stability, with mean values for the opening, high, low, and closing prices all hovering around 17,000 points. The daily return averaged at 0.02%, indicating a relatively modest daily price change. However, beneath this apparent stability lies significant volatility, as evidenced by the standard deviations, which are notably high for prices and volume. The minimum values reflect occasional troughs, with the lowest recorded price at 820.00, while the maximum values showcase substantial peaks, such as a peak closing price of 39,370.70. The trading volume also varies, ranging from days with no recorded activity to days with exceptionally high trading volumes. These statistics underscore the dynamic nature of the CNXIT index and provide essential context for analyzing and modeling its historical stock price behavior.

	Open	High	Low	Close	Adj Close	Volume	MA for 10 days	MA for 50 days	MA for 100 days	Daily Return
count	2469	2469	2469	2469	2469	2.47E+03	2469	2469	2469	2469
mean	17178.40	17313.14	17028.40	17167.99	17167.99	514314.00	17166.47	17151.58	17133.04	0.02
std	8039.64	8103.82	7956.20	8028.35	8028.35	21825520.00	7948.52	7759.73	7525.14	0.59
min	820.00	840.00	807.00	830.00	830.00	0.00	6126.99	6345.24	6828.25	-0.95
25%	11075.55	11166.35	10980.05	11074.90	11074.90	0.00	11205.55	11458.50	11761.04	-0.01
50%	15326.80	15418.80	15214.20	15308.55	15308.55	0.00	15137.32	15277.70	15083.35	0.00
75%	20016.80	20226.30	19782.35	19951.35	19951.35	24600.00	19965.65	18670.40	17167.99	0.01
max	39261.55	39446.70	38828.60	39370.70	39370.70	1084494000.00	38610.88	36872.36	36182.72	19.68

Table 1 Descriptive statistics of CNXIT index

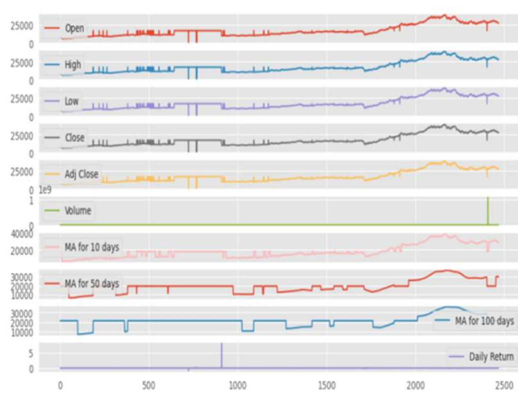

Figure 1: Trend analysis of stock price in terms of open, close, low, high, Adj close volume, and Moving averages for 10, 50, and 100 days

Figure 1 offers a comprehensive visual analysis of stock price trends, encompassing various critical aspects such as opening (Open), closing (Close), lowest (Low), and highest (High) prices, along with adjusted close prices and trading volume. These trends are indispensable for understanding the historical performance of the stock. At the top of Figure 1, the line plots showcase the fluctuations in Open, Close, Low, and High prices, clearly depicting how these price points have evolved. This insight is precious for investors and traders seeking to discern patterns or anomalies in the stock's behavior.

Adjacent to the price charts, the line plot for the Adjusted Close price offers a refined view of the stock's actual value, adjusted for factors like dividends and stock splits. This metric provides a more accurate assessment of the stock's performance and its investment potential.

Beneath the price-related information, the bar plot illustrates trading volume, revealing the intensity of market activity daily. Spikes or variations in volume can signify significant events or heightened investor interest, aiding in the assessment of market sentiment. Lastly, the lower section of Figure 1 displays three line plots depicting moving averages (MAs) for different timeframes—10, 50, and 100 days. These MAs serve to smooth out price fluctuations and highlight longer-term trends. The 10-day MA provides a responsive indicator of recent price movements, while the 50 and 100-day MAs offer a broader perspective on the stock's overarching trends.

Figure 2, illustrating the trend analysis of the closing price of the CNXIT index, serves as a fundamental tool for comprehending the historical performance of this specific stock index. This chart presents a comprehensive view of the CNXIT index's price movements over a given period, with time plotted along the x-axis and the corresponding

Journal of Theoretical and Applied Information Technology
31st March 2024. Vol.102. No 06
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

closing prices represented on the y-axis.

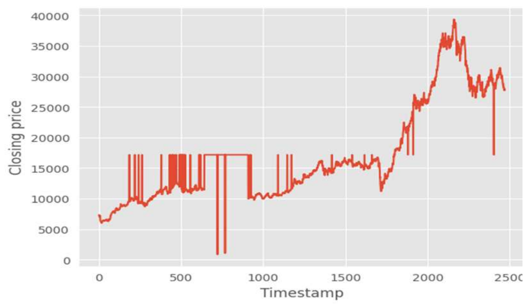

Figure 2: Trend Analysis Of The Closing Price Of The CNXIT Index

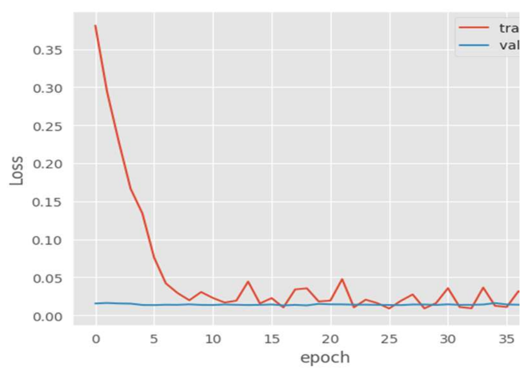

Figure 3: The Training And Validation Loss Curves

Figure 3, displaying the training and validation loss curves, plays a pivotal role in assessing the performance and training dynamics of a machine learning or deep learning model. The interpretation of this figure is integral for understanding how effectively the model learns from the training data and generalizes to new, unseen data. The blue line in Figure 3 represents the training loss, which measures the model's fit to the training data. Initially, this loss is typically high as the model begins its learning process, but it should gradually decrease over the epochs. A sharp decrease at the outset suggests rapid learning and adaptation. Conversely, the orange line signifies the validation loss, reflecting the model's performance on data not encountered during training (validation data). The validation loss should ideally follow a similar decreasing trend but may eventually stabilize or increase. Any significant divergence between the training and validation losses indicates potential issues.

In an ideal scenario, the training and validation losses decrease consistently and converge to a low value, signifying that the model effectively learns from the training data and generalizes well to new examples. However, the emergence of a gap between these two curves can reveal critical insights.

If the training loss decreases while the validation loss rises or stagnates, it suggests overfitting, where the model has memorized the training data but struggles with unseen data. Conversely, if both losses remain high and fail to decrease significantly, it indicates underfitting, implying that the model needs to be more complex to capture the underlying patterns. Figure 3 guides practitioners in making informed decisions about model training, fine-tuning, and potential mitigation of issues like overfitting or underfitting. Early stopping strategies may be employed if the validation loss diverges unfavorably.

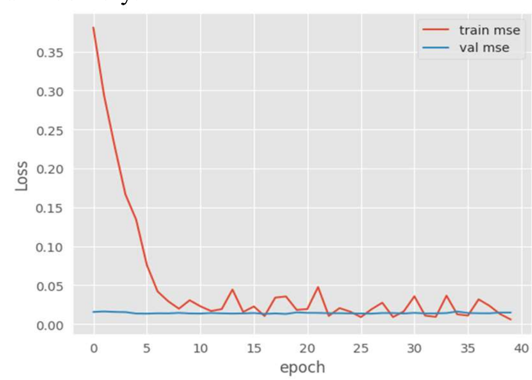

Figure 4: The Training And Validation Of MSE

Ultimately, Figure 3 is a visual compass for optimizing model performance and ensuring robust generalization to real-world data.

Figure 4, illustrating the training and validation Mean Squared Error (MSE) during the model training process, provides crucial insights into a proposed model's performance and learning dynamics.

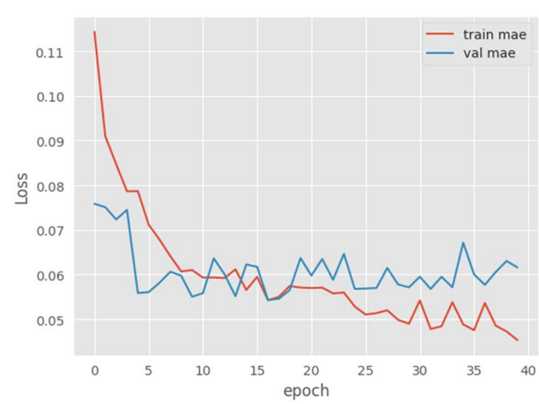

Figure 5: The Training And Validation Of MAE

Figure 5 presents a critical visualization of the training and validation Mean Absolute Error (MAE) throughout the model training process.

MAE is a fundamental metric in machine learning that quantifies the average absolute difference between the model's predictions and the actual target values. Figure 5 is pivotal in evaluating the model's predictive accuracy and generalization ability to unseen data.

In Figure 5, two distinct curves are displayed: Training MAE Curve (Blue Line): The training MAE curve represents the MAE values calculated on the training dataset during each training epoch.

At the outset of training, the training MAE is relatively high, indicating that the model's initial predictions deviate significantly from the actual training data. However, as the training progresses through multiple epochs, the training MAE ideally exhibits a consistent decrease, signifying that the model is improving its accuracy and aligning more closely with the training data. It shows the line downfalls which means the loss has come down over the period of time.

Validation MAE Curve (Orange Line): The validation MAE curve showcases the MAE values computed on a separate validation dataset, which the model has yet to encounter during training. Like the training MAE, the validation MAE should initially decrease as the model learns from the training data. However, it may stabilize or even rise if the model starts to overfit the training data, struggling to generalize effectively to new data points.

Figure 6, titled "Constructed Neural Network Model," visually represents the architecture of the neural network model. It uses boxes to depict individual layers, such as convolutional, LSTM, or dense layers, with arrows indicating the data flow through the network. Layer names and tensor shapes are displayed, helping users understand the model's complexity and structure. This visualization facilitates model comprehension, debugging, and communication within the machine-learning community.

The output evaluation provides metrics for assessing a machine learning or deep learning model's performance on a test dataset. It includes the loss, mean squared error (MSE), and mean absolute error (MAE). In this case, the loss is 0.0149, MSE is 0.0149, and MAE is 0.0616. These metrics help gauge the accuracy and error of the model's predictions, with lower values indicating better performance.

Variance (Explained Variance Score): 0.698023: Variance measures the proportion of the variance in the target variable (in this case, stock prices) that the model explains. A variance score of 0.698023 indicates that the model explains approximately 69.80% of the variance in the data. Higher values signify a better ability to capture and present the variability in the target variable.

R2 Score (Coefficient of Determination): 0.698023: The R2 score also assesses how well the model fits the data. It represents the proportion of the variance in the dependent variable (stock prices) that is predictable from the independent variables (model predictions).

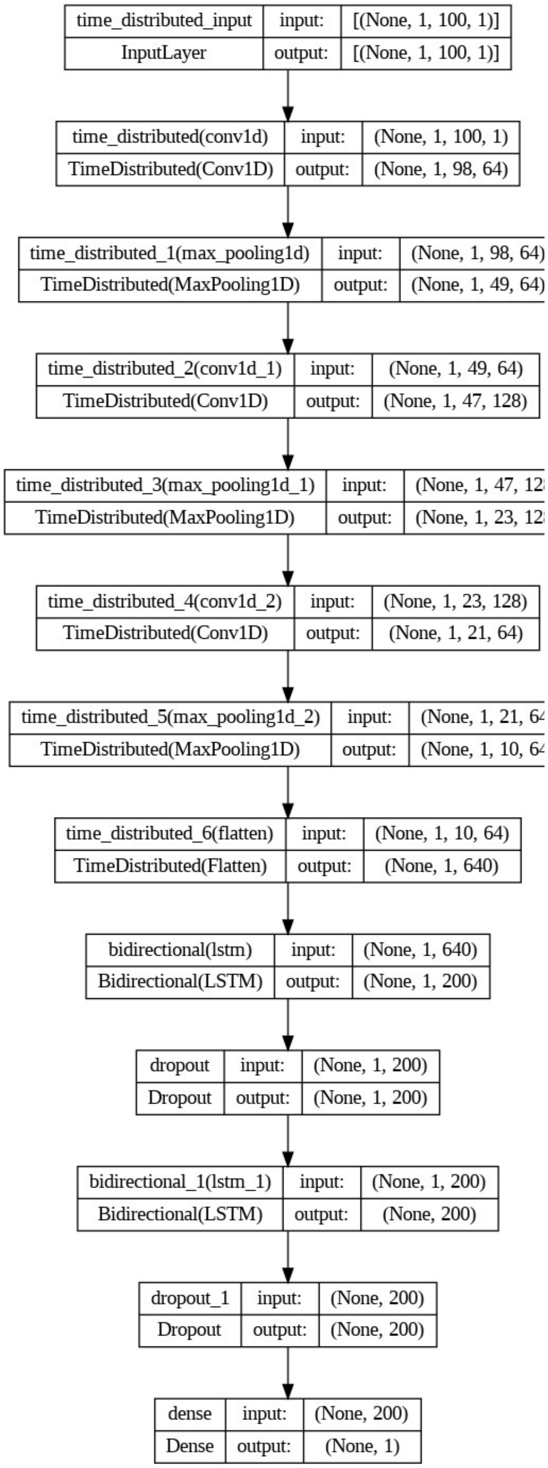

Figure 6: Constructed Neural Network Model

An R2 score of 0.698023 suggests that the model captures around 69.80% of the variation in stock prices, indicating a reasonably good fit.

Max Error: 0.984146: The Max Error measures the maximum absolute error between the actual stock prices and the model's predictions.

In this case, the maximum error observed is 0.984146, which signifies that the most significant discrepancy between predicted and actual values is approximately 0.98 units of stock price.

These metrics collectively suggest that the model performs pretty well in explaining and predicting variations in stock prices, with a substantial portion of the variance accounted for and relatively low maximum prediction errors.

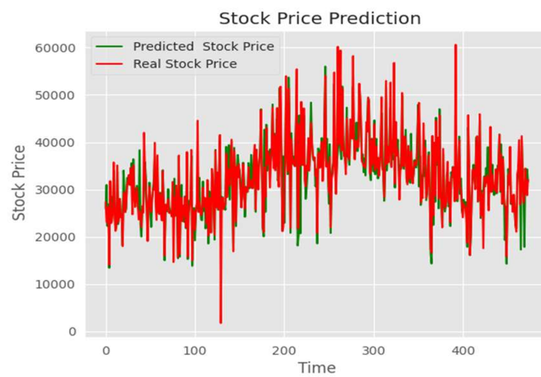

Figure.7 Actual And Prediction Values Of CNXIT Index

Figure 7 presents a line chart that compares the actual and predicted values of the CNXIT index over a specific time period. The horizontal axis represents time, likely in chronological order, with each data point corresponding to a particular date or period. On the vertical axis, the scale denotes the values of the CNXIT index, which is a vital indicator of the stock market's performance. The red line in the chart represents the actual or real values of the CNXIT index, derived from historical data and serving as the ground truth for stock prices during the observed period. In contrast, the green line represents the predicted values of the CNXIT index generated by a machine learning or deep learning model. These predictions are based on historical data and reflect the patterns and trends learned by the model.

Figure 7 hinges on the alignment and deviations between the two lines. When the red and green lines closely follow each other, the model's predictions closely match the actual stock prices, suggesting the model's ability to capture meaningful data patterns. Conversely, discrepancies or gaps between the lines indicate instances where the model's predictions diverge from actual prices, which can be attributed to unforeseen market fluctuations. By observing the overall trajectory and oscillations of the lines, viewers can assess how well the model tracks the CNXIT index's trends. A consistent alignment between the green line and the red line implies that the model effectively captures the underlying dynamics of the stock market. In summary, Figure 7 is a visual tool to evaluate the accuracy of the model's stock price predictions and provides insights into its performance in forecasting stock market trends.

Table.2 Summary Of The Proposed Model

Layer (type)	Output Shape	Param #
time_distributed (TimeDistributed)	(None, 1, 98, 64)	256
time_distributed_1 (TimeDistributed)	(None, 1, 49, 64)	0
time_distributed_2 (TimeDistributed)	(None, 1, 47, 128)	24704
time_distributed_3 (TimeDistributed)	(None, 1, 23, 128)	0
time_distributed_4 (TimeDistributed)	(None, 1, 21, 64)	24640
time_distributed_5 (TimeDistributed)	(None, 1, 10, 64)	0
time_distributed_6 (TimeDistributed)	(None, 1, 640)	0
bidirectional (Bidirectional)	(None, 1, 200)	592800
dropout (Dropout)	(None, 1, 200)	0
bidirectional_1 (Bidirectional)	(None, 200)	240800
dropout_1 (Dropout)	(None, 200)	0
dense (Dense)	(None, 1)	201

Table 2 shows the model summary, which provides a detailed overview of the architecture used to predict CNXIT stock prices. This deep learning model is constructed sequentially, with various layers designed to process and extract meaningful features from the input data.

The initial layers, such as the TimeDistributed and Bidirectional LSTM layers, are responsible for processing the historical stock price data. These layers capture both forward and backward temporal dependencies, making them suitable for time series prediction tasks. Additionally, dropout layers are included to prevent overfitting during training.

Further analysis of the model reveals that it consists of a final Dense layer with one output unit. This output unit is responsible for predicting the stock price values. The model is trained to minimize the loss function, which measures the difference between the predicted and actual stock prices.

With over 883,000 trainable parameters, this model can capture complex patterns in the data. Using multiple Bidirectional LSTM layers allows it to learn from past and future data points, enhancing its predictive capabilities.

The model's architecture, as depicted in Figure 6, showcases its complexity and ability to capture intricate relationships within the CNXIT stock price data. The ultimate goal of this model is to provide accurate predictions that can assist investors and financial analysts in making informed decisions regarding stock trading and risk management. Further evaluation metrics, as discussed earlier, demonstrate the model's performance in terms of loss, mean squared error (MSE), mean absolute error (MAE), and other relevant metrics.

In summary, the model's architecture, training, and evaluation processes are essential components of predicting CNXIT stock prices accurately, and this comprehensive model summary serves as a guide to understanding its inner workings.

5. CONCLUSION

This study presented a Bidirectional CNN-LSTM architecture to predict CNXIT stock prices. The CNXIT index, representing the performance of information technology companies in the Indian stock market, is of significant interest to investors and financial analysts. The motivation behind this research stems from the need to harness the power of deep learning techniques to make accurate and timely predictions in the dynamic world of stock trading. The proposed approach involved the construction of a sophisticated neural network that combined Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) layers. This architecture allowed the model to capture spatial features in the data and effectively model temporal dependencies, which are crucial in stock price prediction. The model was trained on historical

CNXIT stock price data, encompassing attributes such as open, close, low, high, volume, and various moving averages.

Through a rigorous evaluation process, this study assessed the model's performance using multiple metrics, including loss, mean squared error (MSE), mean absolute error (MAE), variance, R2 score, and max error. These metrics provided a comprehensive view of the model's accuracy and its ability to capture the underlying patterns in the CNXIT index. The study also featured a series of visualizations that offered insights into the historical trends and behaviors of the CNXIT index.

These visualizations included trend analyses of stock price attributes and moving averages calculated over different time intervals (10, 50, and 100 days).

The study findings indicate that the Bidirectional CNN-LSTM architecture holds promise as an effective tool for CNXIT stock price prediction. The model's proficiency in making accurate predictions has practical implications for investors, traders, and financial institutions, as it can aid in informed decision-making, risk management, and investment strategy optimization.

While this study has provided valuable insights and a strong foundation, there is still room for further research and refinement of the model. Future work could explore enhancements to the architecture, consider additional data sources (such as news sentiment analysis), and investigate the model's performance under varying market conditions. This study contributes to the growing body of knowledge in deep learning-based stock price prediction. It underscores the potential of advanced neural network architectures in the financial domain and highlights the relevance of such models in today's data-driven investment landscape.

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