Intraday Stock Trading Strategy Based on Analysis Using Bidirectional Long Short-Term Memory Networks

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***Abstract*— The issuance of stocks constitutes a means by which ownership in a company is represented, and its distribution may vary depending on whether the company is limited or public. The stock market offers the potential for high returns, thereby serving as an attractive avenue for investment. Against this backdrop, the objective of this study is to develop a predictive model for stock prices that can facilitate profitable trading outcomes. To achieve this aim, the study focuses on intraday and hourly trading and utilizes a hybrid model that integrates Bidirectional Long Short-Term Memory (BiLSTM) and Convolutional Neural Network (CNN) architectures, along with technical indicators. BiLSTM is a neural network architecture that possesses the capability to process sequential data in both forward and backward directions, thereby augmenting the model's ability to capture dependencies within the data. The efficacy of the resulting model is subsequently evaluated through a comparison with technical analysis. Empirical validation of the model is carried out using technology stocks that are listed on the NASDAQ index. The experimental findings demonstrate that the hybrid architecture of CNN and BiLSTM can outperform technical analysis in terms of achieving profitable trading outcomes in the stock market.**

Keywords*— *Intraday stock trading, Trading strategy, Technical analysis, Machine learning, Deep learning, Long short-term memory networks (lstm)

I. Introduction

Equity securities, commonly known as "stocks," are issued by companies to investors to represent ownership rights in the company, proportional to the shares held. The stocks of each company can be distributed to shareholders differently, depending on whether it is a limited company (Company Limited) or a public company (Public Company Limited). Only public companies allow the general public to own shares through trading in the stock market. The stock market is popular nowadays because it can provide relatively high returns, either in the form of price differences (Capital Gain/Loss) or dividends.

The value of stocks does not solely depend on a company's performance, as past events have shown. Factors such as government economic policies, global market trends, and even investor sentiment (Trader Sentiment) can cause stock values to fluctuate. To predict stock prices, many studies have attempted to develop various asset price prediction models, such as Autoregressive Integrated Moving Average (ARIMA) [1], Random walk [1], Genetic algorithm (GA) [2], and later, Support Vector Machine (SVM) [1], which became very popular.

Artificial neural networks have also played a role in model development. Tsantekidis et al. [3] found that Convolutional Neural Networks (CNN) can predict stock prices more accurately than SVM. In the studies of Sisodia [4], Yang [5], and Wisaroot [6], it was discovered that using hybrid models results in better performance than using a single type of model. Therefore, in the field of stock price prediction, it is important to consider all possible factors and use various models to create a more accurate prediction.

Time series data is a commonly encountered type of data that changes over time and processing it can be difficult due to its dynamic nature. To address this, recurrent neural networks (RNNs) have gained popularity for processing time series data, with Long Short-Term Memory (LSTM) networks being particularly effective in capturing temporal dependencies. The advantages of using gated cells in LSTM networks have been further supported by Hasan et al. in their publication "LSTM Cells" [7]. The effectiveness of LSTM networks has been demonstrated in various time-series applications, including credit card fraud detection by Ibtissam [8], semantic similarity prediction by D. Meenakshi [9], and gamelan melody generation by Arry M. Syarif [10], among others.

In this research, the primary focus is directed towards the Bi-directional Long Short-Term Memory (Bi-LSTM) neural network architecture, which represents an extension of the LSTM network. The Bi-LSTM model processes the input sequence in both forward and backward directions, allowing it to capture contextual information from past and future time steps. This feature renders the Bi-LSTM network particularly well-suited for time series prediction tasks that rely on leveraging historical and future data. A recent investigation by Sunny et al. [11] implemented the Bi-LSTM model for predicting stock prices, demonstrating the efficacy of this model for prediction tasks. In further recent research, Ibrahim et al. [12] proposed a hybrid CNN-BiLSTM model for univariate time-series anomaly detection using artificial intelligence. This model captures both temporal and spatial features of input data, resulting in superior anomaly detection compared to traditional methods. The study's contribution to the field of time-series anomaly detection is noteworthy, and the reference may be valuable for future research in this area. Specifically, researchers seeking to improve traditional anomaly detection methods for time-series data can benefit from examining the proposed hybrid model.

In this study, we present a novel approach that integrates CNNs with LSTM and BiLSTM models for stock trading. To the best of our knowledge, no prior research has investigated the combined use of BiLSTM with these stocks. Our investigation aims to identify the optimal sequence structure for CNN-LSTM and CNN-BiLSTM models, with the ultimate goal of generating stock trading signals that outperform traditional long-term indicators in terms of average returns. Specifically, we focus on a 1-hour timeframe to explore the possibilities and optimize efficiency.

II. RELATED THEORY

A. *Convolutional Neural Networks (CNN) [13]*

Convolutional Neural Networks (CNN) are a prominent type of artificial neural network particularly suited for various applications such as computer vision, speech processing, face recognition, and many more. CNNs are capable of learning diverse features from data autonomously, without the need for human intervention. A common CNN architecture resembles a multi-layer perceptron (MLP) and is composed of several Convolution layers, followed by Pooling (sub-sampling) layers, and ending with a Fully Connected layer.

B. *Long Short-Term Memory Networks (LSTMs) [14]*

LSTMs are a type of Recurrent Neural Networks (RNNs) designed to overcome the limitations of standard RNNs, particularly in learning long-term dependencies. Introduced by Hochreiter & Schmidhuber (1997), LSTMs have since been widely used in applications like speech recognition, language modeling, and translation. Their unique architecture, featuring a cell state and gates, allows for the regulation of information flow through the network, helping LSTMs to remember information over extended periods. Various LSTM variants have been developed to improve performance, but all share the fundamental concept of learning long-term dependencies, making them crucial in deep learning.

C. *Bidirectional Long Short-Term Memory Networks (Bi-LSTMs)[15]*

Bi-LSTMs are a type of recurrent neural network that can capture dependencies in both the forward and backward directions. In Bi-LSTMs, the input sequence is processed in both directions, with two separate hidden layers, and the outputs from both directions are combined. This allows the network to capture not only the current input but also the context in which it appears. Bi-LSTMs have been used in various applications such as speech recognition, image captioning, and sentiment analysis. They have shown to outperform traditional LSTMs in tasks where the context of the input sequence is crucial.

III. LITERATURE REVIEW

The prediction of stock prices through machine learning techniques has gained significant attention, primarily due to their ability to learn from time series data. LSTM neural networks have emerged as a popular machine learning technique for time series data, owing to their ability to process and forecast data with longer time frames than conventional neural networks. Researchers have employed LSTM models in various studies, including the prediction of Nifty50 stocks by Sisodia et al. [4], crude oil prices by Wisaroot et al. [6], and daily gold prices by Z. He et al. [16]. These studies have demonstrated the potential of LSTM models in accurately predicting stock prices.

Sunny et al. [11] conducted a study to examine the efficacy of RNNs, particularly LSTM and BiLSTM, in the context of stock price prediction. The authors reported that both LSTM and BiLSTM models demonstrated superior predictive accuracy relative to other models. Remarkably, the BiLSTM model exhibited higher accuracy than the LSTM model. These findings indicate that the BiLSTM model holds promise for accurate forecasting of stock prices.

Market profile theory and technical analysis are commonly used to analyze stock prices. Research has shown that market profile theory is effective in predicting stock prices and providing insights into market structures. Neural network architecture has also been used to improve investment decision-making. Chen et al. [17] combined market profile theory and neural network architecture to create a market profile indicator that considers long-term and short-term trends, leading to better forecasting performance and profitability. The combination of these two approaches provides a comprehensive method to analyze financial markets.

Ganatra et al. [18] propose using an artificial neural network approach for predicting stock prices, which can outperform traditional techniques such as fundamental and technical analysis. They design a spiking backpropagation multilayer neural network with various network parameters to optimize the accuracy of the predictions. Their study demonstrates the potential of artificial neural networks for predicting unpredictable stock market prices and highlights the factors that affect their performance.

Based on these research studies, the use of a hybrid neural network model can lead to more accurate predictions in stock market forecasting. Therefore, this approach will be applied in this research.

IV. PROPOSED METHOD

The proposed methodology of this study involves an assessment of the predictive performance of three widely used neural network architectures, namely CNN, LSTM, and BiLSTM, for stock price prediction using technical indicators.

To evaluate the effectiveness of these models, four different configurations were considered: CNN-LSTM, LSTM-CNN, CNN-BiLSTM, and BiLSTM-CNN, as presented in Figures 1, 2, 3, and 4. Each configuration includes batch normalization, dense, and dropout layers, which are fundamental components of modern neural network architectures. Batch normalization is a layer that normalizes the input values of each mini-batch to mitigate the problem of internal covariate shift, thereby improving the stability and convergence of the model during training. Dense layers, also known as fully connected layers, connect all neurons from the previous layer to every neuron in the current layer, enabling the model to learn complex non-linear relationships between input features and output predictions. Dropout layers randomly remove some of the neurons during training, preventing the model from overfitting to the training data and improving its generalization capability. By incorporating these layers, the models' robustness and generalization capabilities are expected to be enhanced, enabling them to generate more accurate predictions of stock prices using technical indicators.

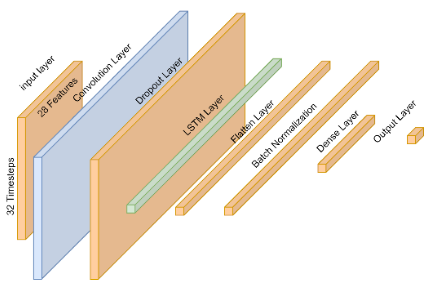

Fig. 1. CNN-LSTM architecture

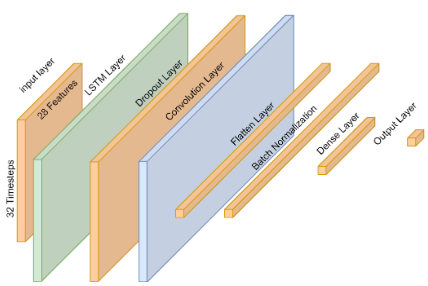

Fig. 2. LSTM-CNN architecture

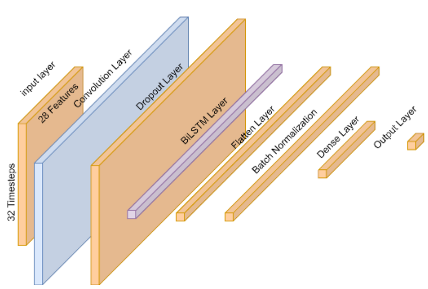

Fig. 3. CNN-BiLSTM architecture

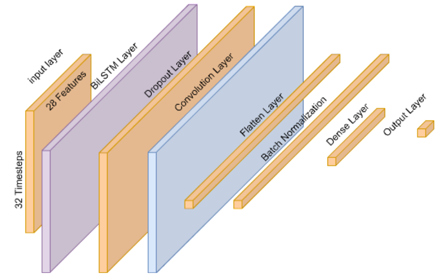

Fig. 4. BiLSTM-CNN architecture

V. EXPERIMENTAL DATASET

This research project analyzed the stock prices of 12 select stocks, namely AMD, APA, DVN, GOOGL, MOS, MRNA, NFLX, NVDA, OXY, SQQQ, TQQQ, and TSLA. The study specifically concentrated on technology stocks that demonstrate notable growth potential and attract significant investor attention in the NASDAQ market. The data covers the period from 2019 to 2022 and includes the opening price, highest price, lowest price, closing price, and trading volume for each day. To calculate the technical indicators, the TA package [19] and methods proposed by Kumar et al. [20] were used, and the details of the technical indicators are shown in Table I.

The collected data were divided into three groups: training data (first 3 weeks of the month), validation data (1 week after the training data), and testing data (1 year after the validation data), based on the time periods shown in Table II. The data in this section used 1-hour data, with the average number of data points used being 253 for training, 105 for validation, and 3,683 for testing, annually.

TABLE I. LIST OF INDICATORS

Indicator Type	Indicator Name
Trend	Simple Moving Average (SMA)
	Moving Average Convergence (MACD)
	Average Directional Movement Index (ADX)
	Commodity Channel Index (CCI)
Momentum	Rate of Change (ROC)
	Relative Strength Index (RSI)
	True Strength Index (TSI)
	Stochastic RSI %K (%K)
	Stochastic RSI %D (%D)
	Williams %R (%R)
Volatility	Bollinger Bands (BB)
	Average True Range (ATR)
	Ulcer Index (UI)
Volume	Accumulation/Distribution Index (ADI)
	On-balance volume (OBV)
	Chaikin Money Flow (CMF)
	Force Index (FI)
	Money Flow Index (MFI)
	Volume-price trend (VPT)
	Volume Weighted Average Price (VWAP)

TABLE II. TRAINING, VALIDATION, AND TEST DATA FOR THE EXPERIMENT.

Dataset	2019			2020			2021			2022		
	Jan-Nov	Dec		Jan-Nov	Dec		Jan-Nov	Dec		Jan-Nov	Dec	
2020												
2021												
2022												

Training Validation Test

VI. DATA PREPROCESSING AND LABELING

Data transformation is necessary in this research due to the differences in the variable ranges. To prepare the data for neural network training, it will be transformed using the normalization method proposed by Kumar [21], which scales the data to the range of [0, 1] using the equation (1).

$$Scaled\ X_t = \left(\frac{X_t - X_{t-1}}{X_{max} - X_{min}}\right) \quad (1)$$

The label used in this research is the percentage change in the daily average price, calculated based on the previous day's closing price, as shown in equation 2.

$$y_t = \left(\frac{C_{t+1} - C_t}{C_t}\right) \quad (2)$$

VII. EXPERIMENT RESULTS

The performance of the neural network model was evaluated using two methods. The first method involved calculating the mean squared error (MSE), which measures the average squared difference between predicted and actual values. A lower MSE indicates better accuracy of the model in forecasting outcomes. The second method involved backtesting the model using a trading strategy to evaluate its profitability. Historical data was used to test the model, and signals to buy or sell were generated based on the percentage prediction of the daily average price change. A prediction value greater than 0 was interpreted as a buy signal, while a value less than 0 was interpreted as a sell signal.

Using both methods to evaluate the performance of the model is important to ensure its accuracy and profitability in a real trading environment. The predictive error measurement evaluates the accuracy and reliability of the model's predictions, while the trading strategy comparison assesses its profitability. The study compared four types of neural network models, CNN-LSTM, LSTM-CNN, CNN-BiLSTM, and BiLSTM-CNN, in interpreting buy-sell signals using a testing dataset. Additionally, traditional trading strategies such as buy-and-hold, RSI-based buy and sell signals, MACD-based buy and sell signals, SMA-based buy and sell signals, and Stochastics RSI %K and %D-based buy and sell signals were also compared to the neural network models.

A. Prediction error

The objective of this study was to assess the performance of four different neural network models for sequence prediction tasks, namely BiLSTM-CNN, CNN-BiLSTM, LSTM-CNN, and CNN-LSTM, by utilizing the mean squared error (MSE) metric. The training and evaluation of these models were carried out using the configuration specified in Table III. A grid search was conducted on the hyperparameters of the models, where the number of filters in the CNN layer (32, 64, 128, and 256), the number of nodes in the LSTM layer (32, 64, 128, and 256) were varied using validation data. The selection of the optimal hyperparameter configuration was based on the lowest MSE, which was determined through performance evaluation on test data.

Upon examination of Table IV, it becomes apparent that the mean squared error (MSE) values of all four models are indicative of their aptitude for trading, with the average MSE for the entire year 3 being ranked in order from BiLSTM-CNN, CNN-BiLSTM, LSTM-CNN, CNN-LSTM at 83.591×10^{-2}, 61.45×10^{-2}, 65.64×10^{-2}, and 52.96×10^{-2}, respectively. Nevertheless, in making an informed decision as to which model to employ, the return on investment (ROI) values presented in the Trading Performance section ought to serve as the paramount criterion.

TABLE III. MODEL TRAINING CONFIGURATIONS

Parameters	Configuration
Number of filters in the CNN layer	{32, 64, 128, 256}
Number of nodes in the LSTM layer	{32, 64, 128, 256}
Batch size	32
Optimize	Adam
Learning rate	1×10^{-4}

TABLE IV. SHOWS THE MSE VALUES OF EACH STOCK IN THE TEST DATASETS FOR THE YEARS 2020, 2021, AND 2022. THE UNIT IS 1X10^-2, AND THE BOLDED VALUES INDICATE THE MINIMUM MSE FOR EACH DATASET.

	2020				2021				2022			
STOCK	**BiLSTM-CNN**	**CNN-BiLSTM**	**LSTM-CNN**	**CNN-LSTM**	**BiLSTM-CNN**	**CNN-BiLSTM**	**LSTM-CNN**	**CNN-LSTM**	**BiLSTM-CNN**	**CNN-BiLSTM**	**LSTM-CNN**	**CNN-LSTM**
AMD	93.71	**26.96**	93.61	83.65	76.10	68.90	54.20	**20.08**	86.35	**33.58**	38.01	59.32
APA	64.32	74.02	**62.08**	70.45	75.33	62.79	78.81	**47.30**	92.81	82.16	93.50	**24.59**
DVN	85.00	98.76	100.03	**72.19**	84.55	47.76	78.34	**43.64**	93.04	**25.85**	33.67	70.20
GOOGL	87.11	88.73	93.61	**16.11**	91.95	**60.06**	96.35	81.00	94.10	90.98	72.17	**50.22**
MOS	94.07	98.75	99.88	**15.75**	81.40	87.37	**42.71**	70.71	94.73	79.66	**29.03**	49.02
MRNA	92.95	33.73	85.91	**17.81**	75.68	74.92	**54.73**	59.99	48.62	38.00	**35.00**	45.76
NFLX	81.23	79.29	**56.04**	56.32	54.17	**25.48**	88.43	58.94	91.55	**35.97**	47.10	62.13
NVDA	65.37	**48.84**	76.72	64.93	97.88	80.59	**21.13**	60.30	68.33	73.36	61.21	**53.76**
OXY	94.08	**45.90**	65.52	55.49	80.27	50.95	95.05	**14.05**	95.36	86.44	82.07	**60.42**
SQQQ	80.98	62.50	48.45	**48.18**	82.98	73.73	**31.09**	49.69	97.65	**42.17**	83.63	67.81
TQQQ	94.78	79.01	93.07	**50.54**	95.50	**30.42**	46.10	54.96	79.78	80.73	**28.49**	53.57
TSLA	66.98	**24.62**	54.90	54.60	88.33	**79.80**	85.76	91.41	82.47	**39.49**	56.78	51.64
Average	83.38	63.42	77.49	**50.50**	82.01	61.90	64.39	**54.34**	85.40	59.03	55.05	**54.04**

B. Trading Performance

The efficiency of trading is a measure of portfolio performance resulting from past trading at prices. In the trading simulation, investing $100 USD and buying stocks at the closing price of the day based on signals from the simulation model and selling all of them when a sell signal occurs. This research compares this trading strategy with traditional trading strategies such as buy-and-hold, RSI-based trading, MACD-based trading, SMA-based trading, and Stochastics RSI %K and %D-based trading.

The results of this study demonstrate the effectiveness of the trading strategies employed in the simulation and provide insights into the performance of different investment portfolios. The ROI was used as performance indicators to evaluate the trading strategies, and the results were compared to the traditional buy-and-hold strategy, as shown in equation 3.

$$ROI = \frac{(Portfolio\ Value_i - Portfolio\ Value_{i-1})}{Portfolio\ Value_{i-1}} \quad (3)$$

Tables IV, V, and VI present the ROI for each dataset, with green indicating a positive ROI and red indicating a negative ROI. The intensity of the color indicates the magnitude of the ROI, with darker shades of green representing higher profits and darker shades of red representing higher losses. Bold text denotes the highest ROI for each year, and parenthetical numbers indicate the ranking of the comparison models in stock trading.

The results displayed in Table IV for the year 2020 demonstrate a net profit yielded by the average ROI. Notably, the BiLSTM-CNN model proved to be the most effective approach, with an average profit of 127.74% and a favorable average rank of 3.00. The Buy & Hold strategy ranked second as the most successful technique.

Table V presents the ROI outcomes for the year 2021, indicating that all models and trading techniques, with the exception of SQQQ, generated a net profit. The Buy and Hold strategy emerged as the most effective approach, producing an average ROI of 64.71 and an average rank of 3.25. The CNN-BiLSTM method also demonstrated comparable profitability, with an average ROI of 63.46 and an average rank of 3.25. Moreover, BiLSTM-CNN, LSTM-CNN, and CNN-LSTM models outperformed the original trading technique in terms of average ROI and rank values, except for Buy and Hold.

Table VI, which displays the results for 2022, shows an average ROI of 4 for both loss-making and profit-making methods. However, the mean ROI for the profit-making methods does not demonstrate a significant increase when compared to the figures of 2020 and 2021. Notably, three out of the four deep learning structures presented, namely CNN-BiLSTM, LSTM-CNN, and CNN-LSTM, outperformed the market and generated profits. In contrast, only two traditional trading methods, MACD and STO, demonstrated success in outperforming the market

TABLE V. DISPLAYS THE ROI VALUES OF EACH TRADING STRATEGY FOR THE YEAR 2020. THE BOLDED VALUES INDICATE THE HIGHEST ROI FOR EACH DATASET. (%)

STOCK	BiLSTM-CNN	CNN-BiLSTM	LSTM-CNN	CNN-LSTM	BH	MACD	RSI	SMA	STO
AMD	87.29 (2)	72.65 (3)	72.06 (4)	32.55 (8)	**88.34 (1)**	-2.35 (9)	50.19 (5)	40.64 (7)	41.10 (6)
APA	-30.89 (6)	**74.30 (1)**	-4.59 (5)	-48.84 (9)	-44.68 (8)	46.05 (4)	-40.10 (7)	52.82 (2)	51.96 (3)
DVN	-4.76 (3)	-35.45 (4)	-40.02 (6)	-78.04 (9)	-40.02 (5)	**35.63 (1)**	-47.27 (7)	22.85 (2)	-51.25 (8)
GOOGL	12.67 (4)	17.28 (3)	**27.55 (1)**	4.16 (6)	26.33 (2)	7.99 (5)	-1.71 (7)	-4.10 (8)	-4.50 (9)
MOS	**19.38 (1)**	-1.41 (6)	11.76 (4)	-17.86 (9)	9.92 (5)	14.58 (3)	-5.48 (7)	17.03 (2)	-14.77 (8)
MRNA	291.79 (3)	5.87 (8)	66.63 (5)	-65.67 (9)	**486.69 (1)**	163.34 (4)	43.83 (7)	360.59 (2)	61.25 (6)
NFLX	**136.86 (1)**	57.37 (6)	66.52 (5)	95.23 (2)	67.14 (4)	-25.84 (9)	57.29 (7)	1.58 (8)	70.98 (3)
NVDA	**154.87 (1)**	-15.69 (9)	52.6 (4)	47.65 (7)	121.15 (2)	46.29 (8)	47.73 (6)	48.52 (5)	54.52 (3)
OXY	-39.97 (3)	-71.23 (9)	-63.88 (8)	-44.31 (5)	-60.64 (7)	5.80 (2)	-58.75 (6)	**89.89 (1)**	-42.02 (4)
SQQQ	-83.03 (8)	-65.90 (4)	-49.46 (3)	-76.02 (7)	-86.14 (9)	-47.33 (2)	**-35.80 (1)**	-68.56 (5)	-72.24 (6)
TQQQ	66.46 (3)	102.6 (2)	44.84 (7)	-29.81 (9)	**105.56 (1)**	46.96 (5)	45.71 (6)	54.09 (4)	-12.87 (8)
TSLA	**886.27 (1)**	73.38 (9)	408.32 (4)	189.21 (7)	677.83 (2)	401.75 (5)	158.06 (8)	496.34 (3)	299.92 (6)
Avg. ROI	**124.74**	17.81	49.36	0.69	112.62	57.74	17.81	92.64	31.84
Avg. Rank	**3.00**	5.33	4.67	7.25	3.92	4.75	6.17	4.08	5.83

TABLE VI. DISPLAYS THE ROI VALUES OF EACH TRADING STRATEGY FOR THE YEAR 2021. THE BOLDED VALUES INDICATE THE HIGHEST ROI FOR EACH DATASET. (%)

STOCK	BiLSTM-CNN	CNN-BiLSTM	LSTM-CNN	CNN-LSTM	BH	MACD	RSI	SMA	STO
AMD	-1.12 (8)	35.00 (2)	14.13 (4)	-13.12 (9)	**55.12 (1)**	3.17 (6)	-0.56 (7)	32.16 (3)	4.61 (5)
APA	30.51 (6)	**142.29 (1)**	107.52 (2)	43.51 (4)	63.83 (3)	38.87 (5)	2.46 (9)	14.93 (8)	26.78 (7)
DVN	77.45 (5)	**148.67 (1)**	113.52 (4)	136.9 (3)	141.81 (2)	30.96 (9)	76.14 (6)	31.71 (8)	67.98 (7)
GOOGL	**68.44 (1)**	42.98 (6)	66.49 (3)	44.19 (5)	67.54 (2)	21.56 (8)	45.50 (4)	9.17 (9)	21.93 (7)
MOS	26.62 (5)	41.62 (3)	4.84 (8)	5.98 (7)	50.71 (2)	33.43 (4)	**53.78 (1)**	-8.87 (9)	17.79 (6)
MRNA	110.83 (5)	**169.22 (1)**	138.97 (3)	2.22 (8)	135.45 (4)	79.03 (6)	-23.44 (9)	161.85 (2)	51.77 (7)
NFLX	21.37 (3)	**42.91 (1)**	4.06 (8)	30.23 (2)	17.86 (5)	21.07 (4)	4.75 (7)	-13.76 (9)	14.21 (6)
NVDA	117.07 (2)	47.18 (6)	38.96 (7)	96.28 (4)	**119.49 (1)**	106.41 (3)	17.68 (9)	95.4 (5)	30.63 (8)
OXY	93.39 (2)	72.58 (3)	47.07 (5)	30.43 (7)	50.83 (4)	**98.90 (1)**	31.48 (6)	-18.20 (9)	19.5 (8)
SQQQ	-59.66 (8)	-33.38 (4)	**-6.38 (1)**	-40.12 (5)	-61.06 (9)	-16.51 (2)	-24.35 (3)	-52.88 (7)	-49.57 (6)
TQQQ	94.69 (2)	28.17 (6)	67.33 (5)	**153.57 (1)**	94.08 (3)	85.35 (4)	25.29 (7)	9.45 (9)	22.34 (8)
TSLA	53.35 (2)	24.34 (5)	44.89 (3)	**78.90 (1)**	40.86 (4)	15.87 (6)	-0.13 (9)	15.72 (7)	1.31 (8)
Avg. ROI	52.75	63.46	53.45	47.41	**64.71**	43.18	17.38	23.06	19.11
Avg. Rank	4.08	**3.25**	4.42	4.67	3.33	4.83	6.42	7.08	6.92

TABLE VII. DISPLAYS THE ROI VALUES OF EACH TRADING STRATEGY FOR THE YEAR 2022. THE BOLDED VALUES INDICATE THE HIGHEST ROI FOR EACH DATASET. (%)

STOCK	BiLSTM-CNN	CNN-BiLSTM	LSTM-CNN	CNN-LSTM	BH	MACD	RSI	SMA	STO
AMD	-28.55 (6)	-10.86 (5)	16.11 (2)	-36.74 (7)	-54.97 (9)	**17.07 (1)**	-7.21 (4)	-54.01 (8)	-3.45 (3)
APA	47.03 (6)	**83.76 (1)**	32.87 (7)	8.55 (9)	58.53 (5)	63.95 (4)	66.40 (3)	18.12 (8)	75.69 (2)
DVN	22.48 (5)	**38.39 (1)**	-17.71 (8)	5.23 (7)	28.03 (3)	20.73 (6)	27.02 (4)	34.06 (2)	-20.39 (9)
GOOGL	-34.70 (7)	-30.19 (5)	-27.72 (4)	-30.63 (6)	-35.82 (9)	**-4.46 (1)**	-21.40 (3)	-35.15 (8)	-6.63 (2)
MOS	5.03 (3)	-5.78 (4)	-6.58 (5)	**37.03 (1)**	12.49 (2)	-11.43 (7)	-12.29 (8)	-15.72 (9)	-9.23 (6)
MRNA	-27.48 (9)	12.20 (2)	**44.02 (1)**	-8.84 (6)	-22.98 (7)	-8.42 (5)	-25.96 (8)	1.40 (4)	5.76 (3)
NFLX	-49.74 (9)	-25.42 (3)	-12.75 (2)	-36.83 (7)	-49.63 (8)	-26.82 (4)	**-10.93 (1)**	-31.13 (5)	-34.31 (6)
NVDA	-42.99 (6)	-66.78 (9)	-24.66 (5)	-8.07 (3)	-49.58 (8)	9.87 (2)	-21.60 (4)	-44.22 (7)	**51.1 (1)**
OXY	93.23 (3)	123.40 (2)	90.25 (4)	**130.41 (1)**	88.46 (5)	48.28 (7)	52.13 (6)	10.48 (8)	-5.67 (9)
SQQQ	67.80 (5)	98.57 (2)	70.34 (4)	**101.75 (1)**	62.80 (6)	92.32 (3)	11.80 (8)	-1.51 (9)	38.00 (7)
TQQQ	-64.83 (8)	-41.19 (5)	-10.97 (2)	**30.14 (1)**	-76.02 (9)	-22.84 (3)	-62.05 (7)	-61.87 (6)	-38.12 (4)
TSLA	-63.51 (8)	-68.57 (9)	-44.86 (4)	-54.47 (5)	-63.42 (7)	-42.80 (3)	-62.01 (6)	-34.78 (2)	**-33.84 (1)**
Avg. ROI	-6.35	8.96	9.03	11.46	-8.51	11.29	-5.51	-17.86	1.58
Avg. Rank	6.25	4.00	4.00	4.50	6.50	**3.83**	5.17	6.33	4.42

VIII. DISCUSSION

Based on the findings presented in Tables IV, V, and VI, it is evident that the mean Return on Investment (ROI) for the years 2020 and 2021 is notably profitable, with a particular increase in the latter year. The upward trend in the prices of most technology stocks can be attributed to the COVID-19 pandemic situation, which has created a favorable financial outlook. The pandemic has resulted in an augmented demand for technology and digital services, leading to a rise in the stock prices of several technology companies, including those in healthcare, e-commerce, and software industries. Additionally, government stimulus packages and low-interest rates, aimed at stabilizing the economy, have furnished investors with increased liquidity, thereby further stimulating the stock market. These collective factors have facilitated the generation of substantial profits through Buy and Hold trading strategies, with technology stock prices continuing to ascend. Consequently, deep learning or traditional indicators-based trading strategies have demonstrated limited ability in outperforming the Buy and Hold strategy.

The study shows that machine learning (ML) based trading strategies, specifically the BiLSTM-CNN model, have the potential to generate greater profits than traditional trading strategies. The results presented in the table reveal that both the Buy and Hold strategy and the BiLSTM-CNN model yielded high profits in 2020, with an average ROI of 112.62% and 124.74%, respectively. In 2021, both generated profits. However, in 2022, both incurred losses with an ROI of -8.51% and -6.35%. This demonstrates that the Bi-LSTM model has a performance that is in the same direction the Buy and Hold strategy in all three years. While the Buy and Hold strategy may also be profitable in certain years, the ML-based models consistently perform well over multiple years, proving their reliability and robustness. Additionally, ML-based strategies can analyze large amounts of data and make predictions that may be difficult for humans to detect, providing traders with a competitive edge in the market. The study revealed that CNN-BiLSTM, LSTM- CNN, and CNN-LSTM were comparably profitable with slightly higher overall Avg. ROI and Avg. Rank in comparison to conventional trading strategies, except for MACD in 2022. However, the performance of ML-based trading strategies is not always superior to that of traditional approaches. In general, ML trading strategies have a relatively impressive overall performance compared to traditional strategies. The study suggests that incorporating ML-based trading strategies into investment portfolios could be a promising approach to achieving higher returns.

IX. CONCLUSION

"Stocks" or equity securities provide public investment in a company, and their values can be influenced by various factors, including government policies, global trends, and investor sentiment. To predict stock prices, numerous models have been developed, such as the Convolutional Neural Networks and Recurrent Neural Networks like Long Short-Term Memory networks. Recent research has found the Bi-directional Long Short-Term Memory network architecture to be particularly effective in processing time series data and predicting stock prices.

This study proposes a new hybrid technique between CNN and BiLSTM for stock trading algorithms. An assessment was conducted to examine the effectiveness of this novel method in trading NASDAQ stocks from 2020 to 2022. Two primary evaluation measures, prediction error and trading performance, were considered. The experimental results demonstrate that the CNN-BiLSTM model outperforms other competing models. This is attributed to the model's ability to incorporate both CNN and BiLSTM components in an optimal sequence, which enables it to capture intricate relationships within the training data more effectively than alternative techniques.

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