A Comparative Study of Deep Learning Algorithms for Forecasting Indian Stock Market Trends

Mrinal Kanti Paul, Purnendu Das
Department of Computer Science, Assam University, Silchar, Assam, India-788011

***Abstract*—This research underscores the vital significance of providing investors with timely and dependable information within the dynamic landscape of today's stock market. It delves into the expanding utilization of data science and machine learning methods for anticipating stock market movements. The study conducts a comprehensive analysis of past research to pinpoint effective predictive models, with a specific focus on widely acknowledged algorithms. By employing an extensive dataset spanning 27 years of NIFTY 50 index data from the National Stock Exchange (NSE), the research facilitates a thorough comparative investigation. The primary goal is to support both investors and researchers in navigating the intricate domain of stock market prediction. Stock price prediction is challenging due to numerous influencing factors, and identifying the optimal deep learning model and parameters is a complex task. This objective is accomplished by harnessing the capabilities of deep learning, thereby contributing to well-informed decision-making and the efficient utilization of predictive tools. The paper scrupulously examines prior contributions from fellow researchers in stock prediction and implements established deep learning algorithms on the NIFTY 50 dataset to assess their predictive accuracy. The study extensively analyzes NIFTY 50 data to anticipate market trends. It employs three distinct deep learning models—RNN, SLSTM, and BiLSTM. The results underscore SLSTM as the most effective model for predicting the NIFTY 50 index, achieving an impressive accuracy of 99.10%. It's worth noting that the accuracy of BiLSTM falls short when compared to RNN and SLSTM.**

Keyword*—Stock prediction; machine learning technique; deep learning; stock market; National Stock Exchange

I. Introduction

Scholars have been actively engaged in researching the prediction of stock trends due to the stock market's pivotal role as a significant investment avenue across various financial instruments. The goal of stock portfolio selection is to allocate investment funds across multiple stocks in the market, aiming to maximize returns for investors [1]. Investors encounter two broad categories of challenges when creating stock portfolios "The selection of stocks by an investor" and "Allocating funds across various major sectors"

With the advent of faster and high-performance computers, data transfer in the modern computing world has become effortless, making the stock market more accessible to global investors. The internet revolution of the last decade further increased accessibility, as it provides crucial event information that directly or indirectly influences the stock market, leading to the emergence of important tasks like strategy formulation and decision-making support using this information.

Data science (DS) and machine learning (ML) algorithms have become powerful tools in the financial domain, significantly improving stock investments' efficiency. They are extensively utilized to develop innovative ideas and modes that simplify the process of creating stock portfolios for investors [2].

This paper delves into the growing interest among financial researchers in Machine Learning (ML) owing to its success in various domains. It focuses on exploring and comparing the latest prediction algorithms and techniques proposed by researchers for forecasting stock market trends and behavior in both academic and industry settings.

This paper encompasses a concise overview of both Machine Learning (ML) and Deep Learning algorithms. It goes on to conduct a thorough examination of a wide array of algorithms, coupled with an extensive survey of correlated research. This inclusive approach serves to fortify the theoretical underpinnings of the study while also delving into pertinent algorithmic issues. Moreover, the research delves into the practical application of existing work and prevalent deep learning algorithms, commonly employed as the bedrock of numerous researchers' investigations. A pivotal aspect of this study involves a comprehensive comparative analysis of the outcomes achieved through these algorithms.

To accomplish our research objectives, we conducted an extensive survey of prior studies on stock market prediction utilizing data science and machine learning. We meticulously analyzed the methodologies and algorithms employed by various researchers to forecast stock prices. Moreover, we assembled an extensive dataset of NIFTY 50 data obtained from the National Stock Exchange India, covering a period of 27 years. This dataset facilitated a comprehensive evaluation of prediction models across a range of market scenarios.

This study involves a comparative analysis of well-known algorithms: LSTM, BiLSTM, SVM, and RNN. The analysis utilizes a collected dataset as training data to predict NIFTY 50 stock index movement accurately. The primary goal is to identify the algorithm that performs best in terms of predictive accuracy. The algorithms are trained on the dataset, and their performances are evaluated using appropriate metrics. The study aims to offer insights into which algorithm is most effective for predicting NIFTY 50 movement, aiding in more informed decision-making within the financial realm. The study focuses on four algorithms: SLSTM (Stacked Long Short-Term Memory), BiLSTM (Bidirectional Long Short-Term Memory) and RNN (Recurrent Neural Network). Fig. 1 depicts the process flow of our study.

In the upcoming sections of this paper, we will delve into various aspects of our study. Section II will be dedicated to discussing the related work that has shaped the foundation of our research. Moving forward to Section III, we will provide an in-depth description of our implementation plan. Within Section III , specifically in subsection III(A) and III(A)(1), we detail our meticulous implementation process using the RNN model. Furthermore, we will present a comprehensive analysis of the results derived from this implementation. Transitioning to subsection III(B) and III(B)(1), we will outline the steps taken for the implementation of the SLSTM model. Alongside this, we will conduct a thorough examination of the results obtained from this implementation. Similarly, in subsection III(C) and III(C)(1), we will provide insights into our implementation approach for the BiLSTM model and present a comprehensive analysis of the results.

Advancing to Section IV, our focus will shift towards conducting a Comparative Study of the results derived from our various implementations. This section will not only provide a comprehensive comparison of the implementation outcomes but will also identify potential avenues for Future Research Opportunities, illuminating areas that warrant further exploration. As we reach the concluding stages of this paper, Section V will encapsulate our findings and insights. This concluding section will succinctly summarize the key takeaways from our research journey, offering a cohesive wrap-up to our study.

II. Related Works

In the history of the stock market, researchers have employed algorithms like Neural Networks (NN), Support Vector Machines (SVM), Genetic Algorithms (GA), Linear Regression (LR) and Case based Reasoning (CR) for predicting market trends. However, Neural Networks (NN) have gained prominence recently due to their consistent superiority in various scenarios. Their ability to capture intricate patterns in financial data has led to more accurate and adaptable predictions of market behavior, making them the preferred choice among these algorithms [3].

White's implementation of the Feed Forward Neural Network (FFNN) was the pioneering stock market prediction model, inspiring many researchers to develop accurate models for predicting share market trends. Despite continuous efforts, achieving 100% accuracy in stock market forecasting remains elusive due to historical data reliance and external factors' impact on stock prices, driving persistent research in this domain [3].

Earlier research emphasized optimizing learning algorithms but overlooked dimensionality reduction and eliminating irrelevant patterns. To overcome this, Kyoung-jae Kim and Ingoo Han introduced a hybrid model in the early 2000s, blending Artificial Neural Networks (ANN) and Genetic Algorithm (GA). Their model incorporated daily direction of change and technical indicators for Korea Stock Price Index prediction, yet it had limitations in fixed processing elements, input features and optimization objectives in the hidden layer (set at 12) [4].

Mingyue Qiu et al a hybrid solution, GA-ANN, aimed at forecasting the Japanese Stock Market. Their method involved integrating Genetic Algorithms (GA) with a refined Artificial Neural Network (ANN) model, resulting in an enhanced predictive model. This approach combined the strengths of both techniques to achieve improved forecasting outcomes for the Japanese Stock Market [5].

M.R. Hassan and B. Nath proposed the use of Hidden Markov Model (HMM) for predicting unknown values in time-series stock market data. They applied this model to forecast stock prices for four airlines, utilizing a partitioned approach that involved four distinct states for more accurate predictions [6]. The paper's noteworthy aspect is that it doesn't require any specialized knowledge to construct the model. However, the study's limitations are that it's restricted to Airline Industries and was evaluated using a relatively small-scale dataset, which might not result in a general prediction model.

Ming-Chi Lee's paper introduced a Support Vector Machine based prediction model with a hybrid feature selection approach that combined Supported Sequential Forward Search (FSSFS) and F-score filtering wrapping methods. This fusion aimed to identify an optimal feature subset for improved prediction. The study acknowledges feature selection's impact on SVM performance and highlights the need for further investigation into SVM generalization and performance measurement guidelines [7].

Justin Sirignano and Rama Cont introduced a model utilizing Deep Learning on a large-scale, high-frequency dataset from NASDAQ stocks. Their approach involves a Neural Network with three layers, including LSTM, a feed-forward layer with rectified linear units (ReLUs) and the Stochastic Gradient Descent (SGD) algorithm for optimization [8]. The model developed by the authors was regarded as a universal solution but incurred high training costs. They observed that conducting feature selection before training would have been more beneficial, effectively lowering computational complexity.

Li-Ping Ni et al. suggested a predictive model for the Shanghai Stock Exchange Index (SSECI) daily trends. They combined a fractal feature selection method with SVM and compared it against five common feature selection approaches, demonstrating superior prediction accuracy with their method and surpassing both no feature selection and the other five methods [9]. The authors' model, based solely on a technical indicator, should be assessed with additional factors that influence stock prices, given the multifaceted nature of stock price dynamics.

Sean McNally et al. devised a model predicting Bitcoin's USD price using Bayesian-optimized LSTM and RNN networks. LSTM achieved 52% accuracy and 8% RMSE. Comparing to ARIMA, their deep learning models excelled. GPU training surpassed CPU by 67.7%, underscoring research strength in optimization and feature engineering, with implications for dataset processing advancements [10].

Bin Wenga et al. Martinez created a short-term stock price prediction model employing machine learning techniques including Random Forest Regression (RFR), Support Vector Regression Ensemble (SVRE), Neural Network Regression Ensemble (NNRE) and Boosted Regression Trees (BRT) [11].

Yakup Kara et al. utilized ANN and SVM to predict the stock price index, using time series data from Istanbul Stock Exchange between January 1997 and December 2007. Their study lacked clear performance comparisons with prior models. They employed diverse data sets from various sources, including open-source APIs and the Technical Training Rules (TTR) R package, for training their research model [12].

Xinyi Li and colleagues introduced DP-LSTM, an innovative deep neural network for predicting stock prices. By integrating differential privacy, sentiment-ARMA modeling, LSTM, VADER model, and multiple news sources, the approach minimizes prediction errors, enhances robustness, and demonstrates significant advancements in accuracy and Mean Squared Error (MSE) improvement for forecasting the S&P 500 market index [13].

Sidra Mehtab et al. conducted a study using NIFTY 50 index data from India's NSE, covering December 2014 to July 2020. They initially trained on NIFTY 50 data from December 2014 to December 2018, developing eight regression models. Subsequently, they forecasted NIFTY 50 open values from December 2018 to July 2020, employing four LSTM-based deep learning regression models with walk-forward validation. Their research highlighted the efficacy of a univariate LSTM model in predicting NIFTY 50 open values for the following week, utilizing the preceding week's data as input, leading to enhanced predictive accuracy [14].

Hadi NekoeiQachkanloo et al. introduced an artificial stock counselor trading system, combining support vector regression for stock value prediction with portfolio theory and fuzzy investment counsel for optimal budget allocation. Their approach encompasses optimization-based technical analysis and fuzzy logic incorporating technical and fundamental aspects, demonstrating efficacy through experimental results on the NYSE [15].

In their study, M. Nabipour et al. explored the accuracy of tree-based models (Decision Tree, Bagging, Random Forest, Adaboost, Gradient Boosting, XGBoost) and neural networks (ANN, RNN, LSTM) in predicting values for four stock market sectors using regression. Forecasting was done across different time horizons (1, 2, 5, 10, 15, 20, and 30 days ahead), employing exponentially smoothed technical indicators as inputs. The research found that LSTM outperformed other methods, showcasing the highest performance and notably improving the accuracy of stock market predictions within this context [16].

Hiransha M et al. employed MLP, RNN, LSTM, and CNN deep learning architectures to predict stock prices across NSE and NYSE. Using TATA MOTORS' NSE data, these models accurately forecasted prices for MARUTI, HCL, AXIS BANK (NSE), as well as BANK OF AMERICA and CHESAPEAKE ENERGY (NYSE). The study demonstrated the models' ability to identify patterns in both markets, revealing shared dynamics. DL models outperformed ARIMA and CNN excelled in capturing sudden changes, although the research did not explore hybrid network approaches for further improvement [17].

Manuel R. Vargas et al. proposed a deep learning approach combining financial news titles and technical indicators for predicting intraday directional movements of the S&P 500 index. Their study emphasized Convolutional Neural Networks (CNN) for extracting text meaning and Recurrent Neural Networks (RNN) for capturing context and temporal trends, achieving improved results over similar prior work. Notably, the model's utilization of news from the preceding day underscored the short-term impact of news articles on financial market predictions [18].

Qingfu Liu et al. innovatively treat stock price charts as images and utilize deep learning neural networks (DLNNs) to predict short-term price movements by integrating price charts and stock fundamentals. The study highlights the supremacy of deep learning over single-layer models in forecasting the Chinese stock market, underlining the importance of historical price trends in predicting future price changes compared to stock fundamentals [19].

Somenath Mukherjee et al. introduced a pair of approaches for predicting stock market trends. The first utilized a Feed-forward Neural Network with backpropagation, achieving 97.66% prediction accuracy but facing challenges with data volume and overfitting. Regularization was applied to address these issues. The second approach employed a Convolutional Neural Network, offering a more efficient solution with improved accuracy (98.92%) on a smaller dataset and training time, outperforming the initial model [20].

Yanli Zhao et al. proposed an innovative LSTM-based model enriched with sentiment analysis to predict stock market trends, acknowledging the impact of investor psychology. The study integrated sentiment indexes to capture emotional facets, utilizing Sentiment Analysis (SA) to convert textual content into daily sentiment indexes. The model's refinement with Denoising Autoencoders (DAE) improved its performance by extracting crucial information [21].

Abdul Quadir Md and collaborators present an innovative strategy for stock price prediction that employs a Multi-Layer Sequential Long Short Term Memory (MLS LSTM) model integrated with the Adam optimizer. This technique involves dividing normalized time series data into discrete time steps, effectively capturing historical and future associations and yielding remarkable prediction accuracy rates of 95.9% and 98.1% on the test dataset, outperforming alternative deep learning approaches. [22].

Arsalan Dezhkam et al. introduced HHT-XGB, a novel model that merges Hilbert-Huang Transform (HHT) for feature engineering and extreme gradient boost (XGBoost) for close price trend classification, facilitating the prediction of changing trends in upcoming close stock prices. The model's output sequence optimizing portfolio weights demonstrated a remarkable 99.8% improvement over raw financial data, surpassing benchmark strategies even in challenging market conditions, substantiated through back-testing results [23].

Liheng Zhang et al. introduced the State Frequency Memory recurrent network, designed to capture diverse trading patterns and enhance short and long-term stock predictions. Their novel approach demonstrates superior performance compared to conventional methods in real market data analyses [24].

Guanzhi Li et al. presented a novel framework consisting of Pearson Correlation Coefficient (PCC) and Bayesian Regularized Neural Network Least Squares (BLS), applied for short-term stock price prediction in Shenzhen and Shanghai Stock Exchanges. The approach involved using PCC to select relevant input variables from a pool of 35 variables, followed by training the BLS model with these chosen combinations. The PCC-BLS model demonstrated superior accuracy compared to ten other machine learning methods, as evidenced by results across five evaluation metrics [25].

Shouvik Banik et al. created an LSTM-based Decision Support System for accurate stock value prediction, catering to swing traders. The system generates comprehensive reports with forecasts for the next 30 days, incorporating technical indicators like MFI, RSI, Support and Resistance levels, Fibonacci retracement levels, and MACD analysis. The model's strong performance, boasting low error values, underscores its superiority over existing methods [26].

Stock prices are impacted by politics, economics, news, and investors use fundamental and technical analysis for predictions [27]. Fundamental analysis of a company's stock involves evaluating historical performance, anticipated future growth, and key factors such as profits, product quality, industry competition, financial balance, and cash flow projections [28]. Technical analysis involves predicting stock price trends through market trends and statistical data, addressing questions like optimal buying and selling times. It relies on tables, charts, and coefficients to make short-term and long-term predictions for specific stocks [28]. The review of existing studies and comparisons highlights the success of deep learning models like LSTM, ANN, RNN, SVM, SLSTM and BiLSTM in achieving accurate stock price predictions with minimal error. This prompts our exploration into studying these algorithms for potential research opportunities. We did a comparative study of all the machine learning algorithms used till date in financial instruments.

III. Implementation

A. Experimental Setup

In this research paper, our focus lies in implementing and comparing three distinct models: RNN, SLSTM, and BiLSTM. Our primary goal revolves around evaluating and contrasting their performance utilizing data sourced from the National Stock Exchange. Specifically, we're utilizing the NIFTY 50 index dataset, which covers a substantial 27-year timeframe, ranging from January 1, 1997, to December 31, 2021. This dataset comprises an extensive record of over 6000 days, detailing NIFTY 50 movements. The dataset includes data attributes such as Opening, High, Low, and Closing values. However, our primary attention within this study is focused on the Closing value, as our objective centers on forecasting daily index movements.

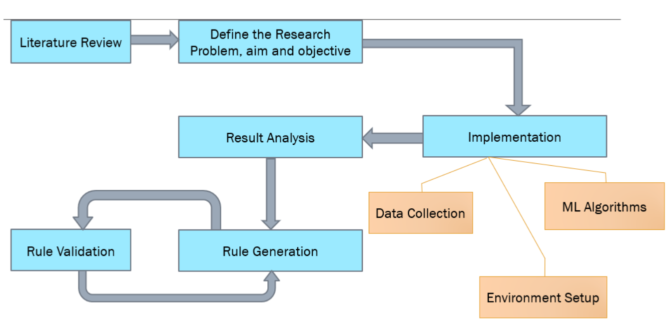


Fig. 1. Process flow diagram.

Throughout our experimental setup, we've meticulously partitioned the dataset into two segments: 70% for training and the remaining 30% for rigorous testing and validation purposes. This meticulous division allows us to methodically appraise the predictive prowess of the RNN, SLSTM, and BiLSTM models when applied to the NIFTY 50 dataset.

It's essential to note that during the data preprocessing phase, we've diligently filtered out records with missing closing values or date fields, as well as those with incorrect data types. This meticulous approach ensures the dataset's uniformity and consistency, providing a solid foundation for our models' assessments. Fig. 2 on page 935 displays the NIFTY 50 closing values from 1997 to 2021.

Fig. 2. NIFTY 50 movement from 1997 to 2021.

The Fig. 3 on page 936 illustrates the sequential process of our experimental framework, which is specifically designed for predicting the closing movements of NIFTY 50. Our approach involves the utilization of the deep learning model mentioned previously. In our experimentation, we systematically evaluated these models across three distinct setups. Our aim was to derive valuable rules from these evaluations and ultimately identify a model and combination of factors that not only yield high predictive accuracy but also enhance efficiency in forecasting NIFTY 50 closing movements.

B. Implementation of Recurrent Neural Network on Nifty 50 Index Dataset

RNNs are a Neural Network variant that handles sequences by utilizing the previous step's output as the current step's input. The standout feature is the hidden state, acting as memory, which preserves sequence information. This memory state, also called the Memory State, empowers the network to grasp sequential relationships and patterns in data. While Recurrent Neural Networks (RNNs) share the input-output structure with other deep neural architectures, they diverge in how information flows. Unlike traditional architectures with distinct weight matrices per layer, RNNs maintain consistent weights across the network. They compute hidden states (Hi) for inputs (Xi) using specific formulas, allowing the network to retain memory across sequences.

We employed the RNN algorithm for predicting NIFTY 50 index movements, utilizing a dataset spanning January 1, 1997, to December 31, 2021. Our strategy centered on forecasting closing values based on historical closing points. The structure consisted of four layers of regressors with a dropout rate of 0.2. Moreover, we integrated a dense layer housing a single neuron. Optimization was achieved through the utilization of the Adam optimizer, aiming to elevate the overall performance of the deep learning model. We systematically endeavored to enhance the model's predictive abilities through 12 diverse

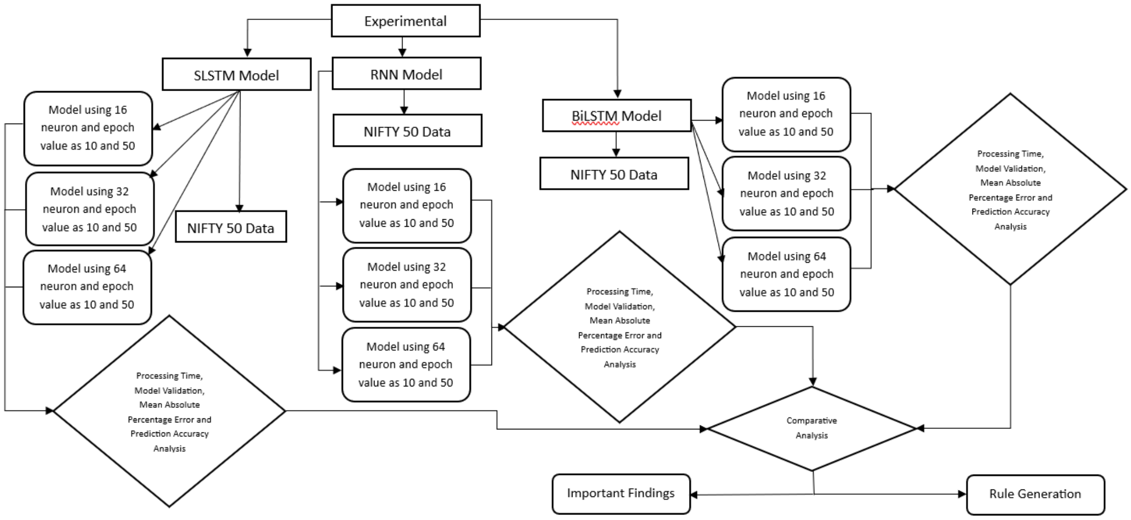


Fig. 3. Overall experimental framework.

TABLE I. RNN PREDICTION RESULTS

Sr.	Number of Neurons in RNN	Batch Size	Number of Neuron in Dense Layer	Epoch	Sequence Length	Training Time	Mean Absolute Percentage Error	Prediction Accuracy
1	16	10	1	10	15	104.81	1.97	98.03
2	32	10	1	10	15	122.66	2.38	97.62
3	64	10	1	10	15	143.77	2.02	97.98
4	16	10	1	50	15	487.67	2.33	97.66
5	32	10	1	50	15	588.08	1.75	98.25
6	64	10	1	50	15	643.61	3.7	96.3
7	16	32	1	10	15	44.19	4.06	95.94
8	32	32	1	10	15	49.04	1.60	98.40
9	64	32	1	10	15	58.62	1.59	98.41
10	16	32	1	50	15	193.112	1.77	98.23
11	32	32	1	50	15	218	1.81	98.19
12	64	32	1	50	15	242.26	1.35	98.65

combinations of neuron counts, batch sizes, and epochs. Here, epochs refer to the total number of complete passes made through the training dataset. The accompanying Table I on page 936 visually presents the outcomes of our tests, offering insights into the predictive efficacy of the RNN models across various configurations.

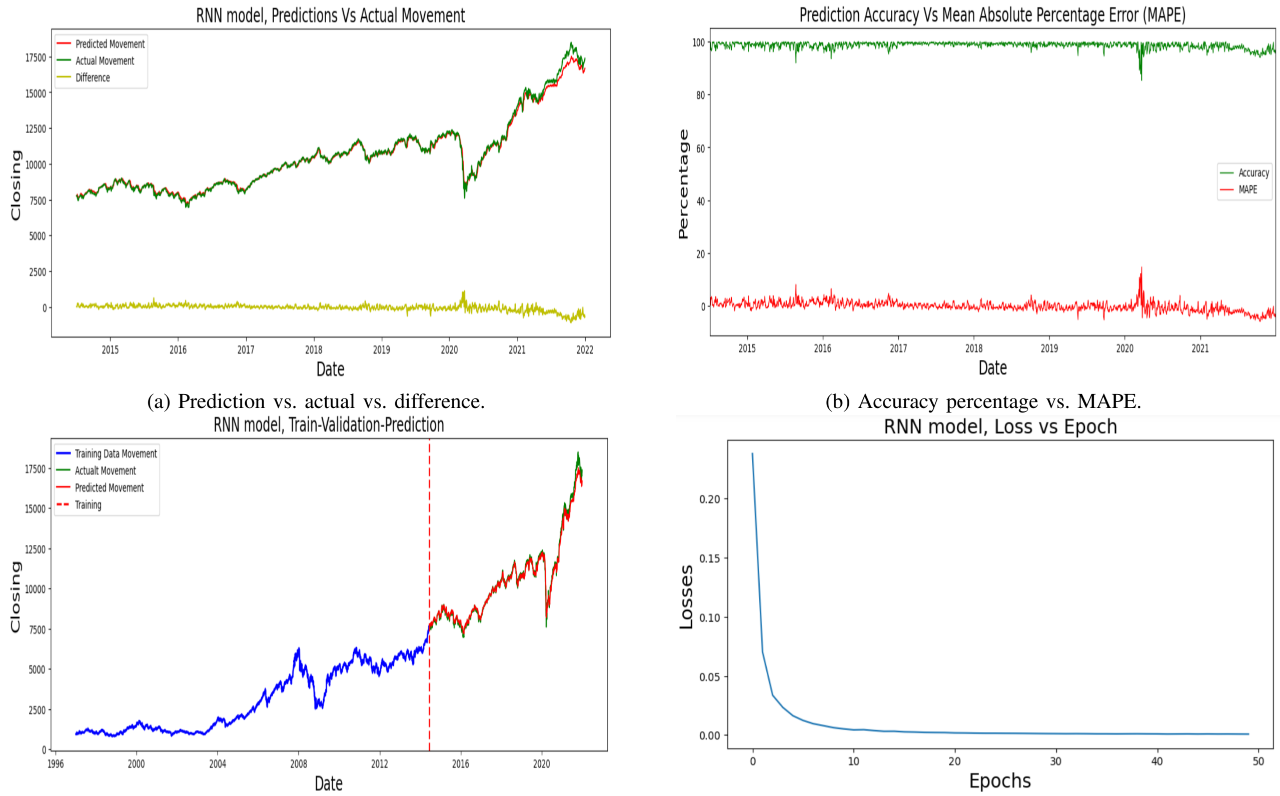
1) Result analysis: After a comprehensive analysis of the NIFTY 50 closing movement predictions using RNN across 12 distinct configurations (as outlined in Table I on page 936), we have identified a standout performer. Specifically, the RNN model with 64 neurons, a batch size of 32, and 50 training epochs consistently outperformed all other combinations in terms of prediction accuracy. Impressively, this configuration achieved an average prediction accuracy of 98.65%, demonstrating its robust performance. Additionally, the training time for this model was deemed satisfactory.

In Fig. 4(a), we present a visual comparison between the predicted and actual movement of NIFTY 50 closing prices, along with the associated differences. This graphical representation showcases the alignment of the predicted movement with the real data. Furthermore, Fig. 4(c) illustrates the training data's movement and provides a detailed comparison between the predicted and actual movements. The chart in Fig. 4(b) provides insights into the prediction accuracy versus error analysis, showcasing the model's proficiency in estimating values.

Graphs depicting the loss vs. epoch are a valuable tool for visualizing the training progress of a neural network. This graphical representation involves plotting the loss metric on the vertical axis against the number of training epochs on the horizontal axis. Each point along the line represents the loss value recorded in consecutive epochs. In this context, the Fig. 4(d) illustrates the loss vs. epoch graph for the RNN model that achieved the highest accuracy in predicting the movement. This visual representation allows for a clear understanding of how the model's loss evolves throughout the training process, offering insights into its learning dynamics and convergence.

C. Implementation of Stacked Long Short-Term Memory on Nifty 50 Index Dataset

LSTM (Long Short-Term Memory) stands out as a highly potent solution for tackling sequence prediction challenges. Its strength lies in its ability to retain past information, a critical factor for predicting future trends and records in daily QC items. Unlike traditional RNNs, LSTM networks effectively mitigate the issues of forgetting and gradient vanishing through the incorporation of self-loops and a unique internal gate structure. LSTM's unique architecture is characterized by four



(a) Prediction vs. actual vs. difference.

(b) Accuracy percentage vs. MAPE.

(c) RNN model implementation data.

(d) Losses vs. epoch.

Fig. 4. RNN model testing matrix (a) Prediction vs. actual vs. difference, (b) Accuracy Percentage vs. MAPE, (c) RNN model implementation data, (d) Losses vs. epoch.

essential gates: Input Gate, Cell State, Forget Gate and Output Gate. The forget gate plays a crucial role in determining which information is allowed to pass through the cell. Subsequently, the input gate decides how much new information should be incorporated into the cell state. Finally, the output gate regulates the information that is used for generating the output message. The development of the LSTM network was motivated by the necessity to address the challenge of vanishing gradients. The critical breakthrough in the design of LSTM involves incorporating non-linear, data-dependent controls into the RNN cell. These controls are trainable elements that serve the purpose of preventing the gradient of the objective function from diminishing in relation to the state signal. This innovation significantly boosts the network's ability to learn during training and enhance its predictive potential [29].

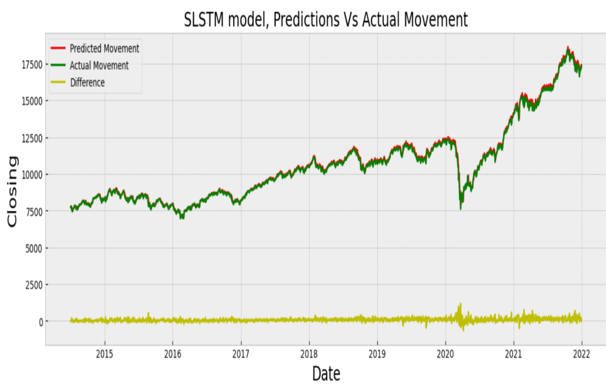
A SLSTM, an extension of the LSTM architecture, involves layering multiple LSTM units to process sequential data. Each layer in the stack handles output sequences from the preceding one, enabling the model to grasp intricate patterns. This layered structure enhances the model's ability to learn hierarchical features and representations in the data, similar to deep neural networks. Stacked LSTMs excel in capturing complex temporal patterns in sequences, making them valuable for tasks like time series prediction, natural language processing, and speech recognition. The accompanying Table II on page 938 visually presents the outcomes of our tests, offering insights into the predictive efficacy of the SLSTM models across various configurations.

1) Result analysis: Upon conducting a comprehensive analysis of NIFTY 50 closing movement predictions using SLSTM across 12 distinct configurations (as detailed in Table II on page 938), a clear standout has emerged. Specifically, the LSTM model featuring 32 neurons, a batch size of 10, and 50 training epochs consistently demonstrated superior predictive accuracy compared to all other parameter combinations. Notably, this configuration achieved an impressive average prediction accuracy of 99.10%, underscoring its robust performance. Moreover, the training time for this model was deemed satisfactory. Similarly, the model with 64 neurons, 50 epochs, and batch sizes of 10 and 32 yielded comparable accuracy rates of 99.01% and 99.08%, respectively. The analysis revealed that even the lowest achieved prediction accuracy was 98.03%. It's noteworthy that all 12 tested LSTM configurations yielded prediction accuracies exceeding 98%.

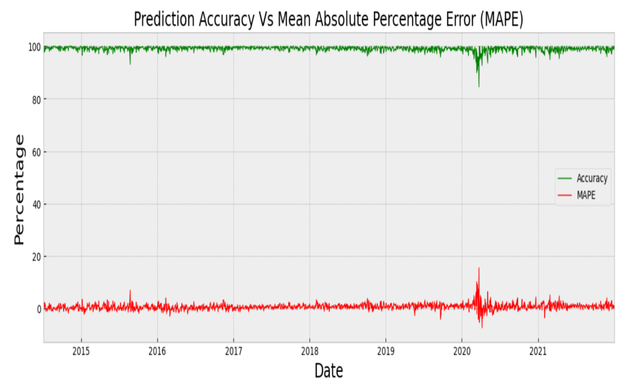
To provide a visual representation of our findings, Fig. 5(a) offers a comparison between predicted and actual NIFTY 50 closing price movements, along with the corresponding discrepancies. This graphical presentation effectively showcases the alignment between predicted and actual trends. Additionally, Fig. 5(c) highlights the movement in the training data and offers a comprehensive juxtaposition of predicted and actual trends. Finally, Fig. 5(b) presents a chart depicting the relationship between prediction accuracy and error, further demonstrating the model's adeptness at value estimation. Fig. 5(d) illustrates the loss vs. epoch graph for the SLSTM model that achieved the highest accuracy in predicting the movement.

TABLE II. SLSTM PREDICTION RESULTS

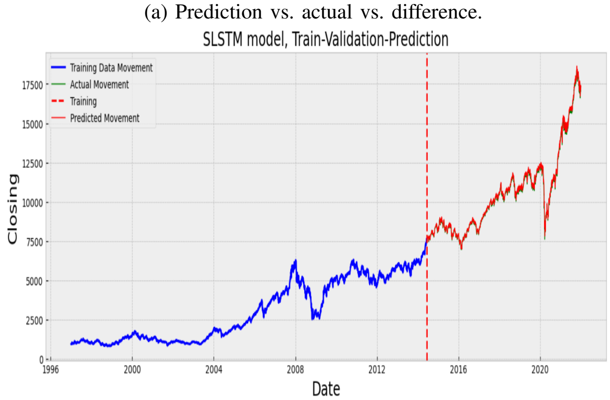
Sr.	Number of Neurons in SLSTM	Batch Size	Number of Neuron in Dense Layer	Epoch	Sequence Length	Training Time	Mean Absolute Percentage Error	Prediction Accuracy
1	16	10	16, 1	10	15	30.60	1.70	98.3
2	32	10	16, 1	10	15	30.14	1.70	98.30
3	64	10	16. 1	10	15	34.19	1.00	99.00
4	16	10	16, 1	50	15	148.07	1.10	98.90
5	32	10	16, 1	50	15	156.50	0.9	99.10
6	64	10	16, 1	50	15	185.01	0.99	99.01
7	16	32	16, 1	10	15	15.94	1.60	98.40
8	32	32	16, 1	10	15	15.46	1.40	98.60
9	64	32	16, 1	10	15	19.08	1.37	98.63
10	16	32	16, 1	50	15	66.77	1.04	98.96
11	32	32	16, 1	50	15	68.68	1.02	98.98
12	64	32	16, 1	50	15	87.23	0.92	99.08



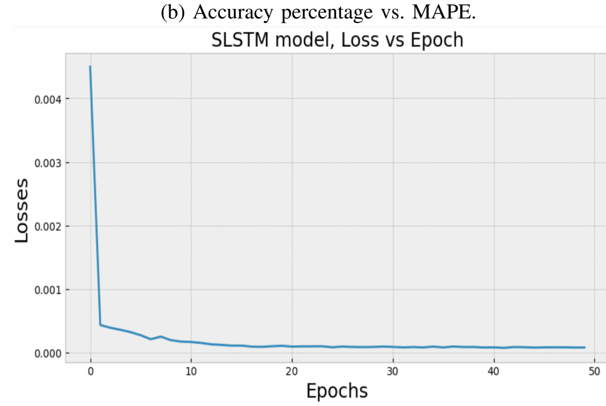
(a) Prediction vs. actual vs. difference.



(b) Accuracy percentage vs. MAPE.



(c) SLSTM model implementation data.



(d) Losses vs. epoch.

Fig. 5. SLSTM model testing matrix (a) Prediction vs. actual vs. difference, (b) Accuracy percentage vs. MAPE, (c) SLSTM model implementation data, (d) Losses vs. epoch.

D. Implementation of Bidirectional Long Short-Term Memory on Nifty 50 Index Dataset

A Bidirectional LSTM, abbreviated as BiLSTM, is a sequence processing architecture composed of two LSTMs. One LSTM processes input data in the forward direction, while the other processes it in reverse. This dual approach significantly enhances the information accessible to the network, thereby enriching the contextual understanding of the algorithm. For instance, in text analysis, a BiLSTM comprehends not only the current word but also the words that follow and precede it in a sentence, amplifying its contextual awareness. The accompanying Table III on page 939 visually presents the outcomes of our tests, offering insights into the predictive efficacy of the BiLSTM models across various configurations.

1) Result analysis: After a comprehensive evaluation of NIFTY 50 closing movement predictions using BiLSTM across 12 distinct configurations (as outlined in Table III on page 939), a prominent frontrunner has surfaced. Specifically, the BiLSTM model with 64 neurons, a batch size of 32, and 50 training epochs consistently exhibited superior predictive accuracy compared to all other parameter combinations. This configuration notably achieved an impressive average prediction accuracy of 96.27%, highlighting its robust performance. Additionally, the training time for this model was satisfactory.

TABLE III. BiLSTM Prediction Results

Sr.	Number of Neurons in BiLSTM	Batch Size	Number of Neuron in Dense Layer	Epoch	Sequence Length	Training Time (Seconds)	Mean Absolute Percentage Error	Prediction Accuracy
1	16	10	10,5,1	10	20	81.76	20.99	79.01
2	32	10	10,5,1	10	20	66.44	47.90	52.10
3	64	10	10,5,1	10	20	177.06	51.10	49.90
4	16	10	10,5,1	50	20	335.74	12.97	87.03
5	32	10	10,5,1	50	20	313.74	13.43	86.57
6	64	10	10,5,1	50	20	677.32	45.25	54.75
7	16	32	10,5,1	10	20	32.86	7.72	92.28
8	32	32	10,5,1	10	20	28.88	4.19	95.81
9	64	32	10,5,1	10	20	96.95	4.69	95.31
10	16	32	10,5,1	50	20	114.81	4.87	95.13
11	32	32	10,5,1	50	20	117.90	6.49	93.51
12	64	32	10,5,1	50	20	377.99	3.73	96.27

However, it's worth noting that the model with 32 neurons, 10 epochs, and batch size of 10 indicated underfitting, while the model with 64 neurons, batch sizes of 10 and 32, and epochs of 10 and 50 demonstrated overfitting. These outcomes yielded prediction accuracies that were suboptimal for our NIFTY 50 trend prediction dataset.

To visually depict our conclusions, Fig. 6(a) provides a comparative view of predicted and actual NIFTY 50 closing price movements, along with discrepancies. Fig. 6(c) presents the movement in training data, effectively comparing predicted and actual trends. Fig. 6(b) offers a chart illustrating the connection between prediction accuracy and error, underscoring the model's proficiency in value estimation. Additionally, Fig. 6(d) showcases the loss vs. epoch graph for the RNN model with the highest predictive accuracy. In summary, the identified BiLSTM configuration demonstrates significant promise for NIFTY 50 trend prediction.

IV. Comparative Study and Future Research Opportunities

Based on our analysis of the RNN, SLSTM, and BiLSTM models, the SLSTM model emerged as the standout performer for predicting NIFTY 50 closing movement, achieving an impressive prediction accuracy of 99.10%. The RNN model also showcased strong predictive capabilities, yielding an average accuracy of 98.65%.

However, in contrast, the BiLSTM model did not demonstrate consistent success across various cases. In its most favorable scenario, the BiLSTM model achieved an average accuracy of 96.27%. It's noteworthy that the training time of the BiLSTM model was comparatively higher when compared to SLSTM and RNN. Additionally, the BiLSTM model was more susceptible to issues of both underfitting and overfitting. In summary, the SLSTM model showcased remarkable predictive prowess, while the RNN model also performed well. On the other hand, the BiLSTM model faced challenges and did not consistently match the accuracy levels achieved by the other two models. Fig. 7(a) illustrates the comparison of predicte values, while Fig. 7(b) depicts the accuracy of predicted movements of the models.

This study has advanced our understanding of stock market prediction but also highlights several promising directions for future research. Enhancing prediction accuracy through the refinement of existing models, including the integration of external data sources, is a key avenue. Exploring alternative deep learning architectures and hybrid models holds potential for improved results. Moreover, incorporating sentiment analysis from various sources such as financial news, social media, and macroeconomic factors can offer a more comprehensive understanding of market movements. Investigating the interpretability of deep learning models and their capacity to capture underlying market dynamics is essential for their practical acceptance and use in the real world.

V. Conclusion

After a thorough exploration of diverse algorithms, we have uncovered their significant relevance within stock markets. Given the intricate interplay of factors shaping stock market dynamics, there exists a compelling opportunity to refine and elevate the algorithms and models employed for predicting stock prices. Our comparative analysis has illuminated the robust performance of deep learning models, including LSTM, ANN, RNN, SLSTM, and BiLSTM, in efficiently forecasting stock prices with minimal errors. To delve deeper, we focused on implementing RNN, SLSTM, and BiLSTM deep learning models within this study, harnessing a comprehensive 27-year dataset of NIFTY 50 data as our input. Our methodology allocated 70% of the dataset for model training, reserving the remaining 30% for validation purposes.

During the validation phase, our findings emphatically underscored the superior predictive capabilities of the SLSTM model. It consistently outperformed the other three models in accurately predicting the closing movement of the NIFTY 50 index, achieving an impressive average accuracy of 99.10%. Our analysis further unveiled captivating behaviors inherent in deep learning models, presenting avenues for subsequent exploration and model refinement. By enhancing the consistency of error patterns and elevating accuracy, these models' efficacy can be further amplified. Furthermore, our research lays the groundwork for extending prediction prowess to both short-term and long-term future movements. The scope of its applicability can be expanded to encompass stock prices within other sectors, thereby fostering new realms of inquiry.

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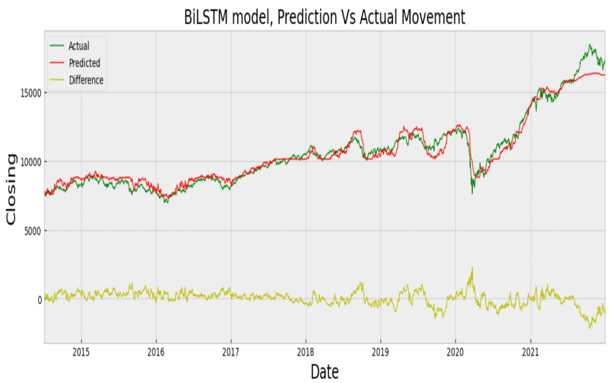
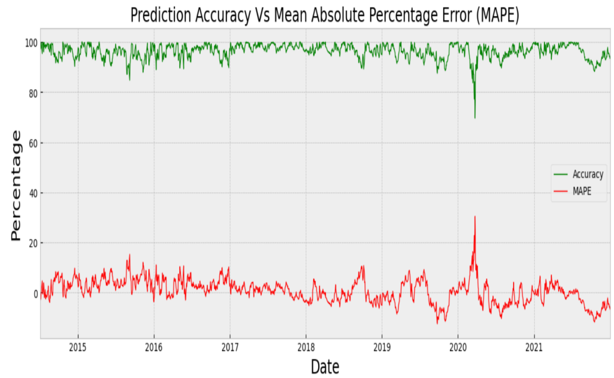
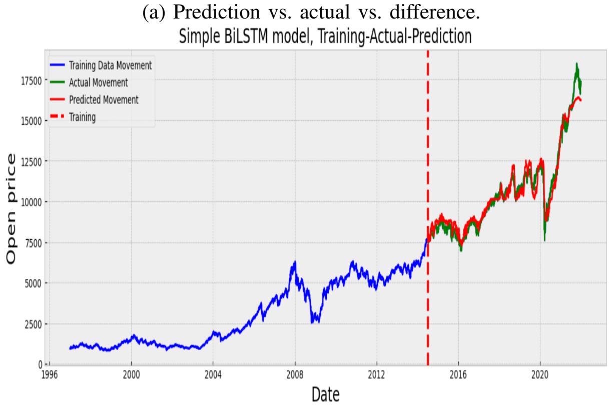


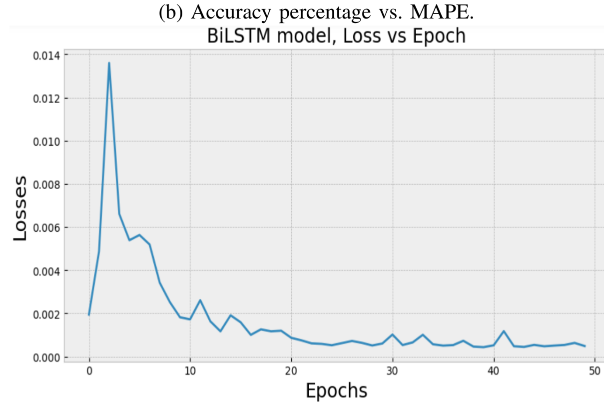
(a) Prediction vs. actual vs. difference.



(b) Accuracy percentage vs. MAPE.

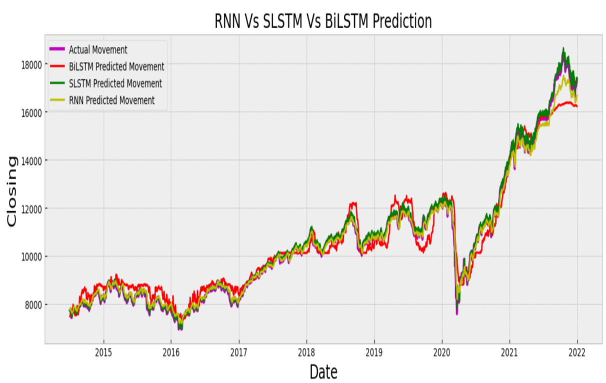


(c) BiLSTM model implementation data.

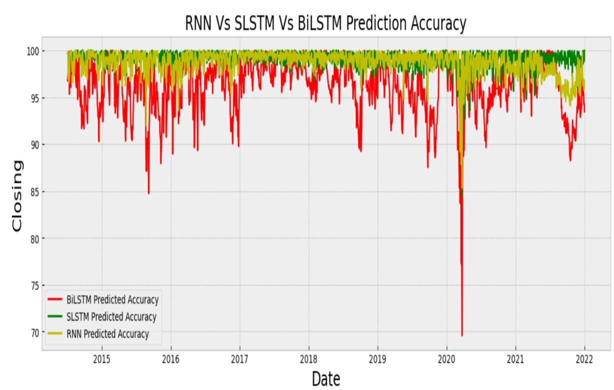


(d) Losses vs. epoch.

Fig. 6. BiLSTM model testing matrix (a) Prediction vs. actual vs. difference, (b) Accuracy percentage vs. MAPE, (c) SLSTM model implementation data, (d) Losses vs. epoch.



(a) RNN vs. SLSTM vs. BiLSTM prediction.



(b) RNN vs SLSTM vs BiLSTM prediction accuracy.

Fig. 7. (a) RNN vs. SLSTM vs. BiLSTM prediction, (b) RNN vs. SLSTM vs. BiLSTM prediction accuracy.

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