Predictive Analysis of S&P BSE Greenex Index: Unlocking Insights for Sustainable Investments

Noella Nazareth[1] and Y V. Reddy[2]*

Abstract

The COVID-19 pandemic has led to reduced economic and industrial activities, prompting a noticeable transition towards a more sustainable way of life. This could indicate that we are on the path to reducing our carbon footprint in the long term. Consequently, analysed the performance of India's sustainability index, the S&P BSE GREENEX, which assesses the sector-wise carbon performance of stocks. It comprises stocks selected based on their energy efficiency performance using publicly disclosed financial and energy data. Forecasting the stock market is critical when formulating investment strategies. Considering the profound negative impact of the COVID-19 pandemic on global stock markets, investment decisions are becoming increasingly challenging and riskier, especially when channelling funds towards green technologies and clean energy. This study analysed the predictive accuracy of the Long Short-Term Memory (LSTM) deep learning model for Indian companies that promote sustainability through their investment decisions during and after the COVID-19 period. The empirical outcomes demonstrate the ability of the LSTM model to generate fairly precise predictions for a wide spectrum of companies across diverse sectors; during and after the crisis. These findings provide valuable insights for investors seeking to make informed decisions regarding sustainability-focused investments as represented by the S&P BSE GREENEX Index.

JEL: C45, C53, D81, Q01 **SDG:** SDG 17, Target 17.J

Keywords: S&P BSE GREENEX, COVID-19, LSTM, Predictive analysis, Time series forecast, Sustainability

[1] Goa Business School, Goa University, Goa, 403206, India.
[2] Goa Business School, Goa University, Goa, 403206, India. Corresponding Author: yvreddy@unigoa.ac.in.

1. INTRODUCTION

The outbreak of the global pandemic in 2019 had far-reaching impacts of unprecedented magnitude on the global economy. The stringent curfew taken to maintain social distancing by restricting travel, locking down populations, and reducing industrial and economic activities has positively contributed to a sustainable environment. Greenhouse gases emitted by transportation, industries, and fossil fuel burning declined during the COVID-19 pandemic (Mohsin, et al., 2021). This implies that controlling human activities can enhance environmental quality. According to the International Energy Agency (IEA) report on Global Energy Review: CO_2 Emissions in 2021, the global economic output of advanced economies such as the United States, European Union, and Japan recovered to pre-pandemic levels in 2021, but CO_2 emissions rebounded less sharply (IEA, 2022). The effects of the pandemic have prompted a global reflection on a more sustainable way of life in various aspects and could be a sign that we are on the path to reducing our carbon footprint in the long run. As governments sought to revive the economy, many included investments in green technologies and clean energy in their stimulus packages. This has accelerated the transition from non-renewable to renewable energy sources. More than 100 national governments, including the EU, China, Japan, and South Africa, have established or are contemplating net-zero emission targets (Höhne, et al., 2020). Moreover, the energy sector contributes three-quarters of the greenhouse gas emissions and is a crucial area for mitigating the worst impact on climate change. Transitioning away from environmentally harmful sources such as coal, gas, and oil-filled power with renewable sources of energy such as wind or solar energy, would drastically reduce carbon emissions. This clearly indicates that clean energy must be a priority for the global economy.

According to a report published by the World Economic Forum (2022), India pledged to achieve net zero emissions by 2070 at COP26 in Glasgow in 2021. India has also announced its ambition to produce 50% of its energy from renewable energy sources by 2030. Commitment to achieving these targets significantly affects businesses and investments in the Indian economy. With an emphasis on reducing emissions, opportunities in the electric vehicle sector, EV charging networks, and public transportation have increased. Sustainable agricultural practices, agroforestry, sustainable packing, recycling, and waste management are areas that align with net-zero goals. Businesses involved in renewable energy production and infrastructure development are likely to experience greater demand.

The concepts of Socially Responsible Investing (SRI) and green financing have gained momentum during the last few years. Responsible investing is an investment approach that considers its impact on both society and the natural environment to ensure sustainability. SRI includes investments in fewer toxic-producing firms, engagement in environmentally sustainable firms, and investment in clean technologies. Green financing channelizes financial resources towards projects considering Environmental, Social, and Governance (ESG) criteria and promotes sustainability through investment decisions. Businesses that prioritize ESG principles and are involved in energy-efficient production and services are likely to attract more investments. There has been a notable shift in global trends, positioning clean energy stocks as increasingly attractive investments (Coskun, et al., 2023). In this context, there is escalating interest in investigating the performance of indices revolving around companies that prioritize sustainable practices. Consequently, we undertake an empirical study focused on India’s financial market sustainability index, namely the S&P BSE GREENEX index.

Sustainable indices offer investors valuable information on companies' emphasis on environmental conservation and social accountability. Several indices are constructed using parameters that assess the trustworthiness of companies in their commitment to responsible practices. While some studies focus on low carbon emissions, others consider a broader ESG approach. For example, The FTSE4Good index of Europe was constructed to reflect companies' performance and adherence to specific ESG criteria. The FTSE Global Climate Index is designed to represent securities whose weights are based on three types of climate-related analyses: carbon emissions, fossil fuel reserves, and green revenue data. The Dow Jones Sustainability World Enlarged Index represents the top 20 percent of the largest 2,500 companies in S&P Global BMI based on their adherence to long-term environmental, economic, and social criteria. The S&P BSE GREENEX index comprises the top 25 companies chosen from the S&P BSE 100 based on factors such as liquidity, size, and minimal greenhouse gas emissions. It is India's first environmentally friendly equity index to be publicly available in real time, and evaluates companies 'carbon performance' solely through quantitative performance criteria. The S&P BSE GREENEX serves as a tool for retail and institutional "green" investors to monitor the performance of the largest and most liquid energy-efficient stocks in the Indian stock market.

International investors and policymakers have shown considerable interest in sustainable financing, particularly in emerging markets. This heightened interest follows a notable surge in investments across diverse asset classes by 2021, as highlighted by Goel et al., (2022). This accelerated momentum came after sustainable finance strategies became more mainstream due to pandemic-induced demand and was also reflected in the adoption of green borrowing strategies in Latin America. The Governments, businesses, and consumers have recognized the need for environmentally and socially responsible practices. Numerous studies have identified a favourable relationship between financial performance and ESG, particularly concerning metrics such as Return on Equity and Return on Asset. This implies that investing in companies with high ESG performance ensures financial returns in terms of value and profitability (Aydogmus, et al., 2022). Strong ESG performance contributes to enhanced market stability and increased market liquidity even during the pandemic, as highlighted by Liu et al., (2023). The NYU Stern Centre for Sustainable Business and Rockefeller Asset Management examined the relationship between financial performance and ESG from 2015 to 2020 and drew interesting conclusions. First, the improvement in financial performance due to ESG became more apparent over extended periods. Second, ESG investment provided downside protection, especially during social or economic crises. Studies indicate that managing a low-carbon future improves a company's financial performance (Whelan, et al., 2021).

On studying the dynamic links between low carbon equities and conventional equities, De Souza Gabriel, Lozano, & Matias (2022) conclude that low carbon economy indices do not behave like conventional indices in the long run. This offers room for diversification by investing in low-carbon investments as an alternative to traditional equity investments in the international context. Wang, Tang, and Guo (2022) employed a hybrid CEEMDAN-LSTM to forecast the CUFE-CNI High-Grade Green Bond Index. Their findings suggest that the crude oil and environmental stock markets influence the green bond market and could be essential predictors in forecasting the same. Numerous studies in this field also employ stock market data to forecast carbon price emissions and carbon emission trading (Hong, et al., 2017) (Dutta, 2018) (Zhang & Wen, 2022) (Zhang, et al., 2022) (Shahzad, et al., 2023).

Predicting stock market behaviour during a crisis is challenging because of market volatility, emotional trading, lack of historical precedent, government interventions, and global interconnectedness, making it non-continuous, non-linear, and highly volatile (Bhadkamar & Bhattacharya, 2022). Existing research demonstrates that events that surpass four to ten times the standard deviation of normal events are commonly categorized as extreme events (Rai, et al., 2023). Mahata et al., (2021) classified the COVID-19 pandemic as an extreme event, where the instantaneous energy surpasses the threshold of the sum of the mean and four times the standard deviation of the energy. The outbreak of the pandemic caused dramatic fluctuations in stock markets, prompting many studies to make predictions in its aftermath. Studies investigating the impact of coronavirus on stock markets recorded fluctuations in the time series of capital markets during various phases of the disease, indicating that the market's response to COVID-19 varied depending on the stage/phase of the pandemic (Ramelli & Wagner, 2020) and had a significant impact on the energy markets (Lahmiri, 2023).

Jena and Majh (2023) compared the performance of statistical and deep learning models to forecast the consumer goods, healthcare, technology, and the financial sectors of Nifty and the DJIA. In their study, ARIMA, linear regression, and Long Short Term Memory (LSTM) were employed, and the findings indicated the superiority of LSTM in generating predictions that were more precise than statistical models. In an alternative comparative study, it was discovered that KNN outperformed LSTM and ARIMA in predicting the CAC40 index of France based on high and low prices for optimistic and pessimistic decision making (Lachaab & Omri, 2023). Omar, Huang, Salameh, Khurram, and Fareed (2022) applied two hybridized models, ARIMA-Deep learning and ARIMA-Random Forest to forecast the Karachi Stock Exchange (KSE) 100 index closing price before and during the COVID-19 pandemic period. The study's findings revealed that ARIMA – deep learning models outperformed ARIMA – Random Forest in the pre-COVID period and vice versa during COVID-19. The authors suggest that these results could be attributed to the substantial volume of pre-COVID observations and fewer observations during COVID-19. Biswas, Bandyopadhyay, & Mukhopadhyaya (2022) analysed the impact of COVID-19 on firm performance in the FMCG and consumer durables sector by considering five dimensions, namely: stock performance, sales and operational performance, dividend pay-out capability, economic sustainability, and financial stability.

Chandra and He (2021) tested the performance of Bayesian Neural Networks in an attempt to predict the prices of stocks belonging to four different regions Germany, China, Australia, and the United States at multi-steps (1-5 days) ahead. On comparing the Root Mean Squared Error (RMSE) of this model with that of feedforward neural networks with Adam optimizer and stochastic gradient descent, the Bayesian neural network demonstrated superior performance with an increase in RMSE as the prediction horizon increased. In another study, Wang and Zhao (2021) validated the performance of Bayesian networks for variable selection in predicting carbon prices

Goel and Som (2023) predicted the Nifty50 index by employing macroeconomic variables and global stock market variables as inputs for the two subperiods, that is, the pre-COVID period and during the COVID period. The ANN model employed in this study achieved 96.99% accuracy pre-COVID and 99.85% accuracy during the COVID-19 period. Mukherjee, Sadhukhan, Sarkar, Roy, & De (2021) showed the outperformance of a Convolutional Neural Network (CNN) over ANN in predicting the Nifty index during extreme market fluctuations, that is, during the peak period of the COVID pandemic from March to April 2020, with an accuracy of 91%.

Machine learning algorithms were able to detect the S&P500 pandemic recession by December 2019, that is, six months before the official announcement by the National Bureau of Economic Research, and the S&P500 market crash two months before its occurrence, using past monthly macroeconomic data as inputs (Malladi, 2022). On studying the importance of predictors before and during the COVID-19 period across 19 equity indices, Wang, Lu, He, & Ma (2020) found that VIX (regarded as the "panic index") was more helpful in predicting stock market volatility as compared to EPU. Budiharto (2021) employed LSTM to forecast Indonesian stock market prices by training the model with historical datasets of 1-year, 3-years, and 5-years. Based on the achieved outcomes with an accuracy of 94.57%, the authors suggest using short-term (1-year) historical data for training. The construction, functioning, and application of LSTM algorithm for stock market forecasting are summarised by Chhajer, Shah, & Kshirsagar (2022).

Concerning the impact of COVID-19 on sustainability indices, a study by Chang, McAleer, & Wang (2020) discovered that the pandemic led to diminished stock returns within the fossil fuels sector. Conversely, investments shifted towards clean energy, which yielded relatively higher returns. Similarly, Vadithala and Tadoori (2021) found that the ESG indices on NSE are more efficient in the post-COVID period than in the pre-COVID period and that investors leaned towards ESG indices post the pandemic. Sharma (2022) observed that post-COVID returns outperformed the pre-COVID returns of the S&P BSE GREENEX index, signalling that sustainable finance brings stability to the financial market. The author also forecasts the returns of this index by employing Value at Risk (VaR) method. Gurung and Sarkar (2023) empirically tested the market efficiency of the S&P BSE GREENEX constituents. The study statistically confirmed that the returns do not obey the 'Random Walk Hypothesis,' Thus concluding that the EMH does not hold well for the S&P BSE GREENEX index.

The S&P BSE GREENEX Index is a crucial benchmark for India's commitment to achieving net-zero emissions by 2070. As this index represents the top 25 environmentally responsible companies in India, it serves as a barometer of the sustainability of these companies and the broader sustainable investment landscape in the country. Indian businesses that prioritize ESG criteria are likely to attract more investment, thus becoming an interesting area of research. In addition, the literature review underscores insufficient research on predicting the S&P BSE GREENEX Index, which serves as the driving force for this study.

In this study, we employed LSTM, a deep learning model, to predict the future values of the S&P BSE GREENEX index. Ample studies have utilized machine learning and deep learning models to forecast the future values of selected stocks/indices. However, to the best of our knowledge, no study has focused on predicting the prices of sustainable indices, particularly the GREENEX index. This research marks pioneering effort in applying deep learning models to forecast the S&P BSE GREENEX index. Furthermore, in line with the literature suggesting a shift towards diversifying investments into ESG indices amid the COVID-19 pandemic, our research aims to forecast not only the index values during the pandemic but also the prices of the individual stocks that comprise the index after this period.

The structure of the study is as follows: The above section on the introduction includes a literature review, research gaps, and motivation for the study. The methodology is explained in section 2, followed by the results and analysis in section 3. The conclusions and implications of this study are provided in Section 4.

2. METHODOLOGY

2.1 Data Collection

This research endeavours to forecast the next trading day's closing price of the S&P BSE GREENEX index and its constituents on the emerging Indian economy during and after the COVID-19 pandemic. Our forecasting analysis includes two datasets. Dataset I range from 22nd February 2012 to 13th September 2022. The start date corresponds to the launch of S&P BSE GREENEX index. The forecasting analysis is limited to 13th September 2022 to ensure that 25% of the data belonging to the test set covers the COVID-19 period, including the lockdown, the declaration of COVID-19 as a pandemic, and the pandemic waves. Dataset II covers the period from 11th May 2021 to 31st December 2023, representing the post COVID-19 period. The beginning of the test period i.e., 5th May 2023, marks the declaration by the WHO that COVID-19 is no longer a Public Health Emergency. In this study, the independent variables include open, high, and low prices, with the close price as the target variable. The daily market data for the index and constituent stocks are sourced from www.bseindia.com.

Table 1: Train test split

	Train (75%)	Test (25%)
During COVID-19	22nd February 2012 to 27th January 2020	28th January 2020 to 13th September 2022
Post COVID-19	11th May 2021 to 4th May 2023	05th May 2023 to 31st December 2023

Source: Author's compilation

Our study aimed to predict the index values during and after the COVID-19 global pandemic, and thus, the dataset was split accordingly. A split was performed on the dataset, allocating 75% for training and 25% for testing (details are provided in Table 1). From the training dataset, 20% was used for validation. As the order of the data is critical in timeseries prediction, it was divided into consecutive windows of validation. For illustration, we employed a sliding window approach in which the initial forty-two observations (from the first to the forty-second) were utilized to predict the subsequent observation. In the subsequent sliding window, we employed observations from the second to the forty-third to forecast the next consecutive observation, and this pattern continues iteratively. Here, 21 observations are the average trading days in a month, while 42 observations (used for training) represent the average trading days in two months. The test set was meticulously formed from 30 time stamps preceding the announcement of COVID-19 as a global pandemic on 11th March 2020. This methodology ensures that our forecasting analysis accounts for the dynamics leading to this critical event.

The constituent stocks selected for the prediction comprise the S&P BSE GREENEX Index as of 31st August 2023. However, due to the unavailability of data for four stocks since 2012, they have been excluded from this study. A compilation of the stocks selected for this forecasting analysis is presented in Table 2.

Table 2: Selected stocks and Sector classification

Sector	Stocks	Industry	Industry Sub Group
Commodities	Pidilite Industries Ltd	Chemicals	Speciality Chemicals
	Adani Enterprises Ltd	Metals & Mining	Trading – Minerals

	Grasim Industries Ltd	Construction Materials	Cement & Cement Products
	Hindalco Industries Ltd	Metals & Mining	Aluminium
	SRF Ltd	Chemicals	Speciality Chemicals
Consumer Discretionary	Tata Motors Co Ltd	Automobile and Auto Components	Passenger Cars & Utility Vehicles
	Mahindra & Mahindra Ltd	Automobile and Auto Components	Passenger Cars & Utility Vehicles
	Maruti Suzuki India Ltd	Automobile and Auto Components	Passenger Cars & Utility Vehicles
	Titan Co Ltd	Consumer Durables	Gems, Jewellery and Watches
	Info Edge (India) Ltd	Retailing	Internet & Catalogue Retail
Health Care	Sun Pharmaceutical Industries Ltd	Pharmaceuticals & Biotechnology	Pharmaceuticals
	Divi's Laboratories Ltd	Pharmaceuticals & Biotechnology	Pharmaceuticals
	Apollo Hospitals Enterprise Ltd	Healthcare Services	Hospital
Financial Services	Bajaj Finance Ltd	Finance	NBFC
	ICICI Bank Ltd	Banks	Private Sector Bank
Industrials	Siemens India Ltd	Capital Goods	Heavy Electrical Equipment
	Bharat Electronics Ltd	Capital Goods	Aerospace & Defence
Services	Adani Ports and Special Economic Zone	Transport infrastructure	Port & Port services
Energy	Reliance Industries Ltd	Oil, Gas & Consumable Fuels	Refineries & Marketing
Utilities	Power Grid Corporation of India Ltd	Power	Power Transmission
Consumer Staples	Hindustan Unilever Ltd	Fast Moving Consumer Goods	Diversified FMCG
Information technology	Infosys Ltd	IT - Software	Computers - Software & Consulting

Source: Compiled from BSE India

2.2 Long Short-Term Memory (LSTM)

Predicting stock market movements necessitates an understanding of a dynamic system because of the highly volatile non-linearity of financial time series (Qiu, et al., 2016). Price return time series exhibit certain regularities associated with market patterns, suggesting the potential to develop trading strategies that could yield risk-free profits (Shternshis, et al., 2022). LSTM can capture and learn these non-linear connections between input data and desired outputs. A neural network is a series of algorithms that endeavours to recognize underlying relationships in data through a set of processes that mimic the manner in which the human brain operates. Hence, numerous considerations are involved in constructing neural networks. These include the choice of number of hidden layers and neurons and their activation functions, network architecture, and parameters. We explored various architectures and parameters through experimentation, to obtain optimal configurations. Subsequently, the performance of the optimal network was employed for further comparison.

Hochreiter and Schmidhuber (1997) introduced LSTM networks that underwent subsequent refinements in the ensuing years by Gers, *et al.,* (2000) and Graves and Schmidhuber (2005). LSTM networks are explicitly designed to grasp long-term dependencies or sequential patterns, overcoming the inherent challenges prevalent in RNNs. It retains information over a longer period than RNNs do (Fischer & Krauss, 2018). The structure of an LSTM network comprises an input layer, hidden layers, and output layer. These networks were distinguished by the incorporation of memory cells. These memory cells serve as crucial network components, facilitating the retention and utilization of contextual information over extended sequences.

LSTM cell takes three different pieces of information: the current input sequence x_t, the short-term memory from the previous cell h_{t-1}, and the long-term memory from the previous cell state c_{t-1} at time t. The forget gate takes the information from x_t and h_{t-1} and produces the output between 0 and 1 through the sigmoid layer, and then it identifies which information to discard from the previous cell state c_{t-1}. When the value is 1, it stores all the information in the cell, while with a value of 0, it forgets all the information from the previous cell state. The calculations for each state and gate are as follows:

$$f_t = sigmoid\ (W_{f,x}x_t + W_{f,h}h_{t-1} + b_f) \tag{1}$$

$$\hat{s}_t = tanh\ (W_{\hat{s},x}x_t + W_{\hat{s},h}h_{t-1} + b_{\hat{s}}) \tag{2}$$

$$i_t = sigmoid\ (W_{i,x}x_t + W_{i,h}h_{t-1} + b_i) \tag{3}$$

$$s_t = f_t \circ s_{t-1} + i_t \circ \hat{s}_t \tag{4}$$

$$o_t = sigmoid\ (W_{o,x}x_t + W_{o,h}h_{t-1} + b_o) \tag{5}$$

$$h_t = o_t \circ tanh\ (s_t) \tag{6}$$

Where, $W_{f,x}$, $W_{f,h}$, $W_{\hat{s},x}$, $W_{\hat{s},h}$, $W_{i,x}$, $W_{i,h}$, $W_{o,x}$, *and* $W_{o,h}$ denote weight matrices, b_f, $b_{\hat{s}}$, b_i, and b_o denote bias vectors, f_t, i_t, and o_t signify vectors representing the activation values of their respective gates, s_t and $\hat{s}_t$ represent vectors corresponding to the cell states and candidate values, h_t signifies a vector representing the output of the LSTM layer.

2.3 Performance Evaluation Metrics

The performance of the LSTM model was assessed using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{7}$$

$$MAE = \frac{\sum_{i=1}^{N}|\hat{y}_i - y_i|}{N} \tag{8}$$

Where;

N is the number of samples,
y is the actual value and

ŷ is the predicted value**2.4 Experimental Setup**

Data preparation and handling were exclusively carried out in Python 3.8, relying on packages such as numpy, pandas, scikit learn, and matplotlib. We applied the min–max normalization technique to scale each feature to the range of [0, 1]. The min-max transformation is achieved using:

$$x_{norm} = (x - x_{min}) \,/\, (x_{max} - x_{min}) \tag{9}$$

We then constructed the LSTM models and fine-tuned the hyperparameters to refine our predictive approach. Each model consisted of an input layer, single/multiple hidden layers, a dropout layer, and a dense output layer. The number of neurons in the input layer corresponded to the number of input parameters in the regression problem. An additional fully connected layer was included with nodes and a Tangent Hyperbolic activation function. A dropout layer was introduced to the model with a dropout ratio set at 0.05. As a result, a portion of the input units was randomly set to zero during training, leading to a decreased risk of overfitting and improved generalization. Subsequently, a single neuron is appended to the ultimate fully connected layer. This layer produces an output prediction for regression tasks.

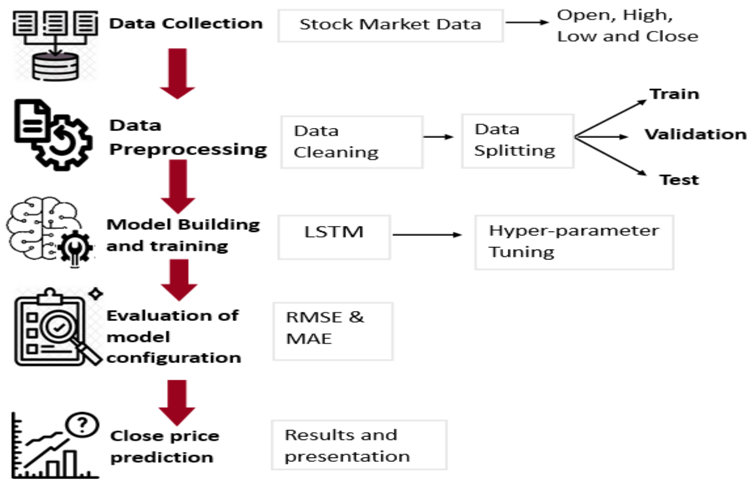
The model was compiled using the Adam optimizer, which is a widely employed optimization algorithm in deep learning. Training was performed for 30 epochs (iterations over the entire dataset) with a batch size of 16. This implies that the model adjusted its weights after processing each batch of 16 input sequences. During training, the model learns to minimize the Mean-Squared Error (MSE) loss between the predicted outputs and actual target values. The validation set was utilized during the training process to validate the value of the loss function for each epoch. The model was trained with several look-back values for 5, 21, and 42-days data. 5-days are the average trading days in a week, while 21 and 42 are the average trading days in 1-month and 2-months, respectively. The complete set of parameters utilized in this study is listed in Table 3.

Table 3: Hyper-parameters and their candidate values

Fine-Tuned Hyper-Parameter	**Candidate Values**
Time Stamp	5, 21, and 42 days
Neurons	30
Dropout Ratio	0.05
Epochs	30
Batch Size	16
Optimization Algorithm:	Adam Optimizer
Loss Function:	Mean Squared Error

Source: Author's compilation

Figure 1: Schematic diagram of the proposed research framework



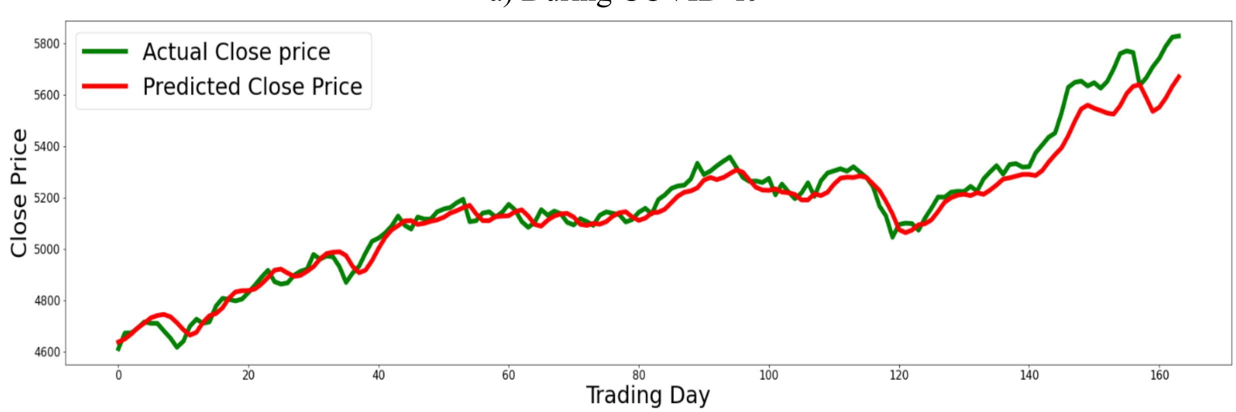
Source: Author's Compilation

The LSTM model was built and trained using the Keras Sequential API. In each layer, neurons return sequences instead of a single output. The input sequences had time steps, each with a selected number of features. The activation function used in each LSTM layer is a hyperbolic tangent. During the processing of an input, the features are sequentially presented to the LSTM network, one timestamp at a time. After processing the final element of the sequence, the overall output for the entire sequence is returned. Following the approach presented by Gal and Ghahramani (2016), we implemented dropout regularization within the recurrent layer. A dense layer with a single output unit is incorporated into the model to produce the final regression prediction. The proposed research framework is illustrated in Figure 1.

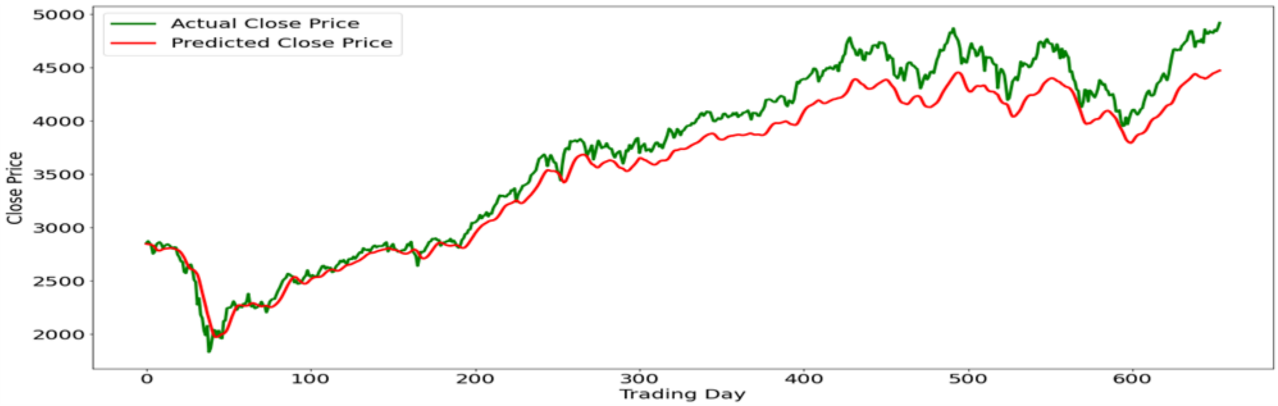
3. RESULTS AND DISCUSSION

This section presents the results and discusses the outcomes of applying LSTM in forecasting the S&P BSE GREENEX index and its constituents during and after the COVID-19 pandemic period.

Figure 2: Prediction of S&P BSE GREENEX index
a) During COVID-19



b) Post COVID-19***Source:*** Author's Compilation



The actual and predicted values of the S&P BSE GREENEX index from 28th January 2020 (i.e., 30 days prior to the declaration of COVID-19 as a pandemic) to 13th September 2022, covering 654 days, are shown in Figure 2a. Figure 2b shows an increasing trend in the S&P BSE GREENEX index after the pandemic. On tuning the hyper-parameters, the lowest RMSE and MAE values were obtained for a single hidden layer with 30 neurons and a dropout rate of 0.05. The model was trained for 30 epochs, with weight updates occurring after each batch of 16 input sequences. The results obtained for varying lookback values are listed in Table 4. During the COVID-19 pandemic period, the lowest RMSE of 0.1206 and MAE of 0.0958 were obtained when training the model with the previous 42 timestamps, indicating that LSTM necessitates the inclusion of data from the previous two months. It is evident from the chart that the predictions were nearly accurate up to 200 trading days (October 2020), that is, around the end of the first wave of the pandemic. Thereon, the model predicted lower index values than the actual values. In the post COVID-19 period, 21 timestamps (or a month's daily data) were sufficient for predicting the next day's closing price.

Table 4: Performance evaluation of LSTM for different look back values

Period	1 week (5-days)		1 month (21-days)		2 month (42-days)	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
During COVID	0.1535	0.1221	0.1313	0.1092	0.1206	0.0958
Post COVID	0.1515	0.1343	0.0869	0.0708	0.0972	0.0876

Source: Author's compilation

Next, we discuss the results of predicting stocks in belonging to the S&P BSE GREENEX index. The graphs portraying the actual and predicted close prices of these stocks during and post COVID-19 are presented in the appendix. From the commodities sector, five stocks feature in S&P BSE GREENEX, namely Pidilite Industries, Adani Enterprises, Hindalco Industries, Grasim Industries, and SRF Ltd. From Figures 3 - 7 given below, we find that the LSTM model predicted the Grasim Industries closing price with the least error. The RMSE and MAE values were 0.0101 and 0.0075, respectively. SRF Ltd and Pidilite Industries, both engaged in the manufacturing of chemicals, had a MAE of 0.0946 and 0.1021, respectively. The average RMSE and MAE for this sector were 0.1543 and 0.0957, respectively. Table 5 indicates provides a more precise prediction after the pandemic in the commodities sector.

The Consumer Discretionary sector is represented by companies dealing in automobiles and auto components (such as Maruti Suzuki India Ltd, Tata Motors Co. Ltd, Mahindra & Mahindra Ltd), consumer durables (Titan Co. Ltd), and retailing (Info Edge India Ltd) on the S&P BSE GREENEX. Companies dealing with automobiles and their components have lower errors in terms of RMSE and MAE compared to Titan Co. Ltd and Info Edge India Ltd during COVID-19, indicating that the LSTM model is capable of predicting the close prices of automobile companies more accurately. As depicted in Figures 8 to 12, automobile companies' predictions were more or less accurate until the end of the test period (i.e., 654 days). In comparison, the predicted values differ from the actual values by a great margin after approximately 300 trading days for Titan Co. Ltd as well as Info Edge India Ltd. The average RMSE and MAE for the consumer discretionary sector are 0.1377 and 0.1014, respectively. However, the LSTM model provided more precise results post-pandemic (Figures 33 and 34).

Sun Pharmaceutical Industries Ltd and Divi's Laboratories Ltd are categorised under the healthcare sector as pharmaceuticals and biotechnology companies, while Apollo Hospitals Enterprise Ltd is a healthcare service provider. The model exhibited favourable performance in predicting Sun Pharmaceutical Industries Ltd, with a low RMSE of 0.0313. Figure 13 also depicts the model's ability to accurately predict the following 1-month close prices until the end of the test period. However, this case is different from Divi's Laboratories Ltd and Apollo Hospitals Enterprise Ltd. After a period of 150 to 200 trading days, that is, immediately after the conclusion of the first wave of the pandemic, the model forecasted prices lower than the actual prices. Post COVID-19 results indicate better predictions in the case of Divi's Laboratories Ltd and Apollo Hospitals Enterprise Ltd with RMSE of 0.0286 and 0.0435 respectively.

Bajaj Finance Ltd. and ICICI Bank Ltd represent the financial services sector in the S&P BSE GREENEX index. The LSTM model demonstrated accurate close prices predictions for both companies during COVID-19 (Figures 16 and 17) with relatively low RMSE and MAE values. The RMSE of Bajaj Finance Ltd. and ICICI Bank Ltd are 0.0186 and 0.0126, respectively. The model's prediction performance was better during the COVID-19 pandemic than post-pandemic.

Siemens India Ltd. and Bharat Electronics represent the industrial or capital goods sector, featuring on the S&P BSE GREENEX index. Siemens India Ltd. exhibited moderate RMSE and MAE values, indicating reasonably accurate predictions. In tandem, Bharat Electronics Ltd has exceptionally low RMSE and MAE values of 0.0020 and 0.0015, respectively, suggesting highly accurate predictions. The results post COVID-19 were on similar lines (Figures 40 and 41).

Within the group of companies included in the S&P BSE GREENEX, Reliance Industries and Adani Ports, and Special Economic Zone exhibit moderate RMSE and MAE values, as indicated in Table 5. The closing price charts (Figures 20 and 21) show that the predictions are accurate up to a certain point. However, the model fails to correct itself. Figures 22 and 23 show reasonably accurate predictions for the Power Grid Corporation of India Ltd and Hindustan Unilever Ltd., respectively. Lastly, Infosys Ltd shows exceptionally low RMSE and MAE values of 0.0097 and 0.007, respectively, suggesting highly accurate predictions.

Table 5: Performance evaluation of LSTM for S&P BSE GREENEX index constituents

Sector	*Company*	*During COVID*		*Post COVID*	
		RMSE	**MAE**	**RMSE**	**MAE**
Commodities	Pidilite Industries Ltd	0.1286	0.1021	0.0315	0.0241

	Adani Enterprises Ltd	0.2647	0.1517	0.0401	0.0331
	Grasim Industries Ltd	0.0101	0.0075	0.0465	0.0340
	Hindalco Industries Ltd	0.1731	0.1227	0.0264	0.0200
	SRF Ltd	0.1950	0.0946	0.0076	0.0065
Consumer Discretionary	Tata Motors Co Ltd	0.0310	0.0215	0.1159	0.1004
	Mahindra & Mahindra Ltd	0.0258	0.0197	0.0509	0.0386
	Maruti Suzuki India Ltd	0.0341	0.0266	0.0631	0.0522
	Titan Co Ltd	0.3210	0.2293	0.1135	0.1032
	Info Edge (India) Ltd	0.2767	0.2099	0.0241	0.0158
Health Care	Sun Pharmaceutical Industries Ltd	0.0313	0.0261	0.0433	0.0354
	Divi's Laboratories Ltd	0.2769	0.2386	0.0286	0.0240
	Apollo Hospitals Enterprise Ltd	0.7890	0.5749	0.0435	0.0353
Financial Services	Bajaj Finance Ltd	0.0186	0.0136	0.0413	0.0306
	ICICI Bank Ltd	0.0126	0.0097	0.0411	0.0350
Industrials	Siemens India Ltd	0.0864	0.0608	0.0432	0.0332
	Bharat Electronics Ltd	0.0020	0.0015	0.0180	0.0146
Services	Adani Ports and Special Economic Zone	0.1634	0.1307	0.0409	0.0266
Energy	Reliance Industries Ltd	0.1935	0.1681	0.0342	0.0230
Utilities	Power Grid Corp of India Ltd	0.0545	0.0381	0.0936	0.0696
Consumer Staples	Hindustan Unilever Ltd	0.0421	0.0324	0.0268	0.0197
Information technology	Infosys Ltd	0.0097	0.0071	0.0327	0.0229

Source: Author's Compilation

4. CONCLUSION AND IMPLICATIONS

This study employs a deep learning model, LSTM, to predict the next day closing price of the S&P BSE GREENEX index and its constituents. The model's performance was tested during COVID-19 when the market was highly volatile and also post COVID-19. The model's performance provides accurate predictions for several companies across different sectors. Most companies had RMSE values ranging from 0.01 to 0.3, suggesting that the model reasonably predicted most stocks. However, there are variations in the prediction accuracy among companies, and further model refinement may enhance the accuracy.

The prediction of companies in the automobile, financial, industrial, and IT sectors showed highly accurate predictions in the long run, even during a crisis using LSTM. On the contrary, the prediction results of specific companies show that the model initially exhibits highly accurate results, but the performance decreases after a particular number of trading days. These variations could be attributed to the individual characteristics of companies during the COVID-19 pandemic. Overall, the model showcased more precise predictions post COVID-19 as compared to the time period during the crisis.

Investors and financial analysts can use these predictive models as valuable tools for taking informed investment decisions during uncertain times or crises. Continued research and development in predictive modelling and sequential modelling during economically challenging periods can yield valuable insights into market behaviour, assisting in informed investment decisions.

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APPENDIX - Stock Price Prediction During COVID-19

Figure 3: Pidilite Industries Ltd

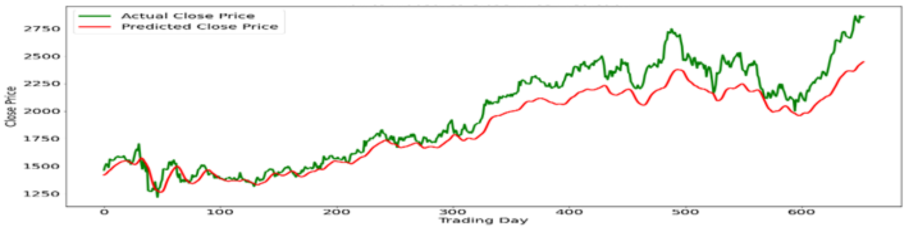


Figure 4: Adani Enterprises Ltd

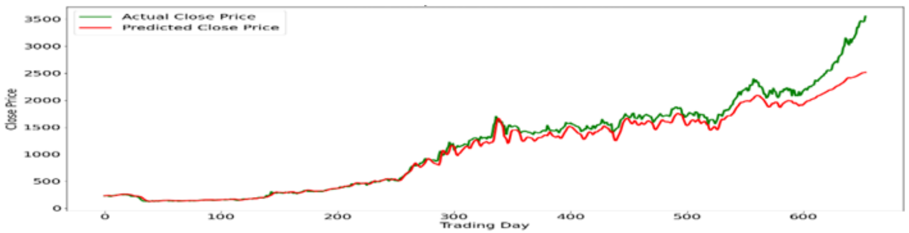


Figure 5: Grasim Industries Ltd

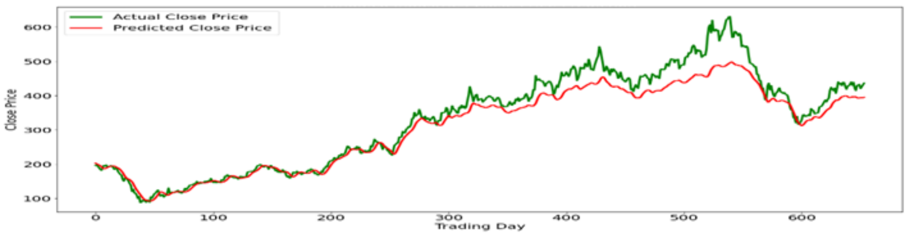


Figure 6: Hindalco Industries Ltd

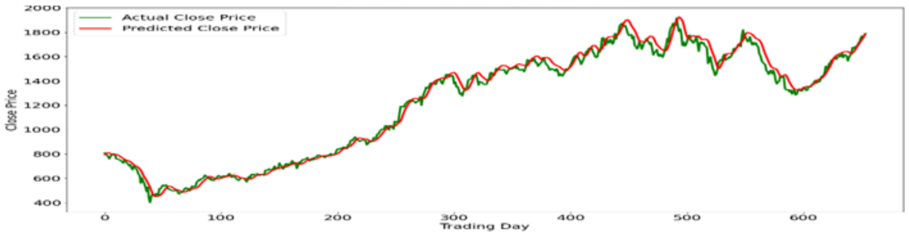


Figure 7: SRF Ltd

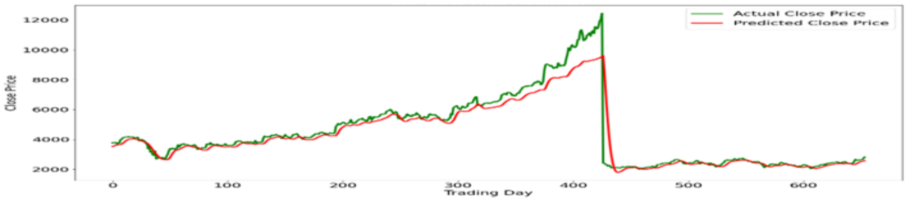


Figure 8: Tata Motors Co. Ltd

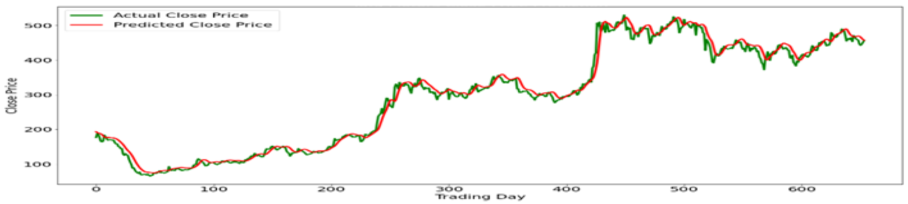


Figure 9: Mahindra & Mahindra Ltd

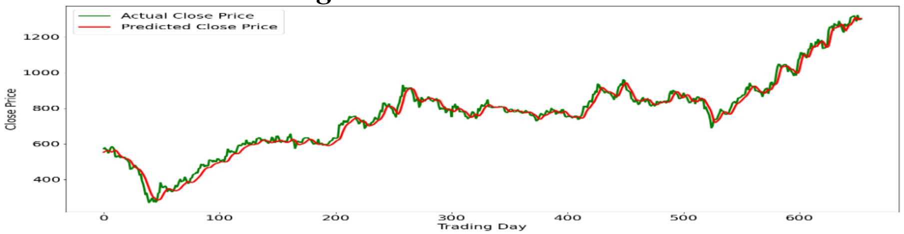


Figure 10: Maruti Suzuki India Ltd

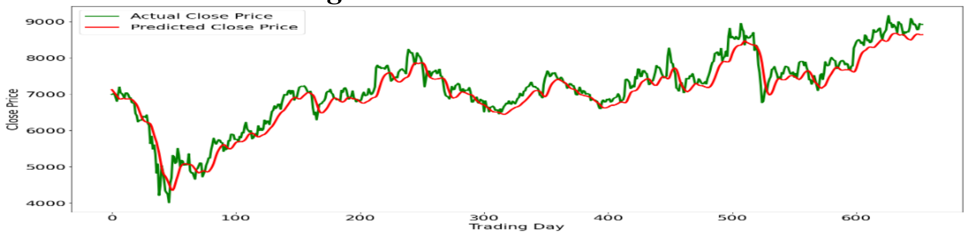


Figure 11: Titan Co. Ltd

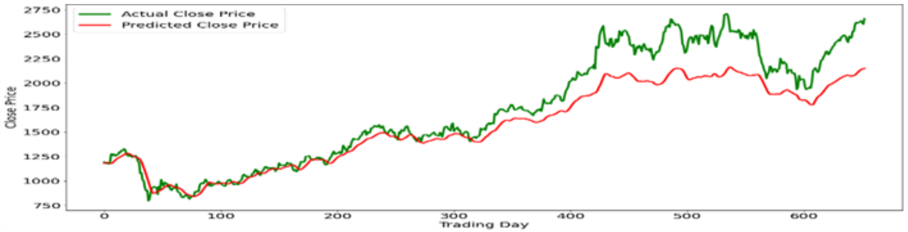


Figure 12: Info Edge (India) Ltd

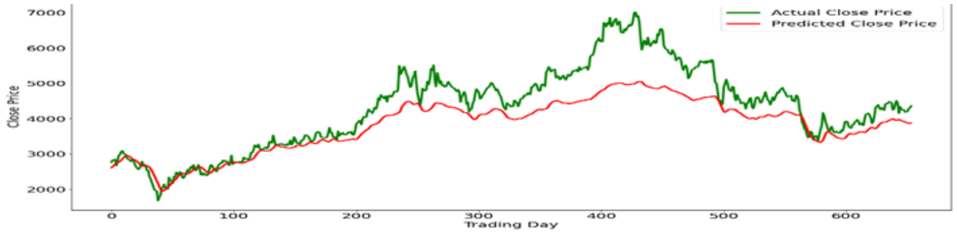


Figure 13: Sun Pharmaceutical Industries Ltd

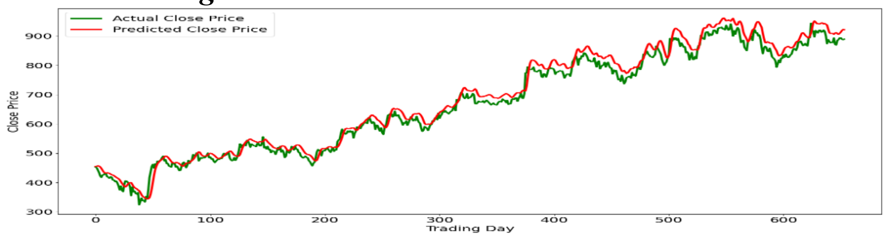


Figure 14: Divi's Laboratories Ltd

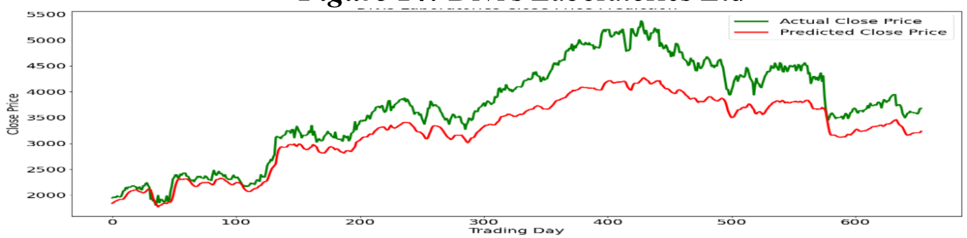


Figure 15: Apollo Hospitals Enterprise Ltd

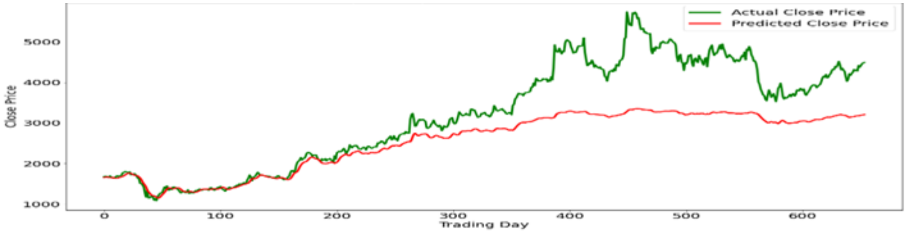


Figure 16: Bajaj Finance Ltd

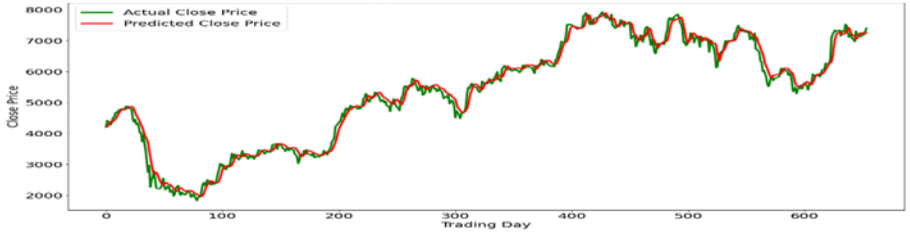


Figure 17: ICICI Bank Ltd

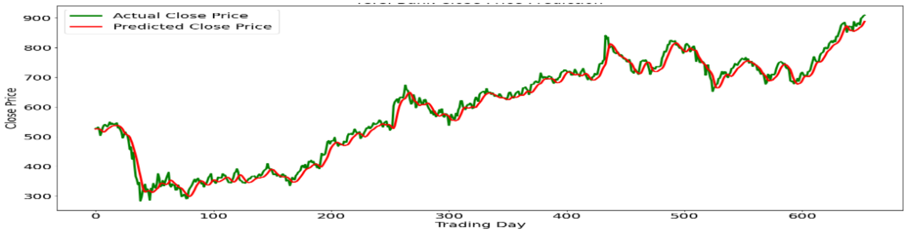


Figure 18: Siemens India Ltd

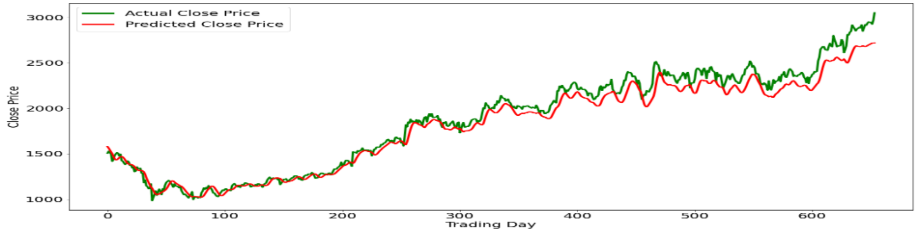


Figure 19: Bharat Electronics Ltd

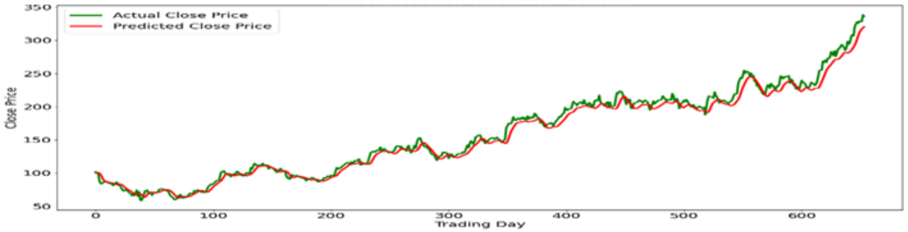
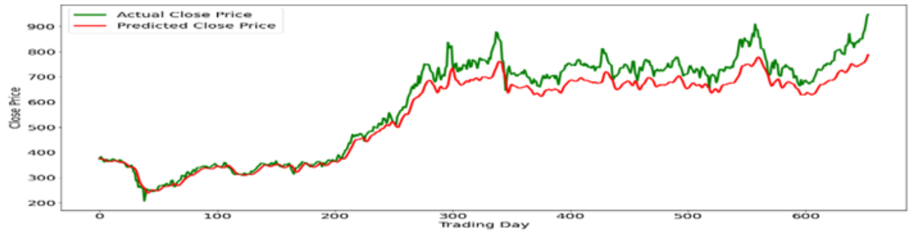


Figure 20: Adani Ports and Special Economic Zone



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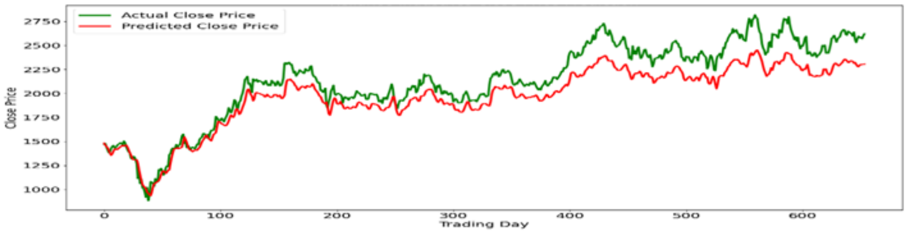


Figure 22: Power Grid Corporation of India Ltd

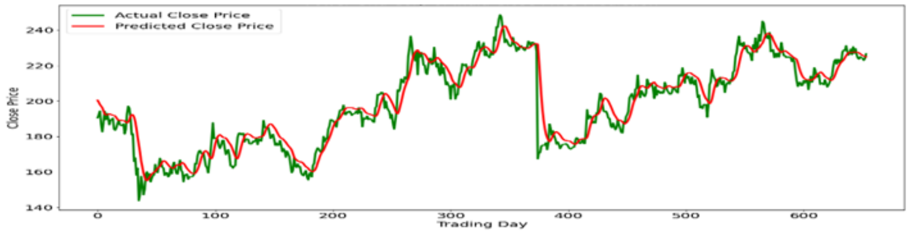


Figure 23: Hindustan Unilever Ltd

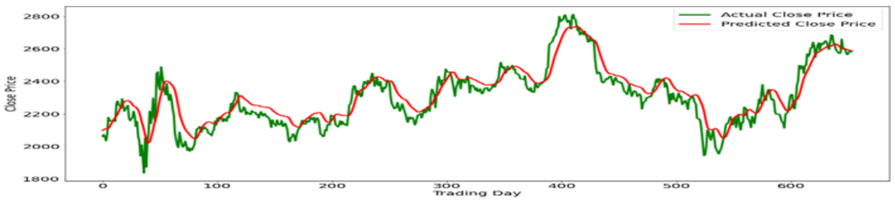
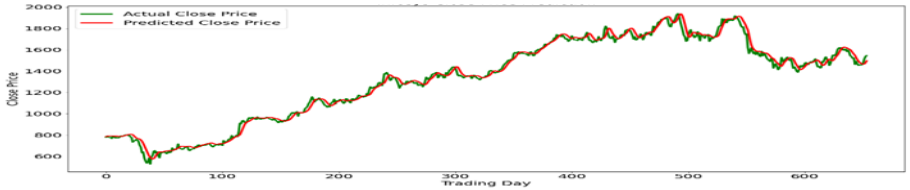


Figure 24: Infosys Ltd



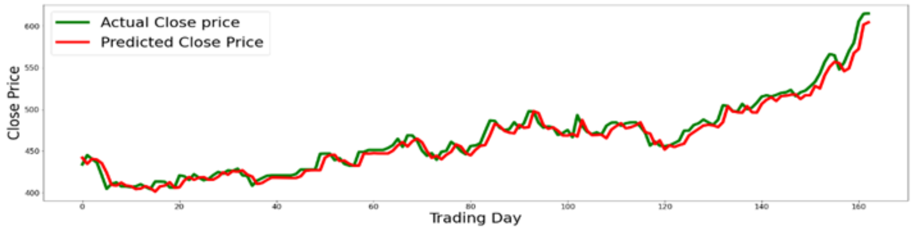
Stock Price Prediction post COVID-19

Figure 25: Pidilite Industries Ltd

Figure 26: Adani Enterprises Ltd

Figure 27: Grasim Industries Ltd

Figure 28: Hindalco Industries Ltd



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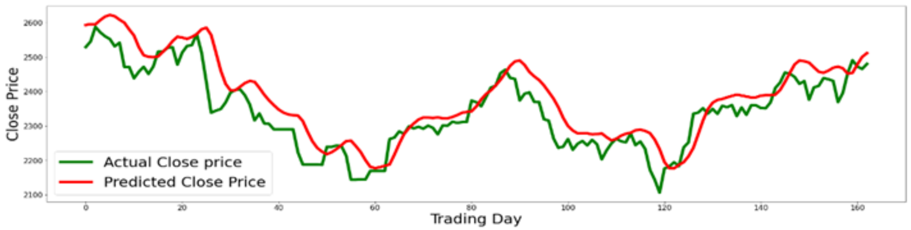

Figure 30: Tata Motors Co. Ltd

Figure 31: Mahindra & Mahindra Ltd

Figure 32: Maruti Suzuki India

Figure 33: Titan Co. Ltd

Figure 34: Info Edge (India) Ltd

Figure 35: Sun Pharmaceutical Industries Ltd

Figure 36: Divi's Laboratories Ltd

Figure 37: Apollo Hospitals Enterprise Ltd

Figure 38: Bajaj Finance Ltd

Figure 39: ICICI Bank Ltd

Figure 40: Siemens India Ltd

Figure 41: Bharat Electronics Ltd

Figure 42: Adani Ports and Special Economic Zone

Figure 43: Reliance Industries Ltd

Figure 44: Power Grid Corporation of India Ltd

Figure 45: Hindustan Unilever Ltd

Figure 46: Infosys Ltd

Source: Author's Compilation