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Impact of COVID-19 on Square Pharmaceuticals Stock Prices: A Comparative Analysis of Machine Learning Models

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Abstract

The aim of this paper is to compare the forecasting performance of different machine learning algorithms in case of the daily stock prices of Square Pharmaceuticals Limited. To ensure the impact of COVID-19 on the stock prices we separated the data into different segments such as pre-COVID period from January 2011 to March 2020, and the COVID period from March 2020 to September 2021 and the whole study period from January 2011 to December 2021. This study compares predicting performance of various machine learning algorithms such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB), and Long Short-Term Memory (LSTM). To ensure a fair comparison of algorithm performance, we implemented the same combination of data splits and time steps consistently across all algorithms, which yielded optimal performance for each model. The empirical findings indicate that the Random Forest model consistently delivered the highest accuracy across all periods, the SVM model showed an unexpected increase in accuracy during COVID period whereas the LSTM model's performance declined. This comprehensive analysis highlights the adaptability and robustness of machine learning models in volatile market conditions, emphasizing their utility in financial forecasting during global disruptions like the COVID-19 pandemic.

Keywords: Stock Market, Machine Learning, COVID-19, Dhaka Stock Exchange, Square Pharmaceuticals.

AMS Classification: 91G15, 91B24, 62P10.

1. Introduction

The stock market serves as a dynamic arena where investors, traders, and analysts converge to engage in transactions and manage portfolios (Badolia, 2016). Among the myriad factors influencing stock market dynamics, the ability to accurately predict stock prices stands paramount, guiding stakeholders in making well-informed decisions. In recent years, the application of machine learning techniques has gained traction in the realm of stock market prediction, offering promising avenues for forecasting market trends and identifying investment opportunities (Angra and Ahuja, 2017). Machine learning, with its inherent capability to extract knowledge from data, has become instrumental in various domains, including stock market prediction (Kubat and Kubat, 2017). Supervised learning, in particular, has emerged as a predominant approach, leveraging historical data to train algorithms for forecasting future market trends.

The integration of machine learning models in stock market prediction has gained traction in recent years. Ayala et al. (2021) proposed a hybrid approach combining technical analysis indicators with machine learning techniques to optimize trading strategies, showcasing the potential of machine learning in refining prediction strategies. Hossain et al. (2020) demonstrated the effectiveness of Support Vector Machines (SVM) in forecasting daily closing prices on the Dhaka Stock Exchange, underscoring SVM's promising predictive power compared to traditional methods.

The COVID-19 pandemic has introduced unprecedented challenges to global financial markets, reshaping investor behavior and market dynamics. As stock prices fluctuated in response to pandemic-induced uncertainties, researchers have turned to machine learning models to forecast stock prices and navigate market volatility. A systematic literature review by Mintarya et al. (2023) highlighted the prevalence of neural networks in stock market prediction, underscoring their role in enhancing predictive accuracy. Similarly, Kumbure et al. (2022) emphasized the significance of machine learning techniques, particularly neural networks and support vector machines, in forecasting stock markets, revealing a growing trend towards deep learning methods and textual data integration.

Sharaf et al. (2022) introduced a hybrid system integrating sentiment analysis and stacked- LSTM for precise stock trend prediction during the pandemic, achieving notable prediction accuracy. Sinha et al. (2022) utilized machine learning approaches to forecast stock closing prices before and after COVID-19, demonstrating the effectiveness of LSTM models amidst market fluctuations. Omar et al. (2022) identified AR-DNN and AR-RF models as effective predictors of stock index prices during the pandemic, offering insights into advanced prediction methodologies amidst crisis periods. Additionally, Ghosh and Chaudhuri (2021) proposed FEB-Stacking and FEB-DNN models for stock trend prediction, addressing pandemic-induced challenges through rigorous feature engineering and AI deployment. Haque and Chowdhury (2020) conducted a comparative analysis of stock exchanges before and after COVID-19, highlighting the economic ramifications and policy interventions' impact on market behavior. Mazur et al. (2020) analyzed the March 2020 stock market crash triggered by COVID-19, uncovering sector-specific impacts and corporate responses to market volatility.

From the above study we found that the study of investing the impact of COVID-19 on the daily stock prices of Square Pharmaceuticals Limited and forecasting it with different machine learning algorithms with different time segments is rare. So, the objective of this study is to evaluate the forecasting performance of various machine learning algorithms concerning Square Pharmaceuticals Ltd which is the listed company of the Dhaka Stock Exchange (DSE). Through this comparative study, we seek to determine the accuracy and reliability of different machine learning techniques in predicting stock prices for this company. Furthermore, we aim to investigate the impact of the COVID-19 pandemic on stock price prediction models and determine the optimal actions to be taken by comparing the performance of different machine learning models. The rest of the paper is organized as follows: Section 2 describes data collection and period segmentation, section 3 present the methodology, section 4 showed the result and discussion and finally section 5 present the conclusion.

1.1 Square Pharmaceuticals Ltd.

Square Pharmaceuticals Ltd. is a key player in the pharmaceutical sector, contributing significantly to the health care and life sciences industry in Bangladesh. The company, listed on the Dhaka Stock Exchange under the symbol "SQURPHARMA". The company operates within the pharmaceutical sector and engages in the manufacture and marketing of a diverse range of products, including pharmaceuticals, basic chemicals, and animal health products. Square Pharmaceuticals' product portfolio spans therapeutic, herbal, and nutraceuticals, in addition to veterinary drugs and pesticides. The company's commitment to delivering quality healthcare solutions is rooted in its foundation, dating back to 1958 when it was established by Samson H. Chowdhury.

In terms of financial performance, Square Pharmaceuticals has demonstrated positive growth over the past five years, ending on June 30, 2023. Key financial indicators include an 8.19% growth in revenue, a 10.02% increase in net income and earnings per share, a 7.57% rise in capital spending, and a gross margin of +50.92%. The company's resilience and growth in the pharmaceutical industry make it an intriguing subject for research, aligning with our focus on stock market prediction and machine learning applications.

2. Data Collection and Period Segmentation

Our study relies on meticulous data collection, focusing on historical stock market data for Square Pharmaceuticals, spanning from January 2011 to December 2021. This comprehensive decade-long dataset allows for an in-depth exploration of model scalability and generalizability, enabling analysis of machine learning models across diverse market conditions over an extended period. A distinctive aspect of our study is the deliberate inclusion of the COVID-19 period, from March 23, 2020, to September 11, 2021. By partitioning the data into pre-COVID-19, during COVID-19, and the full dataset (**Table 1**), we enhance the granularity of our analysis, scrutinizing the impact of the global pandemic on stock market dynamics. This approach facilitates a thorough examination of how the pandemic influenced market behavior and evaluates the adaptability and resilience of our predictive models during both routine and exceptional market conditions, such as the 2020 stock market crash induced by the COVID-19 pandemic.

Table 1: Time frame, sample composition, and number of observations

Data Type	Duration	Train (75%)	Test (25%)
Whole Period	2 Jan 2011-30 Dec 2021 (2597 observations)	2 Jan 2011-18 Feb 2019 (1948 observations)	19 Feb 2019-30 Dec 2021 (649 observations)
Pre-COVID period	2 Jan 2011-22 Mar 2020 (2205 observations)	2 Jan 2011-3 Dec 2017 (1654 observations)	4 Dec 2017-22 Mar 2020 (551 observations)
During-COVID period	23 Mar 2020-9 Sep 2021 (314 observations)	23 Mar 2020-4 May 2021 (236 observations)	4 May 2021-9 Sep 2021 (78 observations)

3. Methodology

3.1 Methods and Materials

This methodology typically involves a series of steps, starting with the selection of relevant data, including time-series data such as stock prices. Pre-processing of data plays a crucial role in preparing it for analysis, involving initial cleaning to remove incomplete or irrelevant data and computation of technical indicators. Further pre-processing may include scaling and dimensionality reduction techniques to derive pertinent variables and filter out irrelevant ones. Once the input data is prepared, machine learning techniques are employed to predict the target variable, with the input data divided into training and test sets. To navigate the complexities of stock market predictions, particularly in volatile periods like the COVID-19 pandemic, we employed workflow of supervised learning models (Figure 1). This workflow encompassed data preprocessing, feature engineering, model training, and evaluation to predict stock prices of Square Pharmaceuticals.

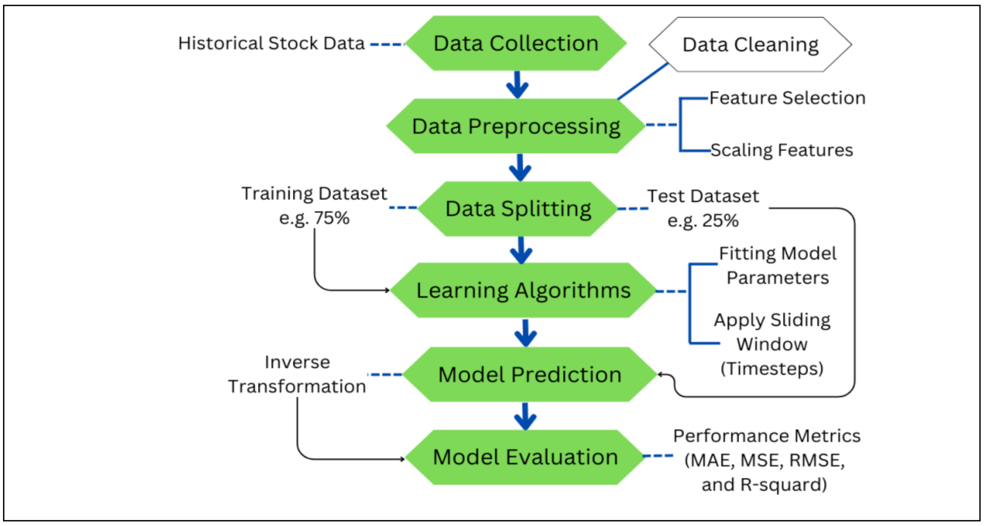


Figure 1: Workflow of a stock market prediction model with supervised learning

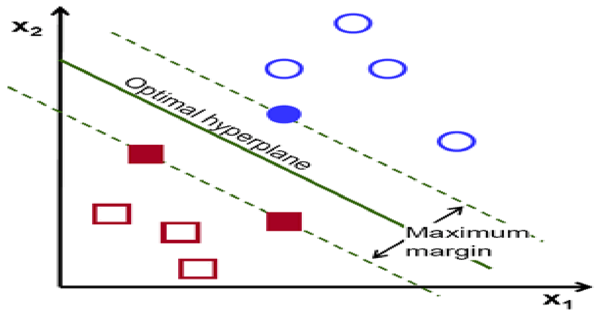
Recent advancements in stock market prediction have seen a resurgence of interest in deep learning methods (Chong et al., 2017). Deep neural networks, convolutional neural networks, and long short-term memory networks (LSTM) have found extensive applications in forecasting stock market prices and returns. These methods are capable of identifying hidden nonlinear relationships and extracting relevant features from intricate and noisy data, independent of human expertise and economic assumptions. In this article, we delve into the impact of COVID-19 on Square Pharmaceuticals stock prices, leveraging machine learning techniques for predictive analysis. Building upon the foundation of supervised learning methodologies and recent advancements in deep learning, we explore the dynamics of Square Pharmaceuticals' shares in the context of the Dhaka Stock Exchange (DSE). By analyzing historical data and incorporating COVID-19-related factors, we aim to provide valuable insights into the effects of the pandemic on Square Pharmaceuticals' stock performance and explore the efficacy of machine learning models in predicting market trends amidst unprecedented economic disruptions.

3.2 Machine learning models

Square Pharmaceuticals Ltd. is a Bangladeshi multinational pharmaceutical company founded in 1958 and listed on the Dhaka Stock Exchange (DSE) and Chittagong Stock Exchange (CSE) in 1991. It started to export different antibiotics and medicine across the world from 1987. In 2008 and 2009 it had the highest market share in the pharmaceutical industry of Bangladesh. So, modelling and forecasting its stock's price is important to the investors. The application of various machine learning algorithms tailored for stock market prediction such as Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), Random Forest (RF), Gradient Boosting and Long Short-Term Memory (LSTM). These are described below.

3.2.1 Support Vector Machine (SVM)

Support Vector Machines are perhaps one of the most popular machine learning algorithms developed in 1990 and continue to be the go-to method for a high-performing algorithm with little tuning. The objective of the support vector machine algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points.



To separate the two classes of data points, there are many possible hyperplanes that could be chosen. The objective is to find a plane that has the maximum margin, i.e. the maximum distance between data points of both classes. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence.

3.2.2 K-Nearest Neighbors (K-NN)

KNN makes predictions using the training dataset directly. Predictions are made for a new instance (x) by searching through the entire training set for the K most similar instances (the neighbors) and summarizing the output variable for those K instances. For regression this might be the mean output variable, in classification this might be the mode (or most common) class value. To determine which of the K instances in the training dataset are most similar to a new input a distance measure is used. For real-valued input variables, the most popular distance measure is Euclidean distance. The value for K can be found by algorithm tuning. Usually it is taking as odd number. The computational complexity of KNN increases with the size of the training dataset. For very large training sets, KNN can be made stochastic by taking a sample from the training dataset from which to calculate the K-most similar instances.

3.2.3 Random Forest

The random forest algorithm is more commonly applied to classification problems, where there is a much larger selection of boosting techniques. For regression, the random forest algorithm fits a number of randomly generated decision trees on subsets of the data and uses averaging to improve accuracy and prevent over-fitting. Each tree is generated by splitting the feature set into subsets. The process continues until a subset at a given node equals the response variable. Least-squares boosting is applied. At every step, the ensemble fits a new learner to the difference between the observed response and the aggregated prediction of all prior learners. Mean-squared error is minimized for every fit. The prediction, based on a feature set, is simply the average of predictions over all learners (Breiman, 2001).

3.2.4 Gradient Boosting

Gradient Boosting is an ensemble learning technique that sequentially combines the predictions of multiple weak learners, often decision trees. Each subsequent tree in the sequence corrects the errors made by its predecessor, leading to progressively refined predictions. The method was introduced by Jerome H. Friedman and has since evolved with variations like XGBoost and LightGBM. Gradient boosting machines is elucidating their adaptability and effectiveness in various practical applications within machine learning (Natekin and Knoll, 2013).

In the context of stock market prediction or time series analysis, Gradient Boosting can be employed to capture complex relationships and patterns in historical stock data. It excels in improving predictive accuracy by iteratively minimizing errors. In regression tasks, various loss functions can be utilized, specified through the loss parameter.

3.2.5 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) represents a specialized form of recurrent neural network (RNN) architecture tailored to overcome the limitations of conventional RNNs in capturing and learning from long-term dependencies within sequential data. Originally proposed by Sepp Hochreiter and Schmidhuber in 1997, LSTM networks stand out as a prominent variant of RNNs.
The fundamental process of a Long Short Term Memory Network closely resembles that of a Recurrent Neural Network, with the key distinction being the forwarding of both the Internal Cell State and the Hidden State.

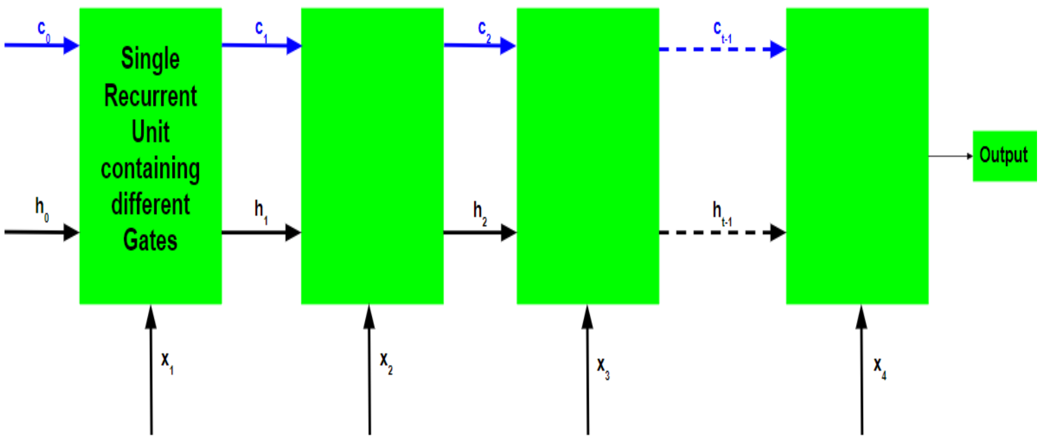


Figure 2: Basic workflow of a Long Short Term Memory (LSTM)

In LSTM networks, the workflow closely resembles that of traditional RNNs, with a notable distinction: alongside the Hidden State, the Internal Cell State is also propagated forward. This architectural aspect empowers LSTMs to efficiently capture and leverage information across prolonged time spans, rendering them highly proficient for tasks revolving around sequential data, such as stock market prediction or time series analysis.

3.3 Data Preprocessing

In our study about predicting stock prices of Square Pharmaceutical Ltd. the first crucial step is deciding which machine learning algorithm will be best for the job. However, before applying these algorithms, we need to clean up the data. Data preprocessing methods are employed to clean and prepare the data, followed by model evaluation using statistical packages like MS Excel and Python. This involves meticulous transformation of the time series dataset, including formatting dates, handling missing values, and addressing outliers using techniques like Box Plot visualization and the Interquartile Range (IQR) method. The final step in our data pre-processing phase involves the application of minimax normalization techniques. Normalization enhances the effectiveness of subsequent machine learning algorithms, promoting accurate and reliable predictions. Through these comprehensive pre-processing measures, our study strives to cultivate a dataset that is not only representative of the underlying market dynamics but also optimized for robust and insightful analysis.

4. Result and Discussion

4.1 Descriptive Analysis

The dataset spans from January 2011 to December 2021, capturing a decade of historical stock prices for selected companies on the Dhaka Stock Exchange (DSE). The variables include Open, High, Low, Close, and Volume, providing a comprehensive overview of daily trading activities. The descriptive statistics for daily stock prices of square pharmaceuticals for the three-time segment is given in Table 1.

Table 1: Descriptive Statistics of Stock prices with different segments

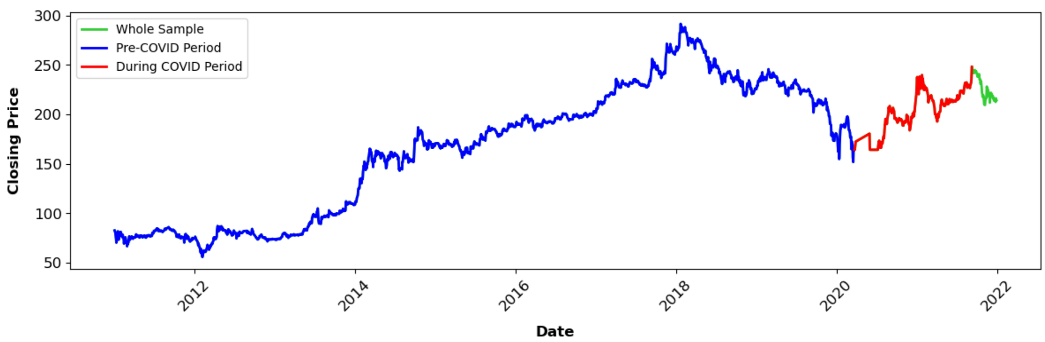
Dataset	Variable	N	Minimum	Maximum	Mean	Median	SD
Whole period	Open	2061	54.37	278.67	166.87	181.42	61.59
	High	2061	57.81	278.67	168.06	182.00	61.88
	Low	2061	52.43	273.67	165.44	180.16	61.25
	Close	2061	53.21	277.67	166.61	181.05	61.53
	Volume	2061	43149	5887531	735970	576648	585100.14
Pre- COVID-19	Open	1705	54.37	278.67	158.96	170.24	64.20
	High	1705	57.81	278.67	160.05	171.50	64.44
	Low	1705	52.43	273.01	157.65	168.52	63.90
	Close	1705	53.21	277.67	158.72	170.24	64.13
	Volume	1705	76110	5887531	730807	551951	586886.37
During COVID-19	Open	259	157.14	244.80	202.75	205.10	21.24
	High	259	162.29	250.00	204.43	206.67	21.66
	Low	259	149.05	243.10	200.83	203.10	20.99
	Close	259	151.90	248.10	202.52	205.10	21.44
	Volume	259	43149	4318881	776476.62	633232	618532.97

Table 1 provides a comprehensive overview of the stock market data for Square Pharmaceuticals across the entire dataset, with a focus on the closing prices. The closing prices spanning from TK 53.21 to TK 277.67 with mean closing price of TK 166.61 and sd Taka 61.53. We observed a slight decrease in mean closing prices compared to the whole sample period. SQURPHARMA mean closing price decreases to TK 158.72. The mean closing price rises to TK 202.52 during the COVID-19 period. The result indicate that the mean closing value is high during the during the pandemic and less before the pandemic compared to whole time period.

4.2 Results and Discussions

Our analysis focused on short-term predictions, specifically forecasting one day ahead. We started by selecting features from the time series index, including variables such as Open, Close, Low, High, and Volume. Our primary focus was to predict the close price of the selected stocks. The closing price is chosen because it reflects all the activities of the index on a trading day (Ariyo et al., 2014). The time-series plot of stock index prices is shown in **Figure 2**, revealing numerous frequent turning points. Usually, the upward trend was shown in the plot. But, there is a sharp decline in index prices at the beginning of the COVID-19 period, likely due to the pandemic's impact.

Overall, significant fluctuations in the stock index prices are evident. Time series train-test cross-validation was employed, with each dataset divided into 75% for training and 25% for testing, preserving chronological in each time frame. The above discussion is summarized in **Table 2**. All of the analyses were programmed in Python language.



4.3 Forecasting Evaluation

Evaluating the machine learning models over different periods revealed interesting insights. During the whole period (January 2011 - December 2021), KNN had a MAE of 8.84 and R^2 of 0.73, while SVM had a MAE of 8.76 and R^2 of 0.72, both showing moderate accuracy. However, Random Forest (RF) stood out with a MAE of 3.32 and an impressive R^2 of 0.95, making it the most accurate model. Gradient Boosting (GB) and LSTM also performed well, with MAE values of 4.61 and 4.59, and R^2 values of 0.90 and 0.91, respectively.

Before COVID (January 2011 - March 2020), the models showed some improvements. KNN had a lower MAE of 7.22 and a higher R^2 of 0.89. SVM's MAE dropped to 6.98 with an R^2 of 0.91. RF maintained its high accuracy with a MAE of 4.73 and R^2 of 0.94, while GB and LSTM showed strong performance with MAE values of 4.74 and 4.48, and R^2 values of 0.93 and 0.96, respectively.

During the COVID period (March 2020 - September 2021), the landscape changed. KNN's performance improved with a MAE of 3.78 but an R^2 of only 0.63. Surprisingly, SVM excelled with a MAE of 1.89 and R^2 of 0.86, possibly due to the shorter dataset length. RF continued its reliability with a MAE of 1.98 and R^2 of 0.88. GB had a MAE of 1.99 and R^2 of 0.87, while LSTM's performance dropped with a MAE of 2.61 and R^2 of 0.81 (**Table 2**).

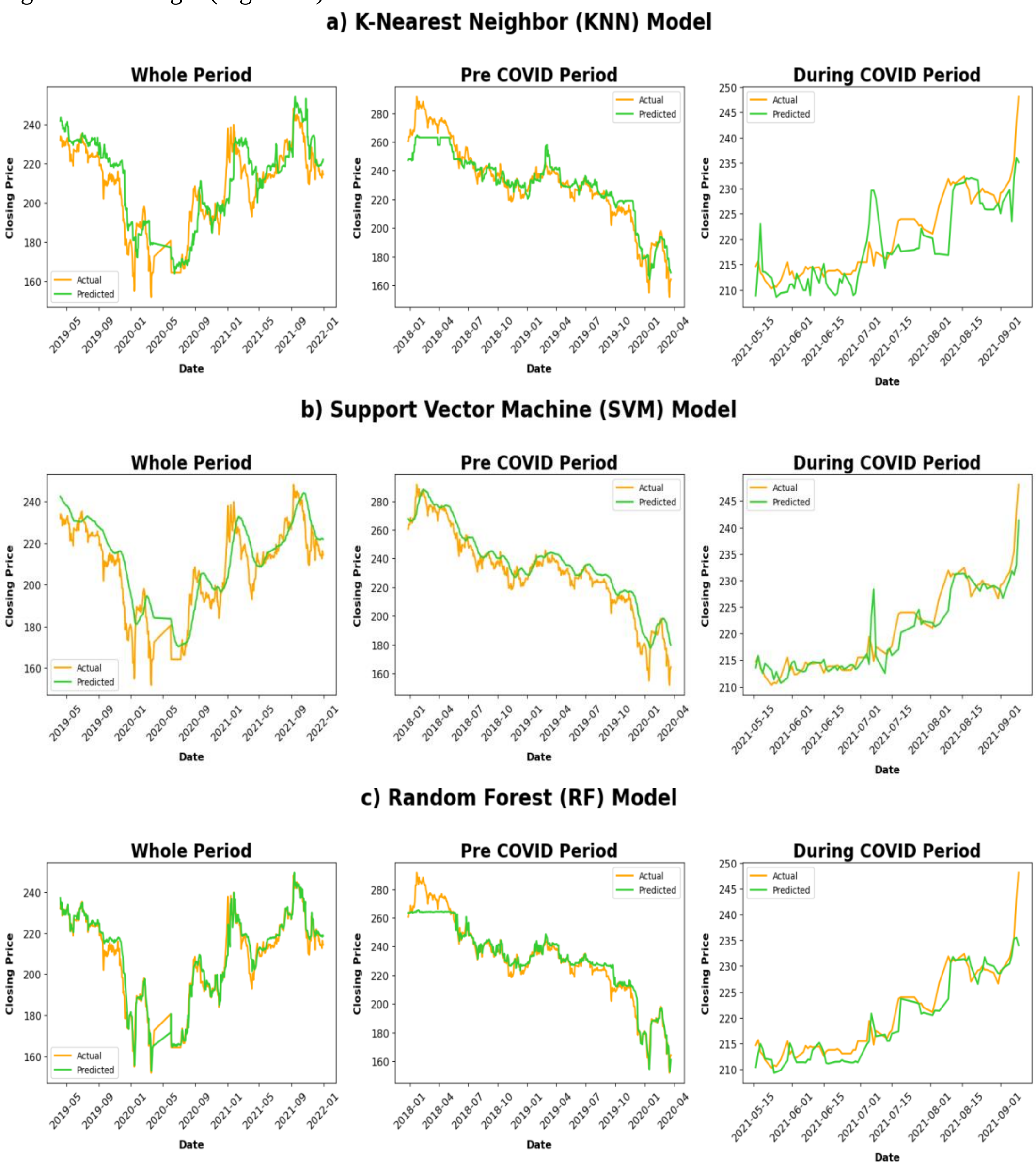
For systematic hyperparameter tuning via techniques like cross-validation experiments with multiple time steps (30, 15, and 5) was applied to each algorithm. By splitting the dataset into training and test sets and iteratively training the model on different subsets, the model's performance was evaluated across various time periods, market conditions, and significant events, particularly focusing on the unprecedented impact of the COVID-19 pandemic. To ensure a fair comparison of algorithm performance, the same combination of data splits and time steps was implemented consistently for each algorithm.

Table 2: Estimated forecasting evaluation criteria

Dataset	Model	MAE	MSE	RMSE	R^2
Whole Period	KNN	8.84	121.25	11.01	0.73
	SVM	8.76	125.09	11.18	0.72
	RF	3.32	22.43	4.73	0.95
	GB	4.61	43.15	6.57	0.90
	LSTM	4.59	39.16	6.26	0.91
Pre COVID period	KNN	7.22	84.38	9.18	0.89
	SVM	6.98	77.61	8.81	0.91
	RF	4.73	48.66	6.97	0.94
	GB	4.74	57.66	7.59	0.93
	LSTM	4.48	31.78	5.63	0.96
During COVID period	KNN	3.78	25.62	5.06	0.63
	SVM	1.98	9.22	3.03	0.86
	RF	1.89	8.55	2.92	0.88
	GB	1.99	8.74	2.95	0.87
	LSTM	2.61	13.20	3.63	0.81

4.4 Actual vs Predicted Plot

To visualize the performance of our predictive models, we compared the actual stock prices of Square Pharmaceuticals with the predicted values for each model. For the whole period, KNN showed moderate predictive power with some deviations (Figure 3a), while SVM exhibited similar performance with slight underfitting (Figure 3b). RF demonstrated high accuracy, with predictions closely aligning with actual prices (Figure 3c). GB provided robust predictions, although with slight overfitting tendencies (Figure 3d). LSTM effectively captured the overall trend with minor discrepancies (Figure 3e). In the pre-COVID period, KNN's performance improved, showing closer alignment to actual prices (Figure 3a). The SVM model also exhibited enhanced accuracy (Figure 3b). The RF model maintained high accuracy, effectively predicting stock prices (Figure 3c). GB remained consistently reliable with minor deviations (Figure 3d), while LSTM showed the best fit, accurately predicting the trend with minimal error (Figure 3e). During the COVID period, the KNN model's performance was moderate, with increased error margins (Figure 3a). The SVM model demonstrated high accuracy with minimal prediction error (Figure 3b). The RF model was consistently accurate, closely matching actual prices (Figure 3c). The GB model provided reliable predictions with slight deviations (Figure 3d), and the LSTM model performed well but with a higher error margin (Figure 3e).



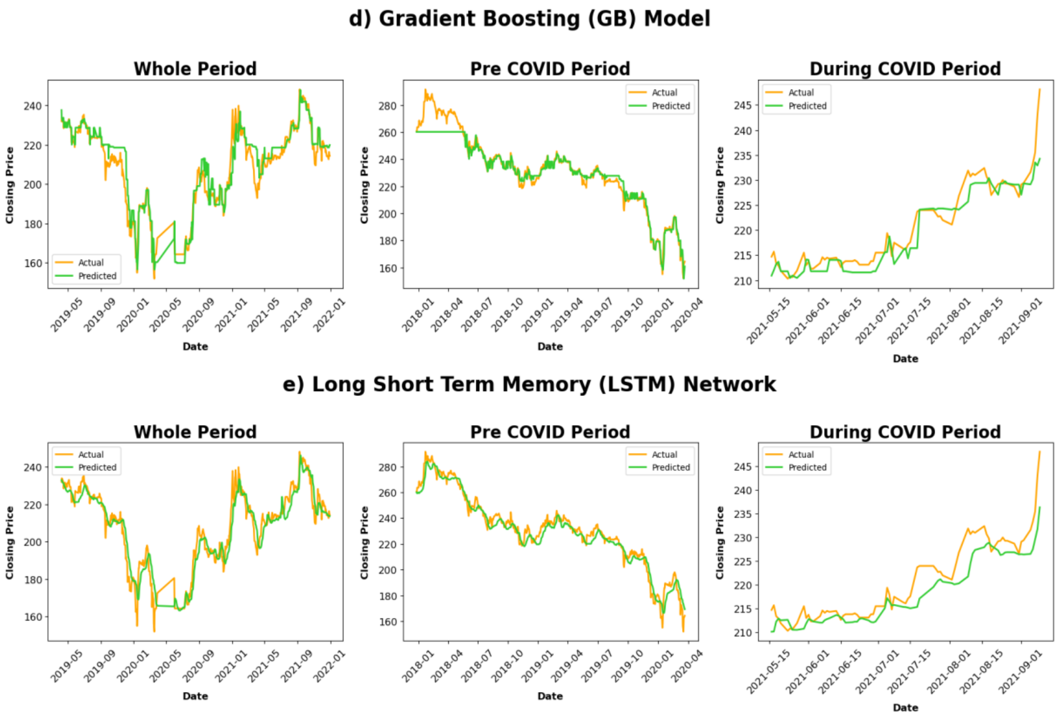


Figure 3: Comparison of Actual vs Predicted stock index prices using test data: **a)** KNN, **b)** SVM, **c)** Random Forest, **d)** Gradient Boosting, and **e)** LSTM

5. Conclusions

The study aimed to evaluate how well different machine learning techniques could predict the daily stock prices of Square Pharmaceuticals Ltd. of DSE with different machine learning algorithms for three segments of time during COVID-19, Pre COVID-19 and whole period. To assess performance, we used metrics like Mean Squared Error, Mean Absolute Error, Root Mean Squared Error, and R-squared to compare the predicted prices with the actual ones. The data ranges from January 2011 to December 2021. The empirical result showed the Random Forest (RF) model stands out as the most reliable across both datasets and different time periods. It consistently aligns closely with actual stock prices, demonstrating robust forecasting accuracy even during the Covid-19 period. Conversely, the K-NN model shows significant discrepancies between predicted and actual prices, suggesting limitations in its forecasting capabilities, especially during periods of market volatility like the Covid-19 outbreak. Interestingly, the impact of Covid-19 on predictive accuracy varies across models. While some models, such as the Gradient Boosting (GB) and Long Short-Term Memory (LSTM) models, show relatively stable performance before and during the pandemic, others, like the Support Vector Machine (SVM) model, exhibit slight decreases in accuracy during the Covid-19 period. This variability underscores the importance of selecting robust forecasting models that can adapt to changing market conditions. Finally, the Random Forest model emerges as the most effective in forecasting stock prices of Square Pharmaceuticals, offering valuable insights for investors and financial analysts.

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