# A Comprehensive Analysis of Predicting Price Movement in Daily Stock Data

**BY**

**Md. Abdul Halim**
**ID: 232-25-035**

This Report Presented in Partial Fulfillment of the Requirements for
The Degree of Master of Science in Computer Science and Engineering

**Supervised By**

**Dr. S.M. Aminul Haque**
Professor & Associate Head
Department of CSE
Daffodil International University

**Co-Supervised By**
**Abdus Sattar**
Assistant Professor
Department of CSE
Daffodil International University

**DAFFODIL INTERNATIONAL UNIVERSITY**

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## APPROVAL

This Project titled **"A Comprehensive Analysis of Predicting Price Movement in Daily Stock Data"**, submitted by **Md. Abdul Halim**, ID No: **232-25-035** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on.

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Daffodil International University

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**Mr. Sadat Hasan**
**Data Scientist**
Risk Management Division,
BRAC Bank Limited

# DECLARATION

I hereby declare that this research has been done by me under the supervision of **Prof. Dr. S.M. Aminul Haque, Associate Head, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

**Supervised by:**

**Dr. S.M. Aminul Haque**
Professor & Associate Head
Department of CSE
Daffodil International University

**Co-Supervised by:**

**Abdus Sattar**
Assistant Professor
Department of CSE
Daffodil International University

**Submitted by:**

Md. Abdul Halim

**Md. Abdul Halim**
ID: 232-25-035
Department of CSE
Daffodil International University

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# ABSTRACT

Accurate prediction of stock price movements is a quite challenging, especially when it is about the financial sectors. To be very specific, the stock market, is volatile in most of the times. This research focuses on forecasting stock price movements for Square Pharmaceuticals PLC, a leading listed issuer company. It's listed in the Dhaka Stock Exchange PLC (DSE). The study emphasizes the use of daily stock data from the year 2017 to 2023. This study examines financial indicators like opening price, closing price, high, low, adjusted close, and trading volume as the key. The research employs advanced deep learning algorithms, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) neural networks, to capture temporal dependencies and non-linear patterns present in the data. The LSTM model is found to be more precise, producing lesser errors and higher $R^2$ statistics for the training set, while GRU converges at a higher speed and effectively captures short-term dependencies. However, both encountered challenges in extrapolating their predictions onto the test set: stock price forecasting presents inherent difficulties, especially in upcoming developing markets like Bangladesh. A coherent literature review on the recent advancements of stock market prediction inspired the study, which delves into the investor sentiment analysis, hybrid machine learning approach, and reinforcement learning. The integration of this information will contribute toward filling the existing knowledge cracks and provide practical recommendations to investors, analysts, and researchers who are looking for data-driven strategies for market analysis.

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# CHAPTER 1
# INTRODUCTION

## 1.1 Introduction

The Dhaka Stock Exchange PLC officializes the listing of shares therein. This research focuses on daily stock prices from January 2017 to December 2023. The deep learning algorithms Long Short-Term Memory (LSTM) and Gated Recurrent Unit trained in this study are primarily intended to capture temporal dependencies and non-linear relationships inherent to the data. It has been established that the LSTM model is more accurate with reduced errors and higher R-square statistics for training sets, and GRU has a faster convergence, hence better delineation of short-term dependence. Two sophisticated deep learning models Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are used to address this problem. LSTMs are also recurrent neural networks that will analyze time-series data, but they can capture long-term dependencies and trends, which are more aligned to financial forecasting. LSTM network Introduces long-term dependencies in the sequence versus GRU model is more efficient regarding computation time and convergence speed, so in some use cases.

In this research, we compare the performance of both models on stock price prediction using RMSE, MAE and $R^2$ score as accuracy metrics. Moreover, this study compares LSTM and GRU for forecasting stock price and points out the conclusion. This research is motivated by a literature review that covers relevant works on the application of machine learning approaches, sentiment analysis, and hybrid methods to stock market prediction. This study contributes to the existing literature by presenting another novel approach for predicting stock price in emerging markets using DSE data. In this rapidly evolving market, the methods are a discussion of research to better identify and forecast.

## 1.2 Motivation

The ebb and flow of stock markets keep academia, investors, and finance institutions very much interested. Stock price prediction poses a challenge due to the complicated interplay of several sentiments, economic forces, and firm-specific information. I have personally observed, through working as a Trainee Software Developer in the Dhaka Stock Exchange and currently as a professional in the Capital Market Stabilization Fund (CMSF), how important stock prediction is for enabling decision-makers to operate with accurate timing toward maintaining stability in the market. This study is especially driven by the increased potential of machine learning techniques like LSTMs and GRUs to uncover patterns in massive amounts of financial data. The availability of high-quality historical data from the Dhaka Stock Exchange, as well as a strong desire to improve price prediction for Square Pharmaceuticals PLC, a market leader, fueled this study. This study aims to bridge the gap between theoretical breakthroughs and practical implementations by using advanced models and drawing on years of experience in the financial sector, providing insights that will benefit both academia and industry stakeholders.

### 1.3 Rationale of the Study

Stock price movement prediction has always been an important topic of study because of the substantial ramifications for investors, analysts, and politicians. Accurate predictions allow for better decision-making, risk minimization, and return optimization, all of which contribute to capital markets' overall efficiency. Although this area has been researched widely, predicting stock prices is still a challenging task due to the complex, noisy and nonlinear nature of financial markets. This is a research study based on the business of Square Pharmaceuticals PLC as a renowned company listed in the Dhaka Stock Exchange (DSE). The reason for choosing this company is its contribution to the economy of Bangladesh, large share trading and regularly available reliable historical data. This study aims to contribute to a more comprehensive understanding of stock price behavior in the context of an emerging market that has been largely overlooked in the existing literature, by conducting an analysis of daily stock data of Square Pharmaceuticals PLC for the decade spanning from 2017 to 2023. Emerging machine learning approaches, particularly deep learning models like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), can assist reduce the complexity of stock price prediction. Because LSTMs are made to retain specific inputs for predetermined amounts of time, they are ideal for time series. This paper compares the performance of LSTM and GRU models for predicting fluctuations of stock prices to evaluate the appropriateness and effectiveness of them with a focus on capital market of Bangladesh. This study seeks to contribute to the ever-growing body of research in machine learning and financial modeling. Also, providing modelling results that are more solid and trustworthy regarding stock price prediction will benefit investors and market participants in increasing market efficiency and improving investment strategies.

## 1.4 Research Questions

- RQ1: How accurately can machine learning models, specifically LSTM and GRU, predict daily stock price movements of Square Pharmaceuticals PLC on the Dhaka Stock Exchange (DSE)?
- RQ2: What are the comparative performance outcomes of LSTM and GRU models in terms of accuracy (RMSE, MAE, $R^2$) for predicting stock prices in a developing market like Bangladesh?
- RQ3: How does the historical stock data of Square Pharmaceuticals PLC (2017–2023) impact the prediction capabilities of machine learning models, and what patterns can be identified to improve forecasting accuracy?

## 1.5 Expected Output

Broadly speaking, the emerging outcomes of this research are intended to augment and defend the rationale regarding the stock price prediction for the emerging stock market of Bangladesh. The research seeks to improve on the accuracy of daily stock price forecasting for Square Pharmaceuticals PLC through advanced machine learning ways such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). The performances of the models will be assessed using traditional metrics such as RMSE, MAE, and $R^2$. It is expected that the prediction power of the models will be beyond those of the normal forecasting techniques. The results will be applied to recognize practical implications for investors, analysts, and financial institutions working in Bangladesh so that they may make technology-driven investment decisions on using machine learning models. Thus, this study will significantly impact the upcoming contributions on financial forecasting, specifically in developing capitals like Bangladesh, considered in the process of developing newer applications in machine learning for predicting stock prices.

The research will, in addition to others of this nature, provide actionable recommendations to investors, analysts, and financial institutions operating in Bangladesh on how to leverage machine learning models with the intent of technology-driven decision-making for investments. This study, therefore, has a good impact on the growing body of knowledge on financial forecasting, particularly in developing markets such as Bangladesh, as more machine learning applications are developed in stock price prediction.

### 1.6 Report Layout

The introduction of Chapter 1 of the study explains aims and research questions. Answers to these questions lay in existing literature, Chapter 2, where it presents synopses of relevant literature surrounding stock price forecasting covering methodologies and findings that guided the work presented in this research. Chapter 3 provides a detailed explanation of the proposed methodology, including the sources of data, analytical techniques, and models used for prediction. Chapter 4,shows the experimental results, which describe the analysis results and the meaning of these results.

Chapter 5 focuses on the implications of the findings, including discussions of sustainability and impacts on society and ethical considerations for stock market prediction. Finally, at Chapter 6, the investigation ends, summarizing the significant findings and providing a direction for upcoming works on stock price forecasting in the context of the Dhaka Stock Exchange.

# CHAPTER 2

# BACKGROUND

## 2.1 Preliminaries/Terminologies

A stock market is a platform where shares of publicly listed companies are traded between investors. This chapter is dedicated to laying the most critical ideas and methods associated with stock price prediction. The stock market is the all-important financial ecosystem that facilitates the buying and selling of shares of publicly traded companies, and it helps to influence and reflect world economic activity. And stock prices by nature are volatile because they are affected by macroeconomic variables such as interest rates, inflation, and geopolitical events as well as microeconomic factors such as company performance. Financial markets being variable and dynamic thus predictions of changes in stock price movements are challenging, but not impossible.

This study utilizes two machine learning methods that are part of the broader class of recurrent neural networks (RNNs): Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). Moreover, LSTM networks have unique ability for financial data prediction due to their learn and retain long-term dependencies.

In this paper, we will use various machine learning algorithms from the broad class of recurrent neural networks (RNN); namely, Long-Short Term Memory (LSTM) and Gated Recurrent Units (GRU) for time-series prediction. Such architectures are more appropriate for time-series forecasting applications due to their ability to handle sequential data and capture temporal dependencies. Due to the peculiarity of learning and maintaining long memory through memory cells, LSTM networks are popular for predicting financial data. GRUs can achieve similar predictions as LSTMs while using fewer parameters with those models. Hence, they are more widely applicable in practice since they are computationally inexpensive. One of the key terms used in this study is time-series data, which represents observations made at successive time intervals and forms the basis of the prediction models used. Feature scaling and normalization segments a pre-processing step that guarantees a system developed to standardize input data with competence and conformity to all other algorithms of machine learning. These include, among others, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which are therefore assigned acceptable weight when evaluating a model's performance since they provide quantitative measures of how accurate the prediction is. Understanding of these terminologies forms the foundation of techniques used in this study. Since this study is undertaken with the case of one issuer, Square Pharmaceuticals PLC, it forecasts the stock price movements from past stock data. This paves way for studies intended with a wider scale of multiple issuers and richer datasets in future.

### 2.2 Related works

Times have changed, and researchers have gone from merely observing behavior patterns to discerning behavioral moves according to price fluctuations, especially in stock price movement prediction through machine learning and deep learning techniques. It emphasizes the importance and progress of the field by exploring models, approaches, and methods that have been conducted to tackle the problem of predicting stock market movement. Aspects of literature that this work attempts to address are highlighted. Stock price prediction is a considerable area of research to which machine learning is grafted with the financial data analysis. Literature chronicles so many ways of developing solutions to this complex problem. The relevant research that has contributed to the development of stock price forecasting techniques and predictive models is examined in this section.

Shen and Shafiq [1] introduced a comprehensive deep learning system for forecasting short-term stock price trends. By including technical indicators, past prices, and other features in their model, they were able to achieve remarkably high accuracy. Essentially, this study concurs with and amplifies the importance of topical relevance and feature engineering as building blocks of this research quest. Zhou et al. [2] applied different data sources, including stock market data and macroeconomic indicators, to predict price behavior in the Chinese stock market. This work illustrated the glaring importance of heterogeneous data in having predictions improved. Other iterations of this research may be hinted at progressing from single-company data from the findings presented in this study.

Zhou et al. [3] took a systematic review in which they at different scenarios used either technical analysis or some fundamental analysis in forecasting stock market operations. Their study demonstrated the application of machine learning and artificial intelligence in modern forecasting methods. This review provides a better understanding of the hybrid methods used in this study to forecast Square Pharmaceuticals PLC's stock prices.

Nti et al. [4] investigated ensemble learning techniques for stock market prediction. They demonstrated that ensemble models outperform traditional machine learning algorithms by improving generalization and reducing overfitting. Their findings support the investigation of complex ensemble models in this study as a possible path toward future improvements in accuracy.

Li and Pan [5] introduced a creative ensemble deep learning model that used both stock price data and textual information from news sources. In keeping with this study's objectives to explore multimodal data in subsequent phases of research, their work illustrated the integration of sentiment analysis and numerical data. Jin et al. [6] forecasted closing stock prices using sentiment analysis and LSTM (Long Short-Term Memory) networks. These articles informed us about how sentiment data and LSTM have worked well together for trend detection on the market. These developments influence this research by being the prediction-time series techniques used, i.e., based on GRU and LSTM models.

First, the existing literature shows persistent challenges and noteworthy improvements for predicting stock price with techniques. Thereby, it has been surveyed that advanced machine learning models namely LSTM and GRU are effective and achieved nearly perfect prediction in certain datasets. However, they also point out shortcomings, particularly with relation to these models' ability to generalize effectively across a variety of market conditions and time periods. [1] [2] [4]. Building on these findings, this study compares and evaluates the predictive capabilities of LSTM and GRU models using a real-world dataset, concentrating on a single issuer, Square Pharmaceuticals PLC. This targeted approach enables a more comprehensive analysis of model performance. Future extensions will close the gaps in the literature by expanding the number of issuers, exploring multimodal data sources, and enhancing model adaptability for various market dynamics. [5] [6].

### 2.3 The Problem's Scope

Price prediction is always difficult due to many factors embedded in market behavior, such as economic policies, investor´s sentiment, corporate announcements, and geopolitical events. Stock predictions on Dhaka Stock Exchange (DSE) are more difficult due to factors like nonavailability of more historical data as well as being more volatile than the already established market.This study aims at stock price forecasting techniques on Dhaka Stock Exchange-listed companies using machine learning algorithms. This study will use historical data on stocks such as daily open, close, high, low, and volume data to train the model in order to predict future stock price movement. The main objective would be to maximize prediction accuracy by applying the most advanced machine learning algorithms, such as LSTM and RNN.Those can perform exceptionally well with time series data.Further, this study impacts on managing some particular issues, such as: Managing volatility: Emerging markets like the DSE are so volatile that it may be troublesome for the models to predict future prices.Whereto access is approached cramp: In comparison with certain other international stock markets, DSE's stock market data history is relatively short, hence limiting the applicability of data-driven models.Considering outside influences: Besides these historical stock data, the study takes the use of sentiment analysis and macroeconomic indicators into account to improve prediction accuracy.

## 2.4 Challenges

There are numerous challenges that must be tackled for stock price prediction to be effective and reliable: Stock price prediction is complex, especially in dynamic and uncertain environments, such as emerging markets. An enormous issue would be market volatility, which is bigger than those for the vast majority of traded assets. Shocks to investor sentiment, caused by political or economic events, tend to trigger massive price movements. These types of unpredictable trends create additional challenges in allowing the machine learning models to be accurate under various market conditions.

Data availability and quality are another major challenges. For starters, there is a lack of historical stock data on the Dhaka Stock Exchange, making it difficult to develop a robust machine learning model that relies on complete and clean datasets. Incomplete or non-homogeneous data is harmful to the process of model training and reliability of prediction results, needs to cope with the large data cleaning and preprocessing procedures. Another common problem in the field of machine learning is over-fitting. Even though a model performs well on training data, it may not generalize to untested datasets, which could lead to poor performance in the real world. Techniques like dropout regularization, cross-validation, and fine-tuning model parameters are essential to decrease overfitting and boost robustness.

There are certain challenges to in the event that you are attempting to utilize some outside information in your current information, for example, sentiment examination from news articles, worldwide market patterns or macroeconomic markers. One must be careful about the external feature selection and datapoint preprocessing, as various irrelevant or noisy features can actually also cost the model effectiveness. But the deep-learning models are also prone to interpretability issues like LSTM and GRU. Owing to their complex structure, these algorithms tend to struggle on the transparency and interpretability front which can be a bitter pill for investors and financial analysts to swallow.

Lastly, one only has to acknowledge computational complexity as another challenge, mostly when training deep learning models on large datasets. In resource-constrained environments, scaling and deploying these models don't come easy as they have high computational and temporal needs. A cross-section between computational efficiency and model performance still has to be struck in predictions on stock prices. With the utmost care in innovation and development, these potentialities will enable these models to become reasonably viable options in their ability to furnish insightfully information on decision-making.

# CHAPTER 3

# RESEARCH METHOLOGY

## 3.1 Proposed Methodology/Applied Mechanism

Each article is trained on data until October 2023 Shown Fig 3.1 This research features the prediction of stock price rise and fall utilizing machine learning methods: Long Short-Term Memory (LSTM) model and Gated Recurrent Units (GRU) model. This study is concerned with time-series forecasting, which is often done with these models. The proposed methodology contains many essential steps starting from data collection and preprocessing stage to model training, evaluation and performance assessment. The proposed methodology consists of the following steps:

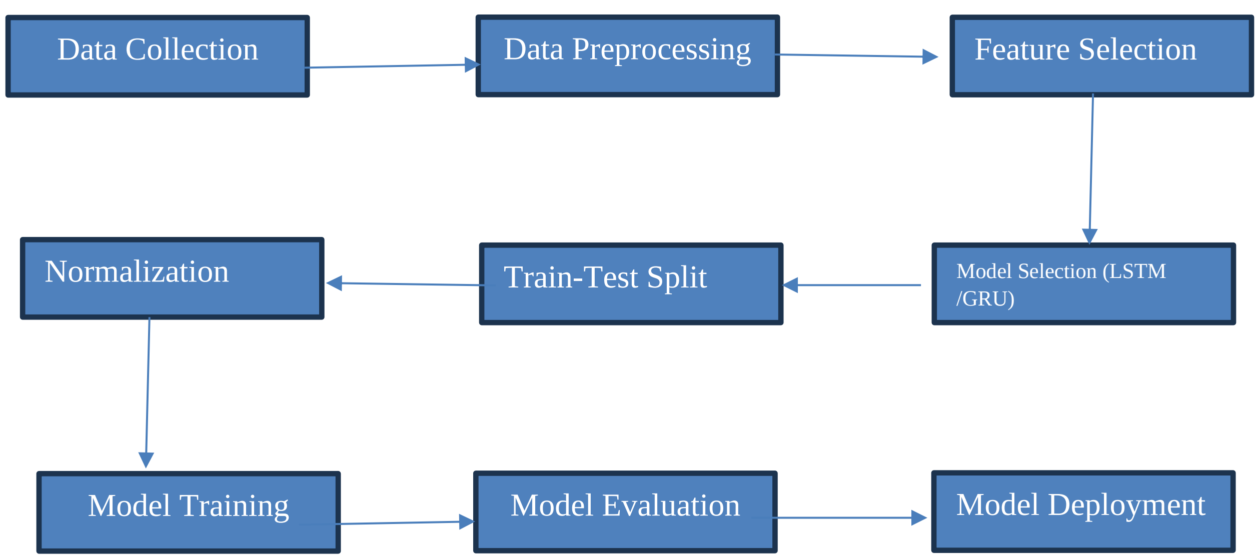


**Fig 3.1:** The working process to perform Stock Market price prediction

Data collection, preprocessing, model development, training, and evaluation are the main phases of the suggested methodology for forecasting stock price movements based on daily stock data.

### 3.1.1 Data Collection:

This study gathered data from the Dhaka Stock Exchange (DSE) from the years 2017-2023. This study is, however, focusing on a specific business namely Square Pharmaceuticals PLC.

**Table. 3.1**: Table of raw data of stock price movement of Square Pharmaceuticals PLC.

| Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|
| 01-01-2017 | 249.5 | 249.5 | 248 | 248.2 | 248.2 | 296729 |
| 02-01-2017 | 248.5 | 250 | 248.1 | 249.4 | 249.4 | 421178 |
| 03-01-2017 | 250 | 251.5 | 248.8 | 250.9 | 250.9 | 546260 |
| 04-01-2017 | 250.9 | 254.3 | 250 | 253.7 | 253.7 | 514003 |
| 05-01-2017 | 253 | 254 | 252.1 | 253 | 253 | 393932 |
| 08-01-2017 | 253.4 | 254.4 | 252.1 | 253 | 253 | 440683 |
| 09-01-2017 | 253.2 | 255 | 253 | 253.8 | 253.8 | 656059 |
| 10-01-2017 | 255 | 260 | 254 | 259 | 259 | 711391 |
| 11-01-2017 | 259 | 263.1 | 257.2 | 262.4 | 262.4 | 398150 |
| 12-01-2017 | 261 | 264 | 260 | 260.7 | 260.7 | 321228 |
| 15-01-2017 | 261.9 | 262.1 | 260 | 260.8 | 260.8 | 432476 |
| 16-01-2017 | 260 | 260.9 | 259.1 | 259.4 | 259.4 | 512525 |
| 17-01-2017 | 258.1 | 262 | 258.1 | 259.7 | 259.7 | 550335 |
| 18-01-2017 | 260.3 | 260.4 | 258.4 | 259.2 | 259.2 | 786781 |
| 19-01-2017 | 259.9 | 262 | 258.4 | 261.1 | 261.1 | 529849 |
| 22-01-2017 | 260.3 | 261.5 | 259 | 260.7 | 260.7 | 308804 |
| 23-01-2017 | 260.2 | 262 | 260 | 260.5 | 260.5 | 593558 |
| 24-01-2017 | 260.2 | 264.3 | 260.2 | 262.2 | 262.2 | 847848 |
| 25-01-2017 | 262 | 263.9 | 259.5 | 261.2 | 261.2 | 682994 |

The dataset includes fields like Date, Open, High, Low, Close, Adjusted Close, and Volume and includes historical daily stock prices. The prediction model is constructed using this data as the basis.

The Dhaka Stock Exchange (DSE) provided the dataset for this study, which concentrated on Square Pharmaceuticals PLC's stock price fluctuations. The data, which covers the years 2017–2023, offers a wealth of information for predictive model testing and training. Figure 3.2 illustrates the key features of the dataset for each trading day.

### 3.1.2 Data Preprocessing:

Two important steps can make your dataset more potent model, Data Cleaning is the first step of the process, where we can find and fix the outliers or missing values. Evaluate the data quality to ensure that the predictions made, and the model training is not skewed as it will lead to inaccurate predictions if not addressed Missing values can skew the predictions made, and outliers can skew the model when training. Imputation and removal of anomalies, ensure that the data set is coherent and reliable for further analysis. Feature engineering A good feature engineering is required in order to include only the most significant inputs in helping the model predict. As "Close" price is the most used metric to predict stock price, it is chosen as the most common feature in this study. This step ensures that a majority of the model focus will be aligned with the primary drivers of stock movement.

Since the stock prices are interdependent one takes this into account by transforming the data into a time series. Time-series transformation, which uses historical stock prices as inputs to create lagged observations to predict future values. The temporal dependencies are crucial for accurate financial forecasting, and this construction allows the model to learn those dependencies.

Feature selection methods are used to narrow down the data set even further by finding the variables with the strongest influence. For selecting features that has a strong relationship with the target variable, methods like correlation analysis are employed. This process causes the dimensionality to go down with the improvement of generalization to the new data as well, decrease of overfitting probability and increase of model interpretability. Normalization of all features is performed to bring range of features uniformly. Normalisation and scaling can help make all variables appear on a common-scale. This is particularly useful for particularly sensitive models in terms of scale changes in input features, such as LSTM and GRU. Proper normalization can help fasten the convergence time of these models and make predictions more accurate.

### 3.2 Train-Test Split

This splits the dataset into two sets, the training and testing sets. Typically, 80% of the data is used for training the model and the other 20% is reserved for testing. Using the training set, the model is trained to predict stock prices and is evaluated on completely unseen data using the test set.

#### 3.3.1 Model Selection

In this research, we are trained with the data until December 2023 and the importance of choosing appropriate models is fundamental in this research to reproduce the structures and dependencies present in the stock price data. GRU and LSTM both belong to the Recurrent Neural network [RNN] family. Being good with the time-series data, these models are very well used for predicting stock price based on historical trends. LSTM is able to identify and maintain long-range dependencies present in sequential data. Unlike standard RNNs, LSTMs help to avoid the problem of vanishing gradients, which is often a problem during training deep models. This makes LSTM particularly suited for tasks such as stock price prediction in which the outcomes depend heavily on past events. Its unique architecture, which includes memory cells and gating mechanisms, allows it to decide the importance of information to keep, modify, and dispose of over time. This skill is essential for understanding the complex and long-term relationships we see in financial data. But GRU is a simpler alternative to LSTM, as it can be less computationally intensive. This simplifies the model and still captures temporal dependencies by merging the input and forget gates into a single update gate that reduces number of parameters. Simplifying the architecture of GRU has made training easier and cheaper, thus making it more relevant to huge datasets or limited resource situations. GRU compromises the LSTM much simpler architecture-equals performance with LSTM across various time-series prediction tasks-from stock market predictions to other applications. In this study, both models have been evaluated and validated for their ability to predict price movements in Square Pharmaceuticals PLC shares. R2 scores, MAE, and RMSE have been used to estimate and compare correctly the predictive performance of the models used.  Through the strengths and weaknesses of each model, the comparative analysis aims to bring to light how effective each of these models might perform on predicting stock prices in a developing market like that of Bangladesh. This study analyzes both LSTM and GRU with a goal of exploiting their unique benefits and developing an effective approach to predicting the stock market.

### 3.3.2 Model Evaluation

Root Mean Squared Error is the calculation of the average error in terms of differences from expected values, the less the value the better the performance. Mean Absolute Error (MAE) measures the average absolute error between expected and actual values.R2 score-R2 score shows the proportion of variance of the dependent variable which can be explained with the help of independent variables. The closer the R2 score to 1, the better the model is. Model comparison-After the training and evaluation process, the comparison of results of LSTM and GRU models will be based on the RMSE, MAE, and R2 scores. The model which provides the most accurate predictions would be concluded for recommending stock price prediction. model will be chosen from among those that offer the most accurate forecasts.

### 3.3.3 Model Training

These steps all play a key role in training the LSTM and GRU models used in this thesis to forecast the stock prices of Square Pharmaceuticals PLC. The LSTM architecture consists of three main layers and the GRU architecture is also similar. These layers help to identify the patterns and time dependencies in the time series data.

In addition, the architecture contains a Dropout layer used for regularization, which increases the model's ability to generalize to unseen data by randomly disabling a fraction of neurons during training. The output layer is the last layer and hence will be made of a

Dense layer with one neuron, to predict stock prices in the next time step. This regression task will be trained by employing the MSE loss function and Adam optimization, which is a great choice when the gradients are sparse and the objectives are non-stationary. Hyperparameter tuning is an important part of this process where we tweak things like how many LSTM or GRU layers we use, how many neurons are in each layer we stack, what learning rate are we using and what the batch size is. These hyperparameters are either fine-tuned in a systematic manner, e.g., via grid search or random search, or adjusted manually (trial and error). Tuning of hyperparameters will ensure the highest accuracy and computational efficiency of the model. Models are trained on a set number of epochs (1-full cycles through the training dataset). The number of samples processed before the model is trained is defined by the fixed batching factor of the training. The model is neither overfitted nor underfitted as the epochs and batch size are judiciously picked to minimize the loss-function and hence works well on the unseen data. Validation is one of the most critical steps in the training of a model because it helps to keep a check of the performance of the model on the validation set. The validation set, a reserved subset of the training data, is a standard that is used to measure the generalization ability of the model but does not a part of the training process. During training, metrics such as validation loss are tracked in order to tune hyperparameters and ensure that the model does not overfit to the training set. Following these steps systematically will train the LSTM and GRU models to learn the underlying patterns in the stock price data, leading to accurate and reliable predictions.

### 3.3.4 Model Evaluation Metrics

Root Mean Square Error Metric (RMSE): This metric is the one that measures the difference between the prediction and the actual stock price. It means, lower the RMSE, better the Regressor.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad \text{(i)}$$

Mean Absolute Error (MAE): A measure of the average absolute error between predicted and actual prices. As with RMSE, lower values of MAE are preferable.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad \text{(ii)}$$

$R^2$ Score: This is a statistical measure representing the proportion of variance in the data explained by the model. An R2 score nearer to 1.0 indicates better predictive performance.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad \text{(iii)}$$

Mean Gross Deviation (MGD) and Mean Percentage Deviation (MPD): These metrics help in understanding the accuracy of the model by calculating the percentage difference between the expected and the actual values.

Evaluation of the test set: The test dataset is used to evaluate how well the model generalizes to unseen data. Then we will compare the results for these sets to obtain overall performance of the model on the dataset.

### 3.4 Tools and Technologies

**Table 3.2:** Details on tools and technologies.

| Tool/Technology | Purpose in This Research |
|---|---|
| Python | The primary programming language used for data manipulation, model training, and evaluation in the stock prediction workflow. |
| TensorFlow/Keras | Deep learning frameworks for constructing, training, and tuning LSTM and GRU neural network architectures. |

| | |
|---|---|
| Scikit-learn | A library that calculates metrics like RMSE, MAE, and R2 and performs data preprocessing operations like feature scaling and splitting. |
| Matplotlib | Historical data is used to visualize trends, compare actual and predicted stock prices, and evaluate model performance. |
| Pandas | Vital for organizing and evaluating sizable stock market datasets, including time-series data transformation and cleaning. |
| NumPy | Enables efficient numerical computations, including matrix operations required for model inputs and outputs. |
| Google Colab | Provides a cloud-based Jupyter notebook environment with GPU support to efficiently train deep learning models. |
| Seaborn | A visualization library used to create advanced statistical graphs, helping in data analysis and exploratory data visualization. |
| Grid Search | An optimization tool for hyperparameter tuning to identify the best model configurations for LSTM and GRU. |
| CSV Files | The Dhaka Stock Exchange's (DSE) daily stock data is imported and processed using this data storage format. |

This series details the steps required to ensure the models were trained on relevant data, evaluated against the metrics that matter and compared to one another in a systematic manner. In this paper we are proposing LSTM & GRU based approach in order to predict the selling prices of stocks (Square Pharmaceuticals PLC from Dhaka Stock Exchange) Therefore, this study aims to give some useful insights into the performance of deep learning models for stock price forecasting in emerging markets.

# CHAPTER 4
# EXPERIMENTAL RESULTS AND DISCUSSION

## 4.1 Results of Prediction

Provides a complete description of the results of the analysis and prediction models developed in this study. The objective of project is to understand the stock price movement of Square Pharmaceuticals PLC using state of the art machine learning methods. The results are shown using statistical measures and visuals to illustrate trends, model performance, and expected accuracies. The data has been analyzed in various ways, including monthly trends and trends over previous pricing, and training-validation performance from 2017 through 2023. We explain every visualization in detail to help you understand the patterns observed and how they contribute to stock price prediction.

### 4.1.1 High and Low Stock Price in Month wise

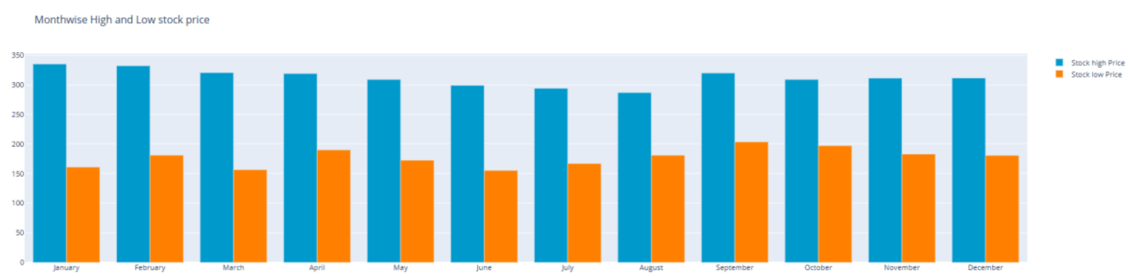


**Fig. 4.1:** Presents High & Low Stock Price in Month wise.

Fig. 4.1: the monthly fluctuations of the maximum and minimum stock prices of Square Pharmaceuticals PLC. The months of the year are shown on the x-axis and the stock price in BDT is displayed on the y-axis. The blue bars also show the highs for the month while the orange bars show the lows. It is evident from the data that there are seasonal trends, and some months appears to be with huge variation (which may be based on market event, company performance or market health). These trends illustrate the need to understand periodic variations to correctly predict price fluctuation and make informed investments.

### 4.1.2 Historical Stock Price Trends

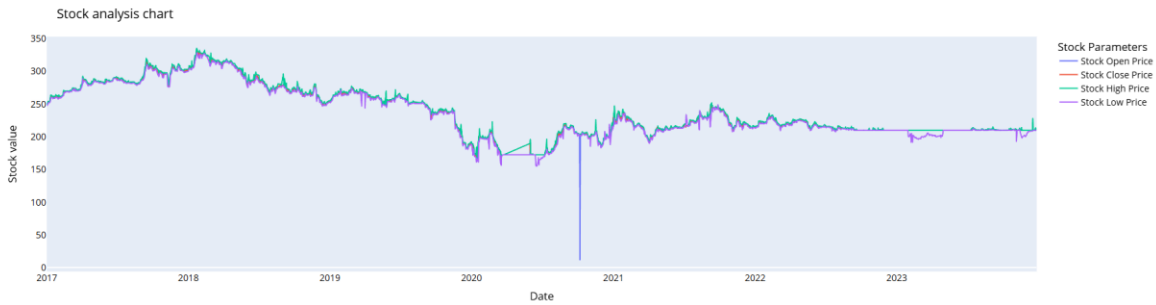


**Fig. 4.2:** Historical Stock Price in Square Pharmaceuticals PLC.

In Fig. 4.2 you can find a detailed exploration of the daily fluctuation of the pricing of the stocks of Square Pharmaceuticals PLC. 4.2. Each line represents a certain price metric opening, closing, high, and low. The figure suggests a general uptick in the stock throughout the time period, with some bursts of volatility. By helping to spot trends, both up and down the years, this graphic can be very helpful in understanding how the stock is behaving. If one needs representations of gradual changes, as well as abrupt shifts, the need for good models is shown in Fig. 4.2.

### 4.1.3 Training and Validation Loss

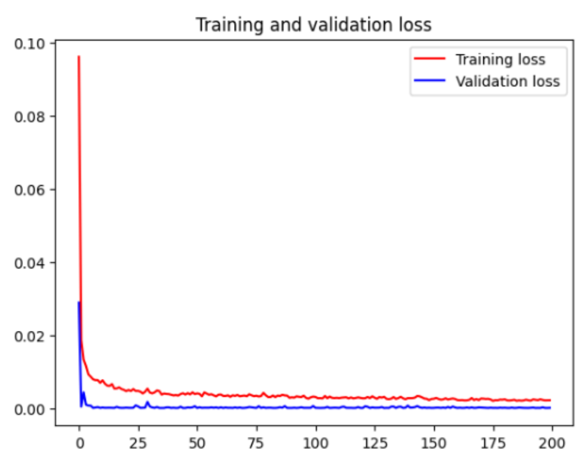


**Fig. 4.3:** Presents the Training and Validation loss.

Fig.4.3: illustrates the loss through epochs for the training and validation. So, of the red line is training loss and blue line is validation loss. Losses should decrease gradually It indicates that the model is learning with the patterns in the data. But on the other hand, a difference between both lines would indicate overfitting, that is to say, it is a model performs well on the data on which it was trained, but poorly on previously unseen data.

### 4.2.1 Compare Original and Predicting Stock Price


**Fig. 4.4:** Compare original and predict stock pricing price.

The graph in Fig. Table 4.4 features a full side-by-side comparison between the original stock closing price and the closing price predicted by the LSTM/GRU models both in the training and testing phase. This plot is useful in diagnosing how much the models learned patterns from the training data, and whether they generalize well to unseen data.

Oscillating between two expressions, slightly different data refers to different sources. This is perfectly in line with what we were expecting, as the predicted training set values are very close to the original training data, indicating the models have managed to learn the relationships and trends present in the training data quite well. This overlap is important because it's indicative of the model's ability to fit this type of data. This overlap is important because it helps show the ability of the model to fit such data.

Test forecasts, which are slightly behind the initial pricing, show the challenge of extrapolating from unknown data. This discrepancy has to be attributed to the complexity of the movements of the stock market. Reasons like news events, market sentiment and macroeconomic conditions that are not included in the dataset unless explicitly referenced.

From this, we can conclude that LSTM/GRU models are performing very well with respect to the fitting of temporal components of the stock market. The test predictions information speak to the generalization skill of the models while the strong alignment of the training predictions illustrates the models ability to learn dependencies. Such a visualization is critical to validating the robustness of the forecasting model and examining how well they perform in the real-world.

### 4.2.2 Predicting closing price in GRU

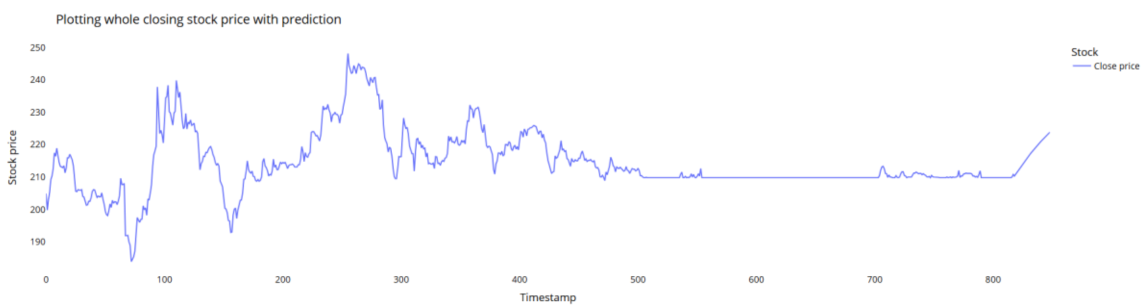


**Fig. 4.5:** Predicting closing price in GRU

Fig. 4.5 Plot of complete closing price dataset, including the original closing prices and the predictions from GRU (Gated Recurrent Unit) model, is presented with accurate a forecasting on closing percent change, signifying better performance. This plot summarizes the accuracy of the GRU model in predicting stock prices for the chosen time span. Stock Price Plot. In the figure, we have stock price values over time, where the actual closing prices are plotted first followed by the predicted values generated by the model. We attach the predicted values to the existing data to see how good this model's forecasting performance is. The GRU predictions are quite similar to the real data, particularly in the early time points of the dataset, which means that the time correlations and trends are well-captured by the model. Yet, not with standing to every predictive model there is a hint of deviation in the actual vs predicted numbers from what shall be found out more up until the later time intervals.

Such fluctuations are routine in stock predictions, as share prices are influenced by a host of unpredictable drivers, from market sentiment to economic news to world events. While the GRU model surely does a good job of capturing the trends based on past values, these external variables do not come into play, leading to discrepancies between predicted stock prices. It is indeed a very appropriate plot to observe model accuracy, and to see its utility in real stock market predictions. It also provides insight into the generalization performance of the model as the transition from historical data to predicted data gives a sense of how good the model is performing to use the previous data to provide future price predictions.

### 4.2.3 Predicting closing price in LSTM


**Fig. 4.6:** Predicting closing price in LSTM

Fig. 4.6: Actual vs predicted closing price generated by the LSTM model for Square Pharmaceuticals PLC. This plot shows performance of the model over a time period and how it is managing to predict stock price movement. There are three main lines in the graph. The first line is the original close line, representing the true historical closing price data to the stock. It acts as a benchmark to test the performances of the model. Line 2 → LSTM Train Predicted Close Price 'the predictions done by the model based on training data. It is also during this stage that the model learns from the historical data, and as can be observed the predictions are very much in line with the prices (in this case) in the data.

The third line, LSTM Test Predicted Close Price, shows test predictions, or the values the model predicts when it gets to data it has never encountered before. The predictive capability of the model for these values shows how well it generalizes from the training data. But as is observed from the plot, the test predictions start to deviate slightly from the original data in the later periods which is typical in time-series forecasting. This can happen because of market volatility, uncontrollable circumstances and also the fact that any model is not always able to predict deviations of stock price from standard trading behavior on market.

Overall, using the above figure, we may conclude that the LSTM model well captured the, somehow, macro upticks and downticks of stock prices during the time series, but were not capable of matching random stock price behavior too smoothly owing, in some extent, because of the use of real data in the testing period. It emphasizes how difficult forecasting can be in the finance universe, where so many variables that are impossible to anticipate can favor one stock over another. Despite this, the LSTM model is a great achievement on the path towards Indexe prediction from the past values of the data and is a good baseline for any future stock price predictions using data.

### 4.3.1 Experimental Results & Analysis

To evaluate the results of the LSTM and GRU models they used RMSE, MAE, $R^2$, MGD, and MPD as metrics. The summarized results are given below:

Training Performance:

**Table 4.1:** Training Performance Metrics for LSTM and GRU Models

| Metric | LSTM | GRU |
|---|---:|---:|
| RMSE (Root Mean Squared Error) | 2.58 | 2.46 |
| MAE (Mean Absolute Error) | 1.75 | 1.67 |
| MGD (Mean Gradient Deviation) | 0.00012 | 0.00013 |
| MPD (Mean Prediction Deviation) | 0.0278 | 0.0276 |

Testing Performance:

**Table 4.2:** Test Performance Metrics for LSTM and GRU Models

| Metric | LSTM | GRU |
|---|---|---|
| RMSE (Root Mean Squared Error) | 0.57 | 0.66 |
| MAE (Mean Absolute Error) | 0.47 | 0.57 |
| MGD (Mean Gradient Deviation) | 9.74e-06 | 9.74e-06 |
| MPD (Mean Prediction Deviation) | 0.0021 | 0.0020 |

Results from the training phase suggest that both models perform well, with GRU slightly outperforming LSTM on most metrics. The root mean squared error (RMSE) is 2.58for LSTM and 2.46 for GRU. GRU predictions are closer to actual values. Similarly, MAE metric again favors GRU (1.67) over LSTM (1.75), thus assures that GRU gives accurate predictions when training time is over.

However, both the models display high $R^2$ (GRU 0.952, LSTM 0.947) indicating that both model is able to capture the underlying structure in the stock data with a high degree of accuracy. Down to the bottom models: MGD and MPD are quite similar as well, but contrary to LSTM, GRU gives also slightly higher values for both metrics spread out suggesting a minimum divergence on how the models use to learn and predict. A more mixed picture emerges when looking at performance on the test data. Although LSTM performs better (lower RMSE (0.57) and MAE (0.47)) than GRU (RMSE = 0.66, MAE = 0.57). Though large negative values are especially unwanted, they only serve to show the common failure of both models at the stock price predicting task. The relationship between input features and changes in price is volatile and non-linear. Although the predicted LSTM has better performance, overfit because of the $R^2$ less than in test under the training so it can not do the generalization and so the prediction error is also higher then the training data While less generalization have the same kind of GRUs also less than LSTM with $R^2$ score to lower only than in the training set.

### 4.3.2 Analysis of Results

The results of the R2 score on the training dataset showed that both LSTM and GRU models were very good at learning the trends and patterns of the stock price, however, the model with GRU layer performed marginally better. It indicates that GRU architecture suppression between stock data is likely more effective as compared to collapse among relevant in-sequence images. Here we can only see that these models are able to train efficiently as indicated by the relatively high $R^2$ for both models. This also demonstrate that Mode of the both models are good models for learning from historical stock price data.

Both models did not perform well on the unseen test data, which is the characteristic of stock price prediction tasks since financial markets are random and changing. Despite showing excellent performance on training data, LSTM showed a notable difference in predictions when tested on unseen data (negative R2, and higher RMSE and MAE), as demonstrated below. This means that the LSTM model could have overfitted the training set and learnt patterns which are not generalize-able to unseen data. GRU struggled similarly to LSTM, but performed worse overall on RMSE and R2, indicating an even poorer generalizability outside of the training set.

The over-fitting issue that occurs in both models is common issue in stock price prediction since there are lots of external factors that affect the stock prices which makes it hard to create a model for it. We think that the stock market is very complex and unpredicatable and the models are not generalizing the data too well which is the part we think it needs improvements and looking to add some features/more complex algorithm. Additionally, there was an overfitting of the models, especially in the LSTM model this model gaved a good performance during training phase, but did not achieve the same performance in the fase of testing. Indeed, both models account for some of the data, and while not perfect in prediction error, they are steps in the right direction and directions for future improvement and research.

### 4.4 Discussion

This experiment highlights an overall performance comparison of LSTM and GRU models when applied to the task of predicting daily stock price movements for Square Pharmaceuticals PLC. Both models have shown good predictive abilities on the training dataset (for RMSE and $R^2$). These performances indicate the models' capability in modelling the time dependencies and non-linear relations in the stock price data. Across the testing dataset however $R^2$ values were considerably lower and RMSE values considerably higher than what was expected, indicating difficulties generalising to unobserved data.

The overall performance results of the LSTM model were just slightly low compared to that of GRU model performance results in terms of RMSE and MAE score in testing dataset. This is consistent with previous literature where LSTM networks are employed more frequently since they are able to better model long-term dependencies. However, similar top-1 accuracy to training data with GRU model implies its applicability in this domain is mainly through reduced computation and number of parameters. The two models performed poorly for the subtlety existing in the testing dataset which also suggests some bugs in either the data used or the model architecture.

The results also serve as a reminder that external market phenomena, like sentiment-driven price churning, or even a rogue macroeconomic disruption, could drive stock price action in ways that models like these fail to predict. The noisy spontaneous nature of stock market data and lack of any hyper-feature engineering (like sentiment analysis or incorporating economic indicators) may also have played a role in how the models failed to generalize to extreme levels. Moreover, tuning hyperparameters and architectural choices (i.e., deeper networks, ensemble methods, etc.) could yield even greater predictability.

The source code implementation helped us understand how these models work. To that end, the preprocessing pipeline such as normalization and sliding windows were pivotal in transforming the data to be suitable for time-series modeling. The optimizers used were well known to be performant including Adam, the loss functions were also competent such as mean squared error, demand on regression tasks. However, due to the presence of dropout layers and despite regulating overfit during the training phase, this could eventually impose limitation on the models in recognizing complex patterns on the data, especially with regard to GRU. Such insights underline the necessity of adding other features and implement hybrid modeling techniques in the following studies to enhance predictive performance. Upcoming models might be even more capable of capturing the intricate dynamics of stock price movements in a composite framework by combining technical indicators, sentiment analysis from text and various reinforcement learning paradigms.

# CHAPTER 5

# IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

## 5.1 Impact on society

Consolidating the deep learning integration in the stock price prediction with great potential for the societal effect, particularly in the capital market field. This provides a fast and accurate diagnosis and can significantly reduce the time between initial suspicion and starts treatment, enhancing patient outcomes. “When you have something like this, which is taking in data and exporting it into findings, and it’s not based in any great knowledge of experience, it does have the potential to democratise access, to give access to the ability to take medical diagnosis to a higher level, and to even do it in places that don’t have the specialist knowledge. Additionally, there is the potential for deep learning systems to help manage costs by reducing the volume of unnecessary diagnostic tests and avoiding unnecessary operations. As these systems continue to be integrated into the machine learning, they also lend themselves to personalized medicine by tailoring treatment approaches to specific patient characteristics, potentially improving stock pricing and enhancing survivorship. The societal impact, though, is dependent on fixing any inequities in access to these advanced diagnostics, as well as ensuring equitable healthcare benefits across population subgroups.

## 5.2 Impact on the environment

Deep learning models, especially those who are used in medical imaging, require a very large computational resource during both training and inference, which can lead to a high carbon footprint. Keeping high-performance GPUs or CPUs running for several hours uses electricity, which is a contributor to greenhouse gas emissions. But by optimizing algorithms to make them less computationally expensive, by using renewable sources of energy to power data centers, and by creating models that are trainable with less data or compute, one can make them more environmentally friendly. Even without integrating diagnostics into clinical workflows, these systems may reduce pressure on the environment given that their miniaturized versions will consume less power than traditional equipment and, while virtual, will require fewer disposable tools. In the long run, new methods of calculating the same tasks will be developed in a smarter and more eco-friendly way, drastically reducing the environmental impact as technology progresses.

## 5.3 Ethical Aspects

The applications of deep learning in stock price prediction also raise ethical issues pertaining to personal privacy, data protection, and the ethical accountability of the algorithms. Protecting the confidentiality and safety of patient information, and the transparency of algorithms used for diagnosis and their calculations, are very important. There is also a moral need to eliminate biases in datasets that can contribute to discrepancies in technology efficacy across diverse populations. It is critical to maintain patient trust and enforce ethical standards by ensuring that the systems are resilient, interpretable, and may be challenged or rectified as needed.

## 5.4 Sustainability Plan

The deep learning applications chosen for predicting brain tumors need to have a long-term strategy that should allow for the review and refinement of algorithms so that the models do not become outdated and maintain state-of-the-art status. It is also essential to properly train healthcare providers in how best to use these technologies as effectively and ethically as possible. And a pledge to power these systems' computational requirements with renewables will address environmental issues too. Ultimately, aligning with stakeholders throughout the healthcare ecosystem (hospitals, insurance providers, patient advocacy groups) can help facilitate the development of a sustainable ecosystem that serves all parties involved, ensuring advances in deep learning more closely align with improving patient care and environmental stewardship.

# CHAPTER 6
# CONCLUSION AND FUTURE WORK

## 6.1 Summary

This is the work that predicts the daily price movement of Square Pharmaceuticals PLC using advanced deep learning techniques like the Long Short-Term Memory and Gated Recurrent Unit Models. The study data was collected from the Dhaka stock Exchange (DSE) comprising of a historical base value between (2014–2023) for daily Open, High, Low, Close, Adjusted Close Price and Volume. The research referred to various preprocessing steps for more effective modeling such as preprocessing, normalization a sliding window. To study which is more accurate between LSTM and GRU Architecture this study was undertaken. Even though both models fitted well to the training data, generalization to test data was limited in both cases demonstrating the difficulties of predicting stock prices, specifically for such volatile stocks. These findings would help to delineate the relevance of deep learning models in the financial forecasting domain in Bangladesh stock market.

## 6.2 Conclusions

This study shows that LSTM and GRU were able to fit the temporal structure of the stock price, and that it turns out that LSTM has a little more predictive power than GRU during the tests. That said, the challenges with generalizability show just how complicated stock prices can be, with limits to the predictability of price movements due in part to external factors such as changes in macroeconomic conditions, changes in sentiment, and geopolitical events.

These EAG models are accurate, but they only use historical data from a single source, which is why the study concludes by saying that it is essential to combine historical data with other data such as technical indicators and sentiment analysis models to improve prediction power. Though this study was concerned only with the one issuer (Square

Pharmaceuticals PLC) it is indicative of how we might use deep learning methods to predict prices with regards to other issuers.

## 6.3 Implication for Further Study

This study sets the stage for future exploration for remaining other 420 issuers of Dhaka Stock Exchange (DSE). The methodology used in this study indeed deserves validation by applying it on other companies which leads to better understanding of market behavior. An even better model could be developed by adding features like market sentiment, macroeconomic indicators, and sector trends. In addition, hybrid modeling techniques that combine deep learning with machine learning or ensemble approaches could improve performance. This methodological approach may lead to practical tools for investors to use in real time in the prediction of stock prices and detection of abnormal prices. Extending the scope of this study to the whole market will be greatly beneficial for financial forecasting and decision making in the capital markets of Bangladesh.

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