Heaven's Light is Our Guide

DEPARTMENT OF ELECTRONICS & TELECOMMUNICATION ENGINEERING

Rajshahi University of Engineering & Technology, Bangladesh

Thesis report

on

Modeling and Analysis of Stock Market Forecasting Utilizing an LSTM Approach

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November 5, 2022

ACKNOWLEDGEMENT

I want to begin by expressing my utmost respect and thankfulness to Almighty God for his mercies and grace, without which I would not have been able to finish this task.

I also like to thank my supervisor, Dr. Mst. Fateha Samad, professor in the Department of Electronic & Telecommunication Engineering at Rajshahi University of Engineering & Technology, for her insightful comments on my research. She continued to have faith in me and let me select the area of interest. She provided me with a lot of helpful advice when I conducted my study, and I appreciate that. It was impossible to do this research work without her guidance, supervision, kindness, amazing feedback, and encouragement. She has assisted me in filling in my weaknesses and encouraged me to continue making progress.

I also want to express my gratitude to Md. Kamal Hosain, who serves as the department head for electronics and telecommunication engineering at Rajshahi University of Engineering & Technology, for providing me with the chance and resources I needed to successfully complete the thesis.

Finally, I want to express my gratitude to my family and friends for their unwavering support during this road to properly complete my thesis.

November 05, 2022 Sabboshachi Sarkar
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CERTIFICATE

This is to certify that the thesis entitled "Modeling and Analysis of Stock Market Forecasting Utilizing an LSTM Approach " by Sabboshachi Sarkar, Roll No. 1604016 has been carried out under my supervision. To the best of my knowledge, this thesis work is an original one and was not submitted anywhere for any degree or diploma.

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ABSTRCT

In this research a Deep Learning model is proposed that uses LSTM for forecasting applications in the stock market. When it comes to making more accurate predictions regarding the movements of the stock market, this model comes highly recommended because it is particularly effective and precise. When making projections about the indexes of the stock market, an approach known as Long Short-Term Memory (LSTM) is applied. LSTM is commonly acknowledged one of the most effective models for making such a forecast. To predict daily returns, the model is trained by using the historical data of stock prices for five different companies across five different industries. This section, mostly focused on attempting to forecast the movement of the Bangladeshi Stock Market. Our Model is trained using data that was acquired from five different companies that are listed on the DSE. For a more in-depth analysis, the model was also trained using historical data from Google, Microsoft, and Tesla—three of the most successful and well-known firms in the world that are traded on the NASDAQ Stock Exchange. While validating the model, it was found that the outcomes can vary. Some of the outputs were satisfactory, but for a select few companies, the results were less than ideal. This is because the chaotic nature of the Bangladeshi Stock Market is to a large extent unexpected. Yet the majority of companies had successful production. The capacity of the proposed model to detect error or deviation in the learning process, which results in RMS Error, Mean Absolute Error and Loss Functions, is a critical factor in determining whether or not the suggested technique will be successful. There is no doubt that our model can assist in predicting the future movement of the stock market price and so limit the amount of risk that an investor is exposed to.

Key Words: Stock Market, Deep Learning, LSTM,

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LIST OF ABBREVIATIONS

ML	Machine Learning
DL	Deep Learning
NN	Neural Networks
RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory
RWT	Random Walk Theory
EMH	Efficient Market Hypothesis
DSE	Dhaka Stock Exchange
NASDAQ	National Association of Securities Dealers Automated Quotations
PLS	Partial Least Squares
SMO	Sequential Minimal Optimization
ExtRa	Extremely Randomized trees
GAN	Generalized Additive Model

CHAPTER 01: INTRODUCTION

This is a deep learning-based model for examining the efficacy of Long Short-Term Memory (LSTM) networks, a deep neural network architecture that enables the network to retain both long and short-term memories, for forecasting the future movement of daily return of American and Bangladeshi stocks in the NASDAQ-100 index and the DSE index, respectively.

1.1 Introduction

The stock market is the engine that drives the modern economy. Every day, billions of dollars are exchanged in numerous global marketplaces. Attempting to predict the movement of stock market indices under these conditions is incredibly challenging. The process of attempting to foresee or forecast the future value of a stock, a market section, or the entire market is referred to as stock market prediction. It is an area that has attracted the interest of a huge number of individuals, including companies, brokers, investment organizations, data scientists, and even computer engineers working in the fields of Machine Learning (ML) and Artificial Intelligence (AI), among others. If it were possible to precisely predict how a market would move, the trading decisions of millions of investors would be significantly more informed. However, achieving a high level of accuracy in stock market forecasting is a big task. This is owing to the chaotic, noisy, nonlinear, and complicated nature of the stock market indexes' historical time series. The value of a company's shares is highly dependent on the organization's profits and success in the market, and can thus fluctuate based on a variety of factors, such as government regulations, microeconomic indicators, demand, supply, etc. Investing in the market is exposed to a number of market hazards, as the market value of a company's shares is strongly dependent on its profitability and performance. These distinctions in the market are being examined in order to produce software and programs utilizing various techniques, including machine learning, deep learning, neural networks, and artificial intelligence.

Deep Learning is one of the subfields of machine learning (ML). Deep learning is a neural network with at least three layers. A neural network attempts, but with little success, to replicate the operations of the human brain, allowing it to learn from incredibly huge amounts of data. Recurrent neural networks (RNNs) have been proven to be one of the most effective models for the processing of sequential input in the context of deep learning [1]. The methodology is widely applied for stock market forecasting and is recognized as one of the most prevalent sequential data processing methods. The architecture known as Long Short-Term Memory (LSTM) is the most successful sort of RNN architecture. Traditional RNNs have both long-term and short-term memory, in contrast to LSTM, which only has feedback connections [2]. This specific variety of RNNs is able to make evaluations on individual data points as well as on complete data sequences. In lieu of artificial neurons, the LSTM method places memory cells, which operate as computing units, in the network's hidden neurons. These memory cells make it simple for networks to link remote input and memories across time, allowing them to comprehend the evolving data structure while preserving a high degree of predictability. This makes them well-suited for comprehending evolving data. [1]

These types of systems and software can provide the investor with the ability to accurately predict the company's situation based on historical and current data, the current state of the market, etc., and point them in the right direction when it comes to making decisions, allowing them to avoid losing their money and maximize their profits.

Although practically all large organizations are hiring data scientists and financial analysts, these professionals are unable to precisely predict specific numbers, but they may reliably predict trends. According to the principles underpinning the stock market, the capacity to predict future trends is highly dependent on the examination of historical time series data. A time series is an ordered sequence of numerical data points gathered over time. It tracks the movement of the selected data points over predefined time intervals and presents the findings. Daily, the stock market generates this information. By keeping these historical patterns in mind, investors can make better selections.

In this paper, I made a conscious effort to provide an overview of a method for predicting stock prices with a higher degree of accuracy. The network consists of a sequential input layer, one LSTM layer, five dense layers with ReLU (Rectified Linear Unit) activation, and a dense output layer with a linear activation function. The daily stock closing price for 5 companies listed on the Dhaka stock exchange and 3 companies listed on NQ-100 is monitored. Using the proposed model, each company's stock price is analyzed separately. I also tried to investigate the different obstacles that affect the performance of the model, as well as the potential for future research in each area.

1.2 Motivation

The objective of stock market forecasting is to assist investors in anticipating future stock market and stock price fluctuations using historical data and other available information. Typically, the dataset is accompanied with a quarterly financial ratio. Consequently, it is feasible that a single dataset is inadequate for the forecast and will produce an erroneous result. If an improved prediction model for the stock market is not proposed, the problem of underestimating stock values will endure. In the stock market, predicting future performance is extremely difficult. The direction of the stock market is often determined by the opinions of thousands of people. To make effective stock market forecasts, one must anticipate how current events will impact investors. Instances of political happenings include a politician's remark or a news item exposing a swindle. Global factors, such as abrupt fluctuations in commodity prices or currency exchange rates, can also have this effect. All of these factors have an effect on business profitability, which in turn has a substantial impact on investor sentiment. The majority of investors lack the requisite resources to produce accurate estimates of these hyperparameters. The combination of these factors makes it extremely difficult to forecast stock values. In light of this, I am considering incorporating machine learning with the integration of several datasets in order to forecast market and stock patterns. If sufficient meaningful data is gathered, it can be used to train a machine, which will subsequently make more accurate predictions.

1.3 Related Work

Contradicting the fundamental theory of finance, the Efficient Market Hypothesis, is the prediction of financial market trends (EMH). Predicting stock prices is also one of the most essential aims in the field of finance. In this research project, we aimed to develop an effective LSTM model and assess how well Deep Learning can forecast future stock market movements.

Roondiwala et al. [1] suggested a methodology for predicting stock market indices. Their algorithm was trained using historical data from the Indian National Stock Exchange. They have developed one of the most accurate forecasting techniques using Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). They have modeled and predicted the NIFTY 50 stock returns using LSTM. Five years of historical NIFTY 50 data were utilized to train and validate the model. Then, they described each procedure in detail as they discussed the methodology. There are visual representations of the analysis of the attained outcomes in the conclusion.

Pang et al. [3] proposed a novel neural network technique for enhancing stock market forecasts. For the purpose of demonstrating the Internet of Things for stock analysis, data from the cattle market was collected for real-time and offline analysis, as well as visualizations and analytics. Using the evolution of word vector in deep learning, they show the concept of "stock vector." The input consisted of historical data with several stocks and high dimensions. They propose employing deep long short-term memory neural networks (LSTM) with embedded layers and long short-term memory neural networks with automatic encoders to forecast the stock market. They employed the embedding layer and the automated encoder, respectively, to vectorize the data in their two models so that a neural network with a long short-term memory could predict the stock. Based on the results of their experiments, the deep LSTM with an embedded layer proved superior. The accuracy rates of two models for the Shanghai A-shares composite index were 57.2% and 56.6%, respectively.

In a separate study, Gunduz et al. [4] employed deep neural networks to predict future movement based on the daily movement directions of three actively traded businesses (GARAN, THYAO, and ISCTR) on the Borsa Istanbul exchange. Using individual stock prices, technical indicators were derived. The dollar gold price was included as a factor in the projection. Using the daily closing stock prices, class labels describing the movement direction were identified and aligned with feature vectors. The prediction was executed using Convolutional Neural Networks, a type of deep neural network (CNN). After CNN model training, the accuracy and F-measure metrics were utilized to evaluate classification performance. Using both price and dollar-gold features, GARAN, THYAO, and ISCTR stock movement directions were predicted with an accuracy of 0.61, 0.578, and 0.578%, respectively, in their experiment. The performance of the classification was improved with the addition of dollar-gold criteria as compared to only price-based characteristics.

Billah et al. [5] proposed an improved Levenberg-Marquardt (LM) algorithm for Artificial Neural Networks (ANN). This enhanced algorithm was implemented in order to forecast the closing price of the stock market. Recent research has showed that an adaptive Neuro Fuzzy inference system outperforms a neural network for market prediction. Given past historical stock market data from the Dhaka Stock Exchange, such as the opening price, highest price, lowest price, and total number of shares traded, an enhanced Levenberg Marquardt neural network algorithm can predict the potential day-end closing stock price with less memory and processing time. If ANN adopts this improved training method, it predicts stock prices 53% more correctly than ANFIS. Additionally, they demonstrated that computation and memory allocation require less time. In the context of the Bangladesh Stock Exchange, their enhanced LM training method reveals that neural networks are a superior computing tool for forecasting the closing stock price.

Sujatha et al. [6] conducted a study to evaluate the predictive power of nonparametric models of stock index closing prices for non-normal data. Comparing their suggested neural network model to current statistical prediction models reveals that it is highly promising and can be included into real-time trading systems for predicting stock prices.

In an experiment, Liu et al. [7] proposed an LSTM-based model for predicting stock market movement. Using LSTM recurrent neural networks, they filtered, retrieved, and evaluated stock data before developing a prediction model for the linked stock transaction. The results of the test indicate that their model is capable of more accurate predicting, despite the fact that its accuracy was only 72% for the small sample size.

In their work, Gurav et al. [8] investigated stock market technical indicators, mathematical models, the most common algorithms in data science organizations, an analysis of various machine learning algorithm types, and an overall summary answer. In addition, they attempted to analyze a variety of topics related to dynamic stock market forecasting. This was done based on the association between the reduction of investment risk on the stock market and the reduction of forecasting errors.

Ashfaq et al. [9] did research on the NASDAQ stock market with the objective of picking a portfolio of ten distinct firms from different industries. Using historical data, they sought to predict the opening price of the stock on the following trading day. To achieve this purpose, they applied nine unique Machine Learning regressors to the data and evaluated its performance using MSE and R2 values. Their efforts yielded incredibly pleasing results.

The research done by Soni in [10] represented a survey on various current articles of literature in the field of machine learning methods and artificial intelligence systems that are used to predict movements in stock markets. According to the findings of their study, Artificial Neural Networks, often known as ANNs, are among the most effective machine learning approaches for stock market prediction.

Nabipour et al. [11] focused their research primarily on predicting the future behavior of stock market groups. Four groups were recruited from the Tehran stock exchange for the aim of conducting experimental evaluations. These groups consist of diversified financials, petroleum, non-metallic minerals, and fundamental metals. On the basis of ten years of historical records, data was compiled for each of the categories. One, two, five, ten, fifteen, twenty, and thirty-day value projections are generated. Several different machine learning algorithms were utilized to forecast the future values of stock market groups. In addition to artificial neural networks (ANN), recurrent neural networks (RNN), and long short-term memory, they employed techniques such as decision trees, bagging, random forests, adaptive boosting (Adaboost), gradient boosting, and eXtreme gradient boosting (XGBoost) (LSTM). Each prediction model employs ten distinct technical indicators as inputs, and these indicators were selected with care. In conclusion, the results of each method's estimates were offered based on four distinct metrics. According to the results of their investigation, LSTM delivered more accurate results and had the greatest modelfitting capacity. Adaboost, Gradient Boosting, and XGBoost frequently engaged in a fierce competition with one another when it comes to tree-based models.

In a work, Vignesh [13] studied the methodologies used to estimate the future value of a company's stock or any other financial instrument listed on a stock exchange. His forecast plays a significant influence in numerous financial and investment decisions. Machine learning may perform this computation by training a model to recognize the trend in historical data in order to forecast the future. The primary focus of his research was a comparison of the SVM and LTSM algorithms.

Using machine learning techniques, Parmar et al. [14] attempted to forecast the future stock values of a company with more precision and reliability. The most major contribution made by the researchers was the adoption of an innovative pricing model known as the LSTM Model, which was used to assess stock prices. The improved accuracy of these approaches' predictions has resulted in positive outcomes; nevertheless, the LSTM model has been demonstrated to be more successful. The findings are quite encouraging, and they lead the researchers to conclude that it is possible to predict the stock market with improved precision and efficiency using machine learning techniques.

The ability of LR, MLP, SVM, and LSTM models to forecast daily streamflow using time series data was explored and evaluated using three distinct scenarios constructed from an existing data set [16]. These scenarios were designed so that the performance of these models could be compared. In the first possible outcome, estimates of daily runoff are produced using historical streamflow and precipitation data from the research basin. In the second scenario, the effects of daily precipitation on daily streamflow are considered, but in the third scenario, the daily streamflow forecast is based solely on the streamflow from the previous day. For each conceivable outcome, the prediction of daily streamflow was performed using one of the data-driven approaches listed below: LR, MLP, SVM, or LSTM. The four models were evaluated using three distinct training data sets, and the outcomes were defended in three distinct scenarios. The 26 years' worth of data collected from the basin of the Kentucky River were divided into two series for training and testing purposes. In order to evaluate the performance of the model, eleven statistical criteria, including R, E, EH, EL, NRMSE, AARE, REmax, TS25, TS50, and TS100, were computed for both the training data set and the test data set. Using observed and predicted streamflow values beginning in 1986, a time series graph, Taylor diagrams, and scatter plots were created to assist graphical comparisons of the models' respective outcomes. The LSTM model, which was recommended for daily streamflow forecasting in this study, displayed the best performance when compared to the other models. In addition, the LSTM model suggested that the third scenario had the best results. Experiments done for this study proved that black box models are capable of predicting streamflow without taking any regional or physical elements present in the study basin into account. The implementation of digital filters and other data-driven technologies, for instance, will be the key focus of future research; this article did not devote sufficient attention to all essential aspects. Consider the idea of categorizing streamflow on a case-by-case basis and using classifiers to foresee streamflow conditions.

Vohra and Tanna in [17] conducted a survey with the goal of gaining an understanding of the various kinds of research that have been conducted on the Indian stock market. According to the findings of their investigation, there are just a few primary methodologies that are utilized most frequently when attempting to anticipate the trend of the stock price, stock price, or stock index. The data from the Indian stock market is used for virtually every machine learning algorithm. They made the discovery that the same method could be utilized by several researchers, despite the fact that the researchers' input parameters, and hence their output, would be different. The efficacy of the many different types of research is evaluated by a variety of distinct approaches. As a result, comparing any two separate studies is an incredibly challenging endeavor. Some of the studies only look at a limited number of stocks, which makes it difficult to speculate how the results may change if a different group of stock prices is utilized. The equity market is notorious for its great volatility; as a result, the results of a single piece of study are liable to fluctuate from time to time. In spite of this, it has been noticed that, in comparison to other algorithms, fine-tuned SVM and ANN appear to produce superior outcomes.

Soni et al. [20] recommended performing a comparative review of the several algorithms now available for predicting the values of a variety of shares. In addition to traditional machine learning methods such as RF, KNN, SVM, and Naive Bayes, the research was expanded to incorporate Deep Learning and Neural Network models. These include, among others, Convolutional Neural Networks, Artificial Neural Networks, and Long Short-Term Memory. The study also combines a number of additional approaches, such as sentiment analysis, time series forecasting, and graph-based algorithms, and evaluates the results of these algorithms in order to predict the stock values of a number of different firms.

Lakshminarayanan and McCrae [22] suggested research on the creation of SVM and LSTM using moving averages, and they discovered that these two tasks are often carried out separately. For future jobs, intraday prices can be utilized to compare values and obtain a deeper understanding of the volatility of stock, crude oil, and gold prices. These objectives can be achieved with intraday prices. The data on the sale and purchase of stocks can also be used to acquire an understanding of how fluctuations in the stock price and other external factors affect the buying and selling pattern. This will aid in the creation of a more accurate prediction.

Ghosh et al. [24] studied the growth of companies from various industries to determine the optimal time period for predicting the future share price. Their research reaches the significant conclusion that companies in a particular industry have the same dependencies and growth rate. The accuracy of the prediction can be improved by training the model with a larger number of data sets.

In a work, Hiransha et al. [25], utilized four distinct DL architectures to predict the stock values of the NYSE and the NSE, which are, respectively, two of the most major stock exchanges. They trained four neural networks using the TATA MOTORS stock price from NSE: MLP, RNN, LSTM, and CNN. On the NSE stock market, the obtained models were used to forecast the stock prices of MARUTI, HCL, and AXIS BANK. In addition, the models were used to forecast the stock prices of NYSE companies BANK OF AMERICA (BAC) and CHESAPEAK ENERGY (CHK). Following the conclusion of the trial, it became plainly clear that the models were capable of identifying patterns prevalent in both stock markets. This demonstrates that both stock markets are governed by an underlying fundamental dynamic.

Using a formalization that is based on deep learning, Selvin et al. [26] proposed a method for predicting stock prices. It has been demonstrated that deep neural network architectures are able to make accurate predictions and are capable of uncovering previously hidden dynamics. They were able to correctly anticipate the stock prices of Infosys, TCS, and Cipla after training the model with the data from Infosys. This demonstrated that the system being proposed is able to recognize some interrelationships that exist within the data. Additionally, it was clear from the findings that CNN's architecture is able to recognize shifts in patterns because of how well it performed. According to the technique that has been suggested, CNN is the most effective model. It makes predictions based on the information that is available at a certain instant. In spite of the fact that the different two models are utilized in several other time-dependent data analyses, the CNN architecture is not being outperformed in this particular instance. This is as a result of the unexpected shifts that take place in the stock markets. It's possible that the changes that take place in the stock market don't always stick to the same pattern or cycle. This is something to keep an eye out for. The existence of trends and the length of time they remain prevalent will vary depending on the types of businesses and the industries they operate in. The identification and study of patterns of this nature, including trends and cycles, will result in increased profits for investors.

Vargas et al. [29] presented a deep learning model that combines a convolutional layer with a recurrent layer for intraday stock price movement prediction and uses as input a combination of technical indicators and news titles. The RCNN architecture can model the local relation of a sequence of news titles and their temporal features. The proposed model uses only news from the day before the forecasting day and outperform a set of models that uses news from the past day, week and month. This result reinforces the hypothesis that the information in the news articles have a short temporal effect in the financial market. Regarding to the method, it can be concluded that the sentence embedding used in this work is better than the word embedding because the problem of word sparsity in the data set.

In a study, White et al. [30] published some results of an ongoing effort applying neural network modeling and learning techniques to seek out and decode nonlinear regularities in asset price movements. These methods were used to discover and decode nonlinear regularities. The author should focus on the case of the daily returns of IBM common stock. Having to deal with the significant characteristics of economic data calls attention to the role that statistical inference should play and needs the modification of traditional learning techniques, which may be useful in other circumstances.

Sutheebanjard et al. predicted the movement of the Thailand Stock Exchange index in [31]. Currently, the Kingdom of Thailand is home to two stock exchanges: the Stock Exchange of Thailand (SET) and the Market for Alternative Investment (MAI). This study focuses on the performance of an index tracked by the Stock Exchange of Thailand (SET Index). Back propagation neural network (BPNN) technology was applied in order to make an accurate forecast of the SET index. The data obtained during 124 trading days, beginning on July 2, 2004 and ending on December 30, 2004, were used to conduct an experiment. The data were divided into two groups, with the BPNN training group receiving 53 days and the testing group receiving 71 days. The results of the studies indicate that the BPNN can accurately predict the SET Index with an error of less than 2%. The BPNN is able to attain a reduced prediction error when compared to the adaptive evolution method, but a higher prediction error when compared to the (1+1) evolution technique.

In the study of Mehrara et al. [32], non-linear models were simulated using MLFF neural networks equipped with back-propagation learning algorithms and GMDH neural networks equipped with genetic algorithm (GA) learning to predict TEPIX based on the TSE database. Moving average crossover inputs have been applied to technical analysis rules, and the results indicate that exponential moving average yields superior outcomes to basic moving average. In addition, the results demonstrate that GMDH is superior to MLFF neural network in terms of predicting, power monitoring, and profitability.

Studies on artificial neural networks that have the capability to understand the basic mechanics of stock markets were described by Thenmozhi et al. in [33]. In point of fact, artificial neural networks have seen a significant amount of use in the field of financial market prediction. However, there aren't many applications of this kind to the Indian stock market. In this paper, neural network models are utilized to forecast the daily returns of the SENSEX index that is traded on the Bombay Stock Exchange. The daily returns model is constructed with the assistance of a multilayer perceptron network, and the network is trained with the assistance of an error back propagation technique. It has been discovered that the day before is able to have an effect on the predictive capacity of the network model. more return than the inputs for the first three days combined. According to the findings of the study, artificial neural networks can produce predictions of the BSE SENSEX that are accurate enough to be considered satisfactory.

Chandler et al. in [34] had the intention of mining appropriate trading rules by classifying the upward and downward fluctuant direction of the price for the Korea stock price index 200 (KOSPI 200) futures. It can be broken down into two distinct steps. The first stage consists of classifying the fluctuant direction of the price for KOSPI 200 futures using several technical indicators and artificial intelligence techniques. The second stage consists of mining the trading rules in order to resolve conflicts that have arisen among the outputs of the first stage using inductive learning. This study creates four models that are comparable to one another and then conducts statistical analysis so that the effectiveness of the proposed strategy can be evaluated. The classification performance of the suggested model is shown to perform better than that of other models that are comparable based on the results of the experiments. Furthermore, the proposed model generates a greater profit than other comparable models as well as the buy-and-hold investment strategy.

According to a study, RNN can use the network to keep a memory of recent occurrences and develop connections between each unit of a network; hence, it is entirely suitable for making economic forecasts [35,36]. Long short-term memory, often known as LSTM, is a method that is employed in the deep learning field. It is an enhanced subset of the RNN approach. In order to solve the issues that arise in RNN cells, LSTM is equipped with three distinct gates, and it is also able to handle individual data points in addition to entire data sequences.

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The deep convolutional LSTM model was utilized as a predictor by Kelotra and Pandey [39] in order to effectively assess changes in the stock market. The model was trained using an optimization technique based on Rider's monarch butterfly, and the results showed that they attained a low RMSE and MSE of 2.6923 and 7.2487 respectively.

Das et al. [40] developed the feature evaluation by taking into consideration the social and biological components of the firefly technique. They approached the problem by incorporating the evolutionary background of objective value selection into their methodology. According to the findings, the firefly model, which utilized an evolutionary framework and predicted using the Online Sequential Extreme Learning Machine (OSELM) method, performed the best when compared to the other models that were tested.

Chung and Shin [41] used a CNN, which is a type of deep learning approach, to make predictions about the behavior of the stock market. In contrast, the Genetic Algorithm (GA) was used to systematically improve the parameters of the CNN approach. The results showed that the hybrid method of GA and CNN, known as GA-CNN, performed better than the comparison models.

Liu et al. [42] examined a numerical-based attention method with dual sources stock market data to encounter the coexistence between numerical data and news in the forecasting the stock prices. Their goal was to find the "complementarity among numerical data and news in the prediction of stock prices." As a consequence of this, the technique efficiently filtered out noises and performed better than earlier models when it came to predicting stock from dual sources.

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In order to improve a revolutionary stock market prediction model, Chung and Shin [44] utilized a hybrid strategy that combined LSTM and GA. In the end, the comparison between the hybrid model consisting of an LSTM network and GA and the benchmark model revealed that the hybrid version was more accurate.

Zhou et al. [45] applied LSTM and CNN to high-frequency data from the stock market using a rotating division training and testing dataset. Their objective was to determine how

the update cycle affected the overall performance of the models. On the basis of a vast quantity of experimental data, models were able to effectively reduce errors and improve forecast precision.
Sheta et al. examined the performance of Artificial Neural Network (ANN) and SVR algorithms using time series data from the S&P 500 index and discovered that SVR performed better than ANN.

Binary classification models were developed by Nelson et al. [49] using LSTM RNNs. These models, rather than forecasting the price of a stock in the future, predicted whether or not the price of a stock will be either higher or lower than with the current market price 15 minutes within next. Along with a set of technical indicators that were created from the trading data, these were trained on the trading data of equities that were traded on the Brazilian stock exchange. On the five equities for which the findings were released, the authors found that the models had an accuracy ranging from 53.0 to 55.9%, with the best accuracy coming in at 53.0 percent. This study did not, however, investigate the possibility of forecasting the daily returns of a stock.

Althelaya et al. [50] examined a number of different deep learning architectures by applying them to the problem of predicting the value of the Standard & Poor's 500 Index at the close of each trading day. They evaluated models that were based on deep neural networks, LSTMs, and various forms of RNNs such as the stacked LSTM and the Bidirectional LSTM (BLSTM) (SLSTM). The BLSTM is distinct from standard LSTMs in the sense that, at any one point in time throughout the training process, it stores data from both the previous and the future. This gives it the ability to better comprehend the context in which it is being used. Generally speaking, stacked LSTMs make it possible for models to capture more intricate patterns within a particular time series. Their findings showed that LSTMs performed better than deep neural networks in both long-term and short-term prediction, that SLSTMs performed better than both of those models, and that BLSTMs performed the best out of all the models that were considered.

The effect of the indices on the prediction of the stock price is the primary emphasis of [54]. The model overcomes the limits of the classic linear model and makes use of LSTM in order to comprehend the dynamics of the S&P 500 Index. Additionally, the model identifies the factors that make up the relationship between the indices. The research also conducts an investigation on the sensitivity of LSTM modeling's internal memory. The research, on the other hand, has a few shortcomings. After a certain point, the disparity between the predicted value and the actual value becomes quite wide, and as a result, it cannot be used to build a system that provides a lucrative trading strategy.

Sarode et al. [55] suggested the implementation of a system that would provide customers with stock purchasing recommendations. The authors used a technique that utilizes LSTM for prediction and blends predictions based on historical data with those based on real-time data. The most recent data on trade and technical indicators are provided as input in the first layer of the RNN model. This is followed by the LSTM, which is a compact layer, and then the output layer, which provides the forecast value. A report illustrating the percentage of change is generated by further integrating these anticipated values with the summary data that is received from the news analytics.

1.4 Objective

The main objective of this paper is to build a deep learning-based LSTM model which can predict the stock market future movement with higher accuracy. I focused my attention exclusively on the Bangladeshi stock market, which is often regarded as one of the most unpredictable stock markets on the planet. It is my intention to determine how well the model represent the market by employing five DSE-listed equities that come from a variety of sectors. In addition, in an effort to build a more robust empirical foundation, I apply my model to the three most important stocks in the NASDAQ index in the United States.

The objectives of this studies are as followed;

a) Learn the fundamentals of the stock market and comprehend how it works.
b) Become familiar with the many different kinds of Deep Learning algorithms

c) Constructing an LSTM model in order to forecast the movements of the stock market in the future with a higher degree of accuracy
d) By applying the model, individual investors can reduce the likelihood that they will suffer a loss of financial resources.
e) Create an environment for investing that is so user-friendly and reliable that more people will be motivated to invest their money into the stock market.
f) Develop an LSTM model that can be used successfully on all stock markets in the world.

1.5 Thesis Outline

This thesis work is organized as;

The **Chapter 1**, begins with an introduction to this research endeavor. The motivation for the study is then addressed. This identical field has been investigated and assessed in relation to many earlier works. Furthermore, the aims of the research are examined in depth, providing a thorough picture of this research investigation.

Chapter 2, provides a concise introduction to the fundamentals of stock markets. Here, the significance and necessity of the stock market are explained. It also addresses the fundamental laws governing stock markets. In addition, the chapter describes classification and forecasting models for several theories and hypotheses regarding the stock market, such as EMH and RWT.

Chapter 3, explores the theoretical explanation, architecture, and operation of many Machine Learning Algorithms. This section briefly describes Supervised Machine Learning, Deep Learning, Neural Network, Recurrent Neural Network, and Long Short-Term Memory. Classifications of algorithm is discussed here. It also attempted to explain how these algorithms operate.

In **Chapter 4**, we present the architecture and methodology of the proposed investigation. The architecture illustrates the operational flow of this study. The technique for data collecting and preprocessing is then outlined. The explanation and illustration of the dataset's graphical representation have been displayed. The section concludes by describing the construction and operation of the suggested model, including Data Splitting, Feature Scaling Model Training and Testing, etc.

Chapter 5, discusses the results of the proposed model. Here is the model's output graph, representing a Prediction versus Observation perspective. It also includes a data table that calculates the model's precision.

The final and **6th Chapter** of the paper summarizes the investigation and outlines potential future research that may be useful for students who plan to work in this particular subject.

1.6 Summary

This chapter provides an overview of the entire study project. Here, the thesis's goals and objectives are also outlined sequentially.

CHAPTER 02: BRIEF INTRODUCTION TO STOCK MARKETING

2.1 Introduction

A stock exchange is a marketplace where firm shares and derivatives can be traded at predetermined rates. These may be publicly traded securities or ones that are exclusively traded privately. Members who engage in share trading must register with SEBI, the stock market's regulatory agency and the organization that organizes and administers the stock market. The stock market is often known as the secondary market due to the fact that transactions take place between two investors. The stock exchange brings together investors for the aim of buying and selling company shares. The stock market's prices are determined by the relationship between supply and demand. High buyer interest will cause a stock's price to increase, whereas strong selling interest will cause a stock's price to decrease. Companies permitted to trade on this market are referred to as "listed companies" [37].

2.2 Importance of Stock Market

When it comes to capital formation, the stock market is one of the most vital areas for firms to concentrate on. This enables enterprises to participate in public stock trading or acquire more capital for business expansion by selling ownership shares on the public market. Throughout history, it has been established that the price of stocks and other assets is a crucial element of the dynamics of financial activity and can either affect or serve as an indicator of the current condition of public attitude. In fact, the stock market is generally seen as the primary measure of a nation's level of economic progress and strength. Increasing business investment is frequently associated with growing stock prices, and rising stock prices are typically correlated with increasing business investment. The capital and spending habits of household members are also affected by the price of stocks. Consequently, the nation's central banks tend to monitor the management and activities of the stock market closely. In addition to facilitating transactions, exchanges also operate as the transaction's clearing house. This means that exchanges not only collect and deliver shares, but also settle agreements with sellers of securities. Due to this, there is no longer any risk that a seller or buyer's counterparty will fail to uphold their end of the deal. All of these activities contribute to economic progress, which in turn reduces costs, boosts production of products and services, and expands job opportunities. This portion of the financial system's contribution results in increased wealth [37].

Newly issued securities are distributed on the primary market. In primary markets, financial assets are acquired directly from the issuing corporation via the public offering procedure. A document that is published in conformity with the Corporations Law is an official prospectus. This booklet contains all of the information you need to make an informed investing choice on the company. Existing stocks are traded back and forth between buyers and sellers on the secondary market. On the secondary market, outstanding securities are transacted. On the secondary market, investors exchange shares with one another. This market consists of organized exchanges, and it may have a trading floor, which is where orders are conveyed to be executed. This is the location where all stock trading occurs, and the rules established by the exchange are adhered to everywhere [37].

2.3 Basics of Stock Market

The fundamentals of the stock market are comprised of shares and stocks. A share, often known as stock, is a piece of paper issued by a firm that grants the holder the right to be regarded as an owner of that company. In the case of an initial public offering, a share may be purchased on the stock market or directly from a corporation (IPO). A dividend is a percentage of a firm's profit distributed to shareholders who own shares of that company. Additionally, it is possible to generate a capital gain by purchasing and then selling shares. The return is therefore equal to the dividend plus the capital gain. You risk incurring a capital loss, however, if the price at which you sell the share is lower than the one at which you purchased it. Simply speaking, stock is simply a compilation or set of issued shares. There is a possibility that the stock will be preferred rather than common. The majority of a company's assets consist of its common stock. It represents ownership of a firm and a claim to a piece of its revenues in the form of dividends. The dividend amount fluctuates and is not guaranteed in any way. Shareholders have one vote for each share they possess when it comes to voting for board members. These board members oversee the important choices made by the executive leadership. Compared to the vast majority of other types of investments, the returns on common stock are often far higher. Preferred stock is a form of ownership in a firm that grants a certain degree of ownership but often lacks voting rights. Before dividends are paid to equity holders, these particular shares of stock are entitled to a dividend payment at a rate that is guaranteed to remain constant. In the case of dissolution, they are also entitled to a return on their capital investments prior to equity investors [37]. Formerly known as a securities exchange, a stock market is a corporation or mutual organization that offers "buying and selling" facilities for stock traders and brokers by facilitating the trading of stocks and other securities and functioning as a marketplace for these activities (virtual or real). In addition to facilitating the issuing and redemption of securities, stock exchanges facilitate the trading of other financial goods and capital events, such as the distribution of income and dividends. On a stock market, it is possible to trade corporate stock, mutual funds, derivatives, pooled investment products, and bonds, among other types of securities. Before a securities may be traded on a particular stock exchange, it must be listed on that exchange. Members are the only individuals who can buy and sell on an exchange. According to the definition of the primary market, the primary market is where stocks and bonds are initially sold to investors, whereas the secondary market is where additional trading occurs. The stock exchange is commonly regarded as the single most essential component of a stock market. In the majority of circumstances, firms are not obligated to issue stock through the stock market, nor are they required to trade issued shares on the exchange. This sort of trading is referred to as "over-the-counter" or "off exchange." This is the conventional way for trading bonds and derivatives. The global equity market is becoming increasingly interconnected with stock exchanges worldwide. Twenty prominent stock exchanges are found around the world [37]. Stock exchanges serve multiple functions in the economy, including but not limited to: raising capital for businesses; encouraging the saving of money for investment purposes; facilitating the growth of companies; profit sharing; corporate governance; developing investment opportunities for smaller investors; raising capital for the government to use in development projects; and serving as a barometer of the economy. Companies that desire to be listed on a specific stock exchange must adhere to a preset set of conditions known as the exchange's listing requirements. Typically, there are minimum requirements for the number of outstanding shares, market capitalization, and yearly income. Before a firm's stocks and shares may be listed and traded on an exchange, the company in question must meet the exchange's requirements [37]. However, these standards can differ between exchanges.

2.4 Classification and Forecasting Methods for The Stock Market Theories

Numerous research on the stock market have been done in effort to find useful trends and forecast its movements. Academics have always been fascinated by attempting to predict the behavior of the stock market. Although numerous attempts have been made by the scientific community, no method has been discovered to reliably predict the movement of prices. There are numerous methods for predicting the movement of the stock market, and stock market experts have adopted a wide range of these forecasting strategies. In the following paragraphs, we will present a simple description of the two most prominent stock market forecasting theories. As a result of these theories, two typical methods for predicting the financial markets have emerged: technical analysis and fundamental analysis. When attempting to predict the future prices of equities traded on the stock market, there are two important schools of thought to consider. The first is known as the efficient market hypothesis (EMH), and the second is known as the random walk theory [38]. In 1964, the EMH was presented by the FAMI.

2.4.1 Efficient Market Hypothesis (EMH)

According to the efficient market hypothesis (EMH), there is no information that can be exploited to earn a big profit on the stock market because stock prices "completely reflect" all available information. Any new information that becomes available will be immediately and effectively reflected in the share price. Given the manner in which the EMH is defined, it is evident that the results of this study have substantial implications for the EMH's veracity. It has been established that this is true. Fama's contribution to the efficient market hypothesis is significant. Given the transaction history of a stock, the efficient market hypothesis (EMH) states that the future price of a stock is entirely unpredictable. According to the efficient market hypothesis (EMH), the present price being paid on the market is the outcome of the collection of all currently accessible knowledge. This means that, given the available data, it is impossible to anticipate how the price will fluctuate in the future. As new data is entered into the system, the inaccurate change in price [38] reveals and eliminates the poorly balanced stock. Depending on the nature of the data being utilized for predictive purposes, the EMH can be stated in one of three ways. EMH that is defective, semi-strong, and strong.

According to the weak form of the EMH, any information acquired from investigating the past performance of a stock should be quickly reflected in that stock's price. According to the "weak" variant of the EMH, it is impossible to reliably anticipate future stock values using historical stock prices. Only prior prices and the company's history are reflected in the current pricing. Because prices follow a random walk in which subsequent changes have 0% correlation, this EMH precludes any type of prediction based solely on price data [38]. The semi-strong form goes one step further than the strong form by incorporating all publicly accessible information from the past and present. This includes extra trading data such as volume data as well as fundamental data such as profit forecasts and sales projections [59]. The strong form contains historical, public, and private information, such as insider knowledge, regarding the share price. The strong form of the efficient market hypothesis has been difficult to verify due to a lack of evidence, as stated by Fama in his article titled "efficient capital market." He concludes that the efficient market hypothesis must be wrong. According to the "strong" form of the efficient market hypothesis (EMH), it is impossible to predict future stock prices because the current stock price already incorporates all relevant information. Empirical evidence from research into the performance of mutual fund managers in [4] revealed that the managers were unable to exploit classified information to achieve increased earnings for the funds they managed. Several empirical studies have provided sufficient support for both the weak and semi-strong EMH versions [38].

2.4.2 Random Walk Theory

According to the random walk theory, stock prices are independent of historical stock prices. Because there are no discernible price patterns, it is impossible to capitalize on

them. As a result of the development of more potent computing infrastructure, trading businesses today construct highly successful algorithmic trading systems that are able to capitalize on underlying price movements by analyzing a vast quantity of data points (hardware and software). This is now feasible due to the introduction of a more robust computing infrastructure (hardware and software). Clearly, if machine learning algorithms have access to massive datasets, they can offer a substantial threat to the EMH [38]. This is a different perspective on the concept of prediction. On the stock market, where prices are determined at random, it is believed to be impossible to foresee the market and difficult to outperform it. The random walk theory and the semi-strong EMH have a similar theoretical foundation, which assumes that everyone has access to all publicly available information. The random walk theory, on the other hand, maintains that it is impossible to accurately predict the future, even when such information is accessible [38]. Two unique trading philosophies have been influenced by both the EMH and random walk theories.
Technical analysis and fundamental analysis are the two traditional methodologies for financial market forecasting [38].

2.4.3 Technical Analysis

The phrase "technical analysis" refers to a fundamental approach to investing in stocks that utilizes charts as the primary instrument for assessing previous prices. This technique focuses on recent price fluctuations. Extraction of financial time series describes the extraction of rules and patterns from previous stock prices. This methodology is the basis of the system. The essential ideas include the tendency of prices to move in a given direction, validation and divergence, and the impact of total transaction volume. On the basis of these fundamental concepts, tens of thousands of distinct algorithms for predicting stock prices have been devised, and more are being produced constantly. Technical analysis is a method that uses indications generated from technical analysis to attempt to forecast the stock market. It employs numerical time series data. It is founded on the widely held belief that all market reactions to all news are reflected in real-time stock prices. This is the case, according to this hypothesis. In light of this, the news is not considered in technical analysis. The fundamental objective of chart analysis is to identify existing patterns in the stock market and project those trends into the future. In contrast, charts and numerical statistics simply display the outcomes of an event, not its causes. It is often believed that proper timing in the market is crucial, and that opportunities can be identified by methodically averaging historical volume and price fluctuations and examining those fluctuations in relation to the current price. Technicians apply charts and various modeling tools to discover patterns in price and volume movements. In order to predict what will occur in the future, historical data is examined. Several prediction algorithms based on numerical time series have been developed and show promise for predicting the behavior of the stock market [59]. Auto regression and moving average are two well-known stock trend prediction algorithms. Decades ago, these techniques dominated the field of time series prediction. This method involves estimating the stock price based on the stock's historical tendencies using time-series analysis [38]. This technique is utilized by technical analysts to determine how long the stock price remains unchanged.

2.4.4 Fundamental Analysis

Fundamental analysis is the examination of the elements that influence supply and demand. The goal is to collect and analyze this data in order to make choices and take action prior to the relevant data being reflected in the stock price. There is a trading opportunity anytime there is a lag between the occurrence of an event and the market's subsequent reaction. Fundamental analysis is a technique that aims to forecast markets using economic data that corporations are obligated to provide on a regular basis, including quarterly and annual reports, auditor's reports, balance sheets, and income statements [38]. Financial information is utilized in fundamental analysis. Fundamental analysts are accountable for its implementation. This strategy places less emphasis on the stock itself and more on the company itself. When making decisions, the past success of a company, analysts' profit forecasts, and other criteria are taken into account [38]. According to the fundamental trading philosophy, the price of a securities can be determined by analyzing the pertinent financial data. These numbers are derived from the economy as a whole, the industry's sector, or, more frequently, the company itself. [38] A range of factors, including industry return on debt and equity levels, as well as other financial measures, can influence the price of a stock. When using machine learning and data mining to stock market data, our major objective is to conduct a technical analysis to verify if our algorithm is capable of understanding the underlying patterns in the stock time series accurately. In light of the foregoing, it is important to mention that machine learning is also capable of playing a significant role in analyzing and predicting the company's overall performance and other metrics that are useful for fundamental analysis. The most effective automated stock prediction and recommendation systems use a hybrid analysis approach that combines fundamental and technical analysis [38].

2.5 Summary

The fundamentals of the stock market have been explored in this section. This section explains the relevance and necessity of the stock market. In addition, it discusses the underlying laws that govern stock markets. In addition, classification and forecasting models for a variety of theories and hypotheses surrounding the stock market, including EMH and RWT, have been examined.

CHAPTER 03: THEORITICAL DESCTIPTION OF ALGORITHM

3.1 Introduction

Machine Learning and Deep Learning are crucial for addressing regression and classification issues. Theoretical explanations have been provided for the phrases Supervised Machine Learning (SML), Deep Learning (DL), Neural Network (NN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM), which have been utilized in our research.

3.2 Supervised Machine Learning

Supervised learning is a subfield of machine learning and artificial intelligence that is also known as supervised machine learning. It is defined by the use of labeled datasets to train classification or prediction algorithms. As part of the cross-validation process, as input data is entered into the model, its weights are modified until the model is correctly fitted. Using supervised learning, businesses may solve a variety of real-world issues at scale, such as distinguishing spam from inbox communications.

Regression problems and classification problems are two subcategories that can be applied to problems involving supervised learning.

3.2.1 Classification: The classification process makes use of an algorithm to precisely assign test data to particular categories. It can identify particular entities contained inside the dataset and attempts to draw some assertions regarding the appropriate labeling or definition of those entities. Linear classifiers, Support Vector Machines (SVM), Decision Trees (DT), k-Nearest Neighbors (k-NN), and Random Forests (RF) are examples of common classification algorithms; each of these will be discussed in greater detail in the following paragraphs.

3.2.2 Regression: The technique of regression is utilized in the process of gaining an understanding of the connection that exists between independent and dependent variables.

It is a common tool for making projections, such as estimates of future sales revenue for a particular company. The most common types of regression algorithms are Linear Regression, Logistical Regression, and Polynomial Regression.

3.3 Deep Learning

Deep learning is a subfield within machine learning. This area is dependent on self-education and ongoing growth through the study of different computer algorithms. Deep learning employs artificial neural networks, which are designed to mimic the way humans think and learn, as opposed to machine learning, which employs more basic notions. Up until quite recently, the level of complexity of neural networks was bound by the amount of computational power available. However, new breakthroughs in Big Data analytics have made it possible to design increasingly complicated neural networks on computers. These networks allow computers to see, understand, and react to challenging situations faster than humans. Image classification, language processing, and speech recognition are among disciplines that have profited from deep learning. It can tackle any problem that requires pattern recognition without the assistance of a human.

The process of deep learning is powered by artificial neural networks that consist of several layers. Deep Neural Networks, commonly known as DNNs, are a sort of network that can interpret images, audio, and text by performing complicated operations on each layer.

These sophisticated operations involve representation and abstraction. Deep learning is often recognized as the machine learning subfield with the greatest rapid growth. It is an example of a revolutionary change in digital technology, and an increasing number of companies are utilizing it to establish new business models.

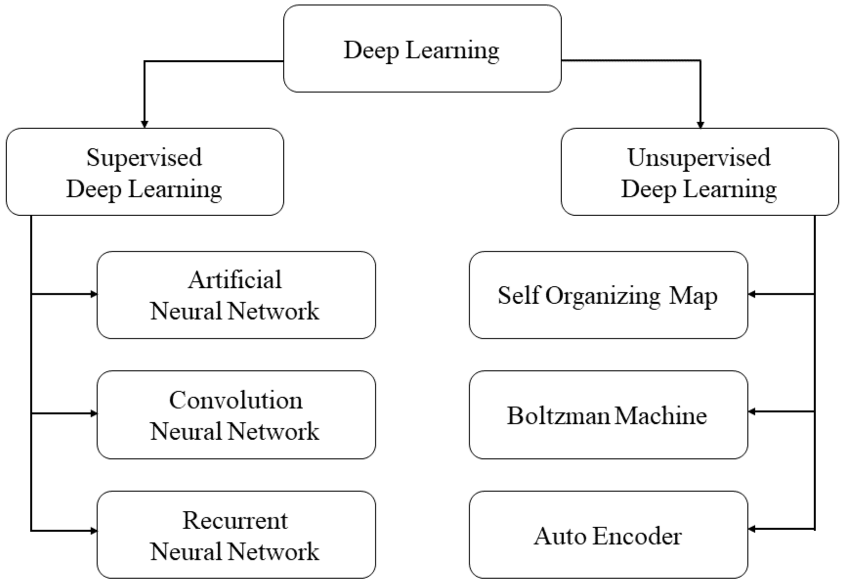

Figure 3.1: Deep Learning Categories

3.4 Neural Networks

Neural networks are a subfield of machine learning and are at the core of deep learning algorithms. They are also renowned as artificial neural networks (ANNs) as well as simulated neural networks (SNNs). The human brain served as an inspiration for both their names and their structures, which resemble the way that nerve cells communicate with one another.

The building blocks of artificial neural networks, also known as ANNs, are called node layers. These layers include an input layer, as well as one or more hidden layers and an output layer. Each node, also known as an artificial neuron, makes a connection to another node and has a weight and threshold associated with it. If the output of any one individual node is greater than the value that has been determined to be the threshold for activation, then that node will become active and will begin sending data to the subsequent layer within the network. If this condition is not met, no data will be sent up to the subsequent layer within the network.

Neural networks can include a single layer or several layers, and they can be fully coupled. In the example of NN shown in Figure 3.2 [11], which was modified from [43], there is an input layer, an output layer, as well as two hidden layers. Each node in a layer is linked to each other nodes in the layer below it via a connection. The depth of the network can be increased by adding more hidden layers, which opens up the possibility of more complex connections.

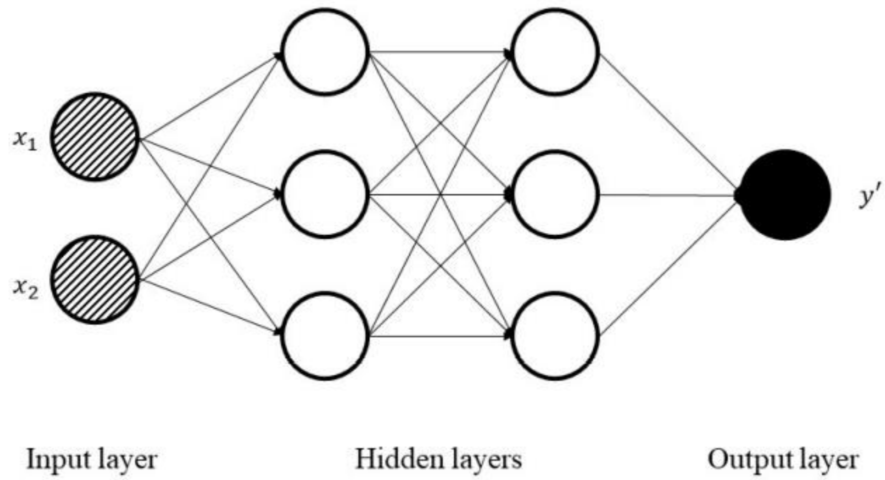

Figure 3.2: Illustration of a Neural Network

Figure 3.3 is depicted every one of the hidden or output nodes, where an activation function is applied to the weighted sum of the inputs plus a bias value (usually a non-linear function). The outcome is the node's output, which serves as an input for the following layer. The operation proceeds from input to output, and the ultimate output is obtained by repeating this process for each node. Training a neural network through the acquisition of biases and weights connected with each node. [11]

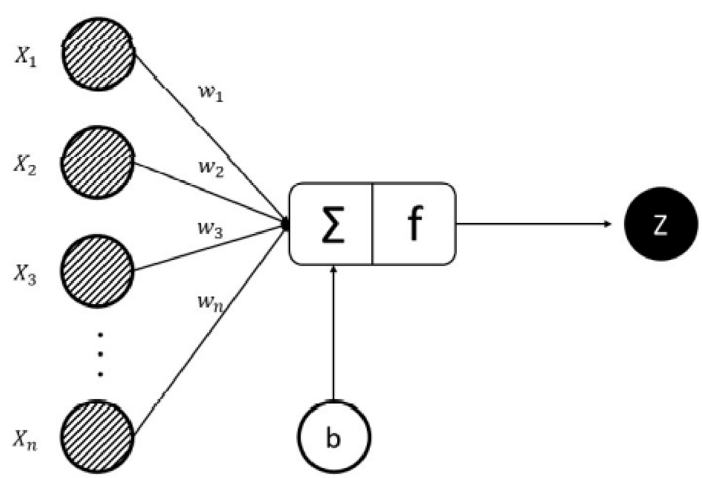

Figure 3.3: Illustration of Input and Output Relation

Training data are necessary for neural networks so that they can learn and enhance their precision over time. However, when these learning algorithms have been fine-tuned for accuracy, they become effective tools in artificial intelligence and computer science by enabling us to characterize and cluster data at quite a high velocity. This opens up a lot of opportunities for research. When tried to be compared to the time it takes human experts to manually identify something, tasks involving natural language processing or image processing could take minutes rather than hours. The search algorithm used by Google is one of the neural networks that has gained the most notoriety.

3.5 Recurrent Neural Network

A recurrent neural network, also known as an RNN, is a type of neural network that can analyze time series data in addition to sequential data. These deep learning algorithms are typically used for ordinary or seasonal challenges, such as language translation, natural language processing (NLP), speech recognition, and image captioning; they are integrated into popular applications such as Siri, voice search, and Google Translate. Among the problems that these algorithms are commonly used to solve is the translation of languages. Recurrent neural networks make use of training data in order to learn, just like feedforward neural networks and convolutional neural networks (CNNs). They are distinguished from other systems by their ability to "remember" information from previous inputs, which allows them to have an effect on both the existing output and the input. The outputs of recurrent neural networks are dependent on the elements that came before them in the sequence, in contrast to the outputs of traditional deep neural networks, which make the assumption that inputs and results are independent of one another. Although future events would be of assistance in determining the outcome of a particular series, unidirectional RNNs are unable to take into account the possibility of such outcomes when making their forecasts.

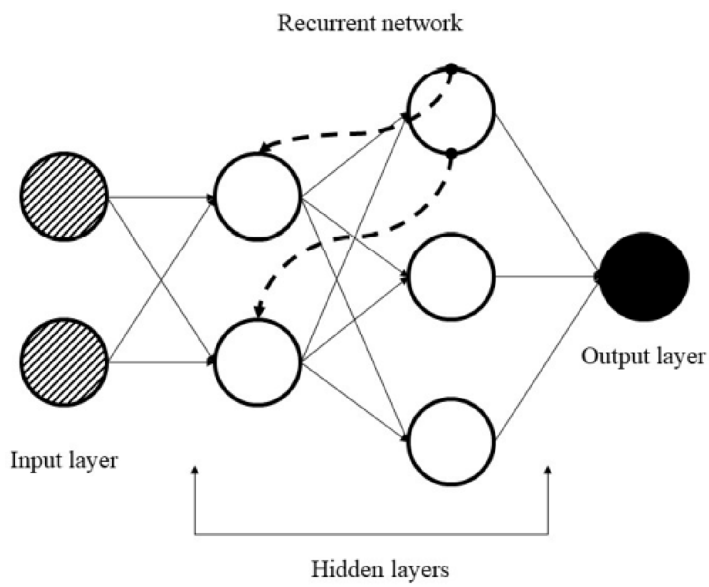

Figure 3.4: Illustration of a Recurrent Neural Network

3.6 Long Short-Term Memory

When it refers to RNNs, there is a concern with the gradient that quickly disappears. There are several different RNN architectures that can be used as an alternative to combat this issue. Long short-term memory (LSTM) is the architecture that has been around the longest and is the most common. A Cell, a Forget Gate, an Input Gate, and an Output Gate make up the architecture of an LSTM unit. Together, these four components make up the unit's architecture. LSTM networks are able to learn long-term relationships [18] thanks to the utilization of these components. This ability is highly interesting for applications including such market prediction.

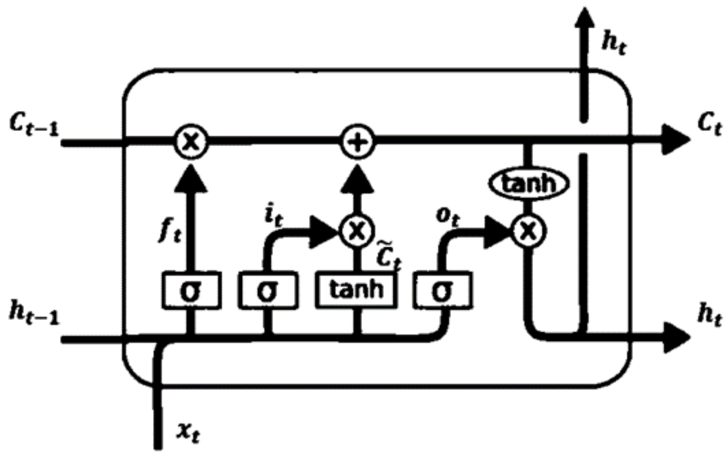

Figure 3.5: Illustration of Long Short-Term Memory (LSTM) Cell

The LSTM cell is a dimensionless addition to the RNN's hidden state, and it shares the same dimensions as the vector that represents the hidden state. The cell state of an LSTM can be considered the short-term memory of the device, while the concealed state is considered to represent the device's long-term memory. Despite the fact that the cell state can be passed on with a significant portion of its information mostly unaltered, the LSTM has the power to alter it via making use of gates. Gates are the techniques that govern what information in the cell state should be forgotten or updated, and they are essentially what sets an LSTM apart from regular RNNs. In contrast to a regular RNN, which would update its hidden state for newly added cells by employing a straightforward hyperbolic tangent function, LSTMs use a method that is rather more complicated. The LSTM employs gates to determine what information to forget and update in the LSTM cell state. It then uses the new cell state data to output an updated hidden state, which is a little reductionist explanation.[18]

The initial gate of an LSTM is referred to as the forget gate. It is a neuron layer that has a sigmoid activation function. It takes in the previous hidden state as well as the input to the LSTM, and it produces a vector of the same dimension as the cell state vector. The integers in this vector range from 0 to 1, and it represents the cell state.[18]

$Output\ vector\ from\ forget\ gate$: $\overrightarrow{f_t}$

$Previous\ hidden\ state$: $\overrightarrow{h_{t-1}}$

$Current\ input$: $\vec{x}_t$

$Weight\ vector\ for\ forget\ gate$: $\overline{W_f}$

$Bias\ for\ forget\ gate$: $\overrightarrow{B_f}$

$$\overrightarrow{f_t} = \sigma\left(\overline{W_f}\ \left[\overrightarrow{h_{t-1}}\ , \vec{x}_t\right] + \overrightarrow{B_f}\right)$$

After determining the forget gate vector, the validity of the input gate is questioned. The input gate determines what fresh information will be used to update the state of a cell. It is composed of two neuronal layers, the sigmoid and tanh layers. The sigmoid layer decides which data will be changed, and the tanh layer makes a transient cell state vector with candidates that can be used to change the actual cell state.

$Input\ gate\ vector$: $\overrightarrow{\iota_t}$

$Candidate\ cell\ state\ values$: $\widetilde{C}_t$

The input gate vector and the candidate cell state are calculated as such:

$$\overrightarrow{\iota_t} = \sigma\left(\overline{W_\iota}\ \left[\overrightarrow{h_{t-1}}\ , \vec{x}_t\right] + \overrightarrow{B_\iota}\right)$$

$$\tilde{C}_t = tanh\left(\overline{W_C}\ \left[\overrightarrow{h_{t-1}}\ , \vec{x}_t\right] + \overrightarrow{B_C}\right)$$

Now that the forget gate output vector, the input gate output vector, and the candidate state are available, it is time to update the old cell state. We begin by multiplying with. If a number in the forget gate output vector is 0, the corresponding number in the old cell status becomes 0 and is forgotten, however if the number is 1, the cell state's number remains unaltered. The input gate output vector and the candidate cell state vector are then multiplied and added to the previous product.

The new cell state, $\overrightarrow{C_t}$

$$\overrightarrow{C_t}\ = \vec{f}_t * \vec{C}_{t-1} + \overrightarrow{\iota_t} * \vec{C}_t$$

The final component is the output gate, via which the new hidden state **h_t** is obtained. This state's output is a simplified form of the subsequent cell state. Similar to the input gate, it has a sigmoid and tanh layer. The sigmoid layer uses the previous concealed state and the input to determine which portions of the cell state will be included in the output. The cell state is then passed across the tanh layer. Next, the composite of these layers is multiplied to produce the final output.

$$\overrightarrow{o_t} = \sigma\left(\overline{W_0}\left[\overrightarrow{h_{t-1}}, \vec{x}_t\right] + \overrightarrow{B_0}\right)$$

$$\overrightarrow{h_t} = \overrightarrow{o_t} * tanh\left(\vec{C}_t\right)$$

3.7 Summary

Here in this section, we tried to explore the theoretical explanation, architecture, and operation of different Machine Learning Algorithms. This section briefly describes Supervised Machine Learning, Deep Learning, Neural Network, Recurrent Neural Network, and Long Short-Term Memory. Classifications of algorithm is discussed here. It also attempted to explain how these algorithms operate.

CHAPTER 04: METHODOLOGY

4.1 Introduction

This research was carried out using the following methodology:

First, we created an LSTM neural network and then trained it to classify whether or not it is capable of predicting the future movement of the stock market. The model was trained by utilizing open-source deep learning frameworks and historical trading data obtained from Wall Street Journal (WSJ) for every selected stock in the DSE and Nasdaq-100. These two data sources were used to collect the information. After that, the RMS Error, MAE, and Loss Function of the forecasts were assessed in order to evaluate the overall accuracy of the models that the LSTM neural network had generated.

4.2 Model Architecture

Here, Figure 4.1 illustrates the structure of the research project. At the outset of the research, we examined a variety of prior studies in this topic. Then, we gathered historical information for the target companies. After processing the data in multiple steps, we used it to train and validate our LSTM model. For a more precise evaluation of the model's efficacy, it was applied to international stock markets.

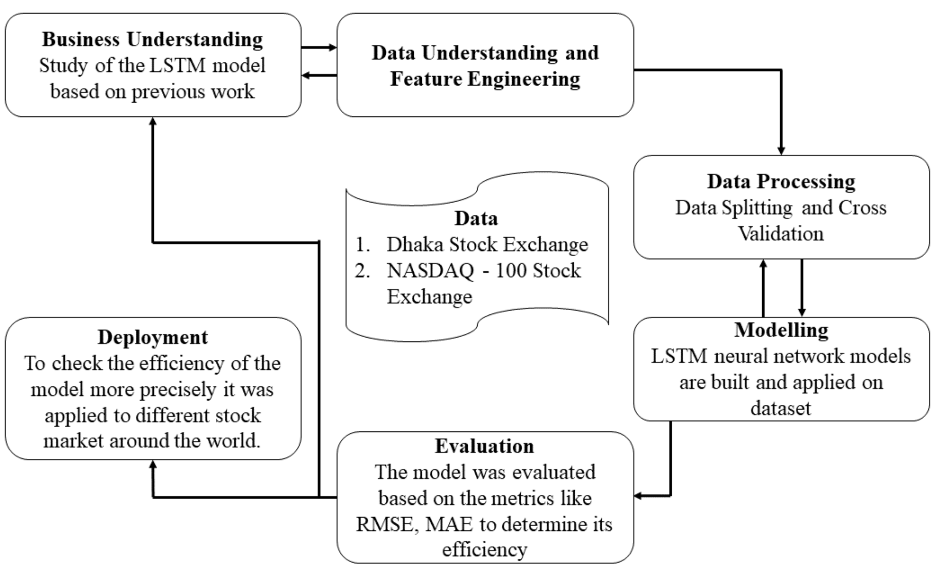

Fig 4.1 Workflow of the Research Study

4.3 Data Collection & Preprocessing

At this stage, historical stock data is acquired from https://www.wsj.com/market-data and utilized to forecast future stock values. Table 1, provides information about the companies which are used for this study. To demonstrate the diversity of this study, five stocks of local companies listed on the DSE from five distinct industries with up to twenty years of historical data are selected at random. We also utilized historical data from the world's three largest corporations (Google, Microsoft, and Tesla) listed in NASDAQ Stock Exchange.

Table 4.1 Name of Stocks Along with Symbols

Sector	Industry	Company	Symbol
Dhaka Stock Exchange			
Finance	Major Bank	BRAC Bank Limited	BRACBANK
Technology	Telecommunication	Grameenphone Ltd.	GP
Energy	Petroleum and Coal Mining	Jamuna Oil Company Ltd.	JAMUNAOIL
Textile	Industrial Manufacturing	Square Textile	SQUARETEXT
Health	Major Pharmaceuticals	Beximco Pharma	BXPHARMA
NASDAQ - 100 Stock Exchange			
Technology	Computer Software	Google	GOOG
Technology	Computer Software and Hardware	Microsoft	MSFT
Technology	Industrial Manufacturing	Tesla	TSLA

4.4 Dataset Description

The description of the dataset that was utilized for the research can be found in Table 4.2 below. The stock symbol, stock date, previous closing, opening, high, low, and volume are some of the pieces of information that are included in the dataset. The day-wise closing price of each stock is the only one that we extract from these datasets. This is done because the day-wise stock price is the one that is most preferred by investors, as investors base their decisions on the closing price of the market regarding which stocks to purchase and which stocks to sell.

Table 4.2 The Description of Stock Data's Index

Index	Description
Open	The initial price of a stock traded at the start of a particular trading day.
High	The highest price at which a security traded on a given trading day.
Low	The lowest price at which a security traded on a particular trading day.
Close	The last transaction price of a stock on a certain trading day.
Volume	The total quantity of shares or contracts traded on a given trading day.

Fig 4.2 represents an example of the used dataset. Only the characteristics that will be supplied to the neural network are selected at this layer. From the options of date, open, high, low, close, and volume, the close value is selected as target.

	Date	Open	High	Low	Close	Volume
0	2009-12-01	182.0	182.9	177.0	177.3	1112600
1	2009-12-02	177.1	177.5	174.2	174.7	921600
2	2009-12-03	174.4	175.4	172.4	173.6	773200
3	2009-12-07	172.0	173.8	170.0	170.1	752800
4	2009-12-08	170.0	171.2	168.6	169.4	555000

Figure 4.2 Example of Dataset

4.5 Illustration of Stock Prices Variation

Figure 4.3 (a): BRAC Bank Ltd.

Figure 4.3 (b): Grameenphone Ltd.

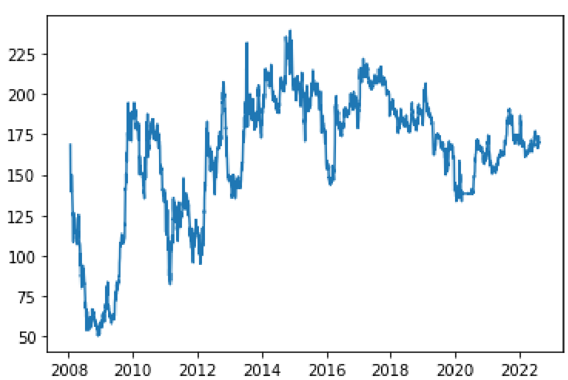

Figure 4.3 (c): Jamuna Oil Ltd.

Figure 4.3 (d): Square Textile

Figure 4.3 (e): Beximco Pherma

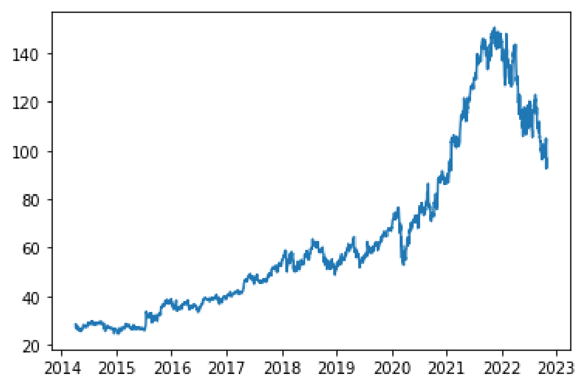

Figure 4.3 (f): Google

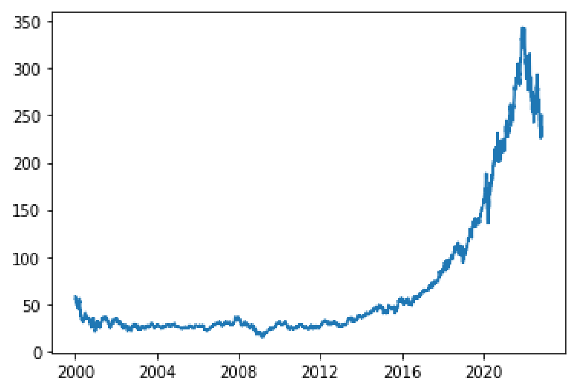

Figure 4.3 (g): Microsoft

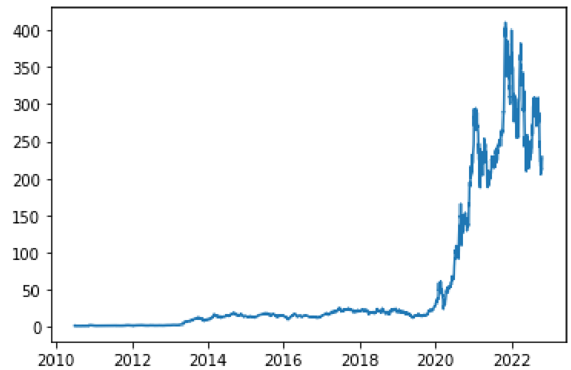

Figure 4.3 (h): Tesla

The graphical representation of the stock prices variation of several firms presented here in the form of a time series is depicted from Figure 4.3 (a) to Figure 4.3 (h), respectively. This demonstrates the daily variance in stock prices in near value, which is the value that we are aiming for with this model.

4.6 Processing

As all graphs are quite similar, we will focus on a single company stock price, here we used BRAC Bank Stock Price for reference.

4.6.1 Feature Selection: As feature, the "close" values for last 6 days are considered. Figure 4.4, represents the feature selection method.

	Target Date	Target-6	Target-5	Target-4	Target-3	Target-2	Target-1	Target
0	2007-03-05	5.15	4.90	4.61	5.07	5.00	4.99	4.73
1	2007-03-06	4.90	4.61	5.07	5.00	4.99	4.73	4.81
2	2007-03-07	4.61	5.07	5.00	4.99	4.73	4.81	4.87
3	2007-03-08	5.07	5.00	4.99	4.73	4.81	4.87	4.77
4	2007-03-12	5.00	4.99	4.73	4.81	4.87	4.77	4.60

Figure 4.4: Feature Selection

4.6.2 Data Splitting: The dataset is split into training (80%), validation (10%), and testing (10%) set for the evaluation after it has been cleaned up and turned into a clean dataset. The splitting of date set is shown Fig. 1. The values used in this situation are obtained from the training.

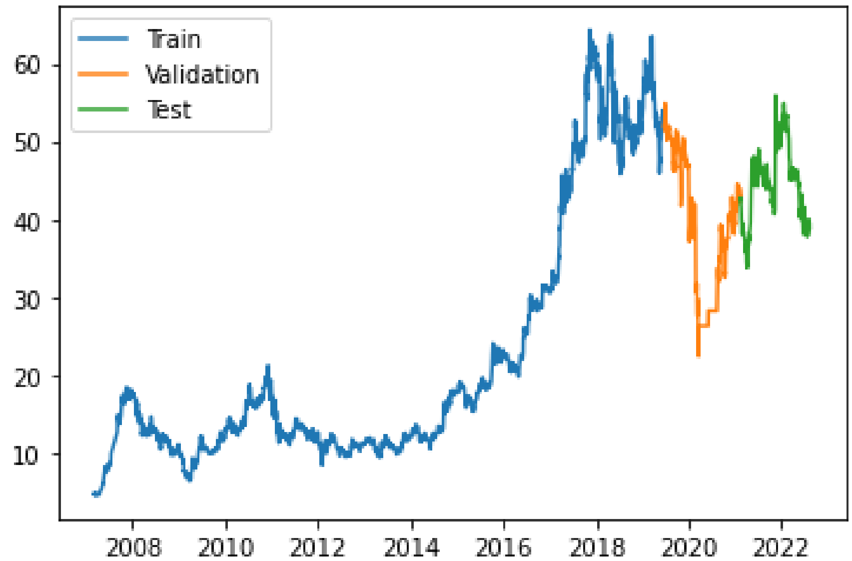

Figure 4.5: Data Splitting (BRAC Bank Stock Closing Price)

4.7 Training LSTM Model

During the creation and training of the LSTM network, Python 3.10 and Google Colab, a web service that enables us to construct Python Notebooks in the browser, were the key tools utilised. It was intended that completing the research in Google Colab would allow others to duplicate our findings in the online application, as well as eliminate the need to locally configure the same hardware, system, or Python settings. Additionally, the open-source deep-learning library Pytorch was employed. This package provides an application programming interface (API) for Python, which simplifies the building and training of neural networks. In addition, deployments of loss functions and optimization algorithms are provided to users.

Our LSTM model consists of the following layers: a sequential input layer, an LSTM layer, five dense levels with ReLU activation, and a dense output layer with linear activation. Figure 4.6 depicts an overview of the suggested model. Following this, 500 iterations of full gradient descent were utilized to train the model using the stock's training dataset.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 128)               66560

 dense (Dense)               (None, 64)                8256

 dense_1 (Dense)             (None, 64)                4160

 dense_2 (Dense)             (None, 64)                4160

 dense_3 (Dense)             (None, 64)                4160

 dense_4 (Dense)             (None, 64)                4160

 dense_5 (Dense)             (None, 1)                 65

=================================================================
Total params: 91,521
Trainable params: 91,521
Non-trainable params: 0
_________________________________________________________________
```

Figure 4.6: LSTM Model Description

4.7.1 Activation Function

Activation functions are an integral component of any neural network and perform a very significant role. The activation function is what causes a neuron or node to become active and also decides whether or not the data from such a node will be passed on to the following node. In normal operation, it converts the signal being input into the signal being output. There are several activation functions that are utilized for the various application cases. When the range of the input is between 0 and infinite, the Rectified Linear Unit (ReLU) is the unit that is used. The tanh function is the one that is used when the range of the input is between -1 and +1. The sigmoid function has a range that goes from 0 to 1, inclusive. Relu, Tanh, and Sigmoid functions are depicted accordingly in Figures 4.7, 4.8, and 4.9.

$$g(x) = \max\{0, z\} \tag{4.1}$$

$$f(x) = \tanh(0) = \frac{2}{1 + e^{-2}} - 1 \tag{4.2}$$

$$f(x) = \frac{1}{1+e^{-x}} \tag{4.3}$$

The equations for the ReLU, Tanh, Sigmoid, functions are shown here in numbers 4.1, 4.2, and 4.3, respectively. [59]

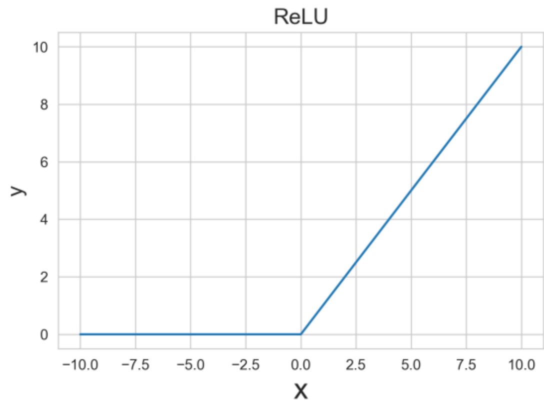

Figure 4.7: ReLU Activation Function

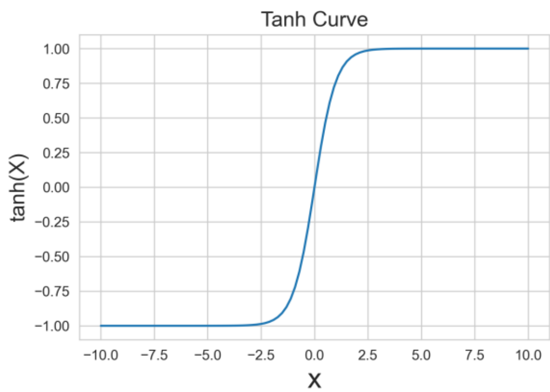

Figure 4.8: Tanh Activation Function

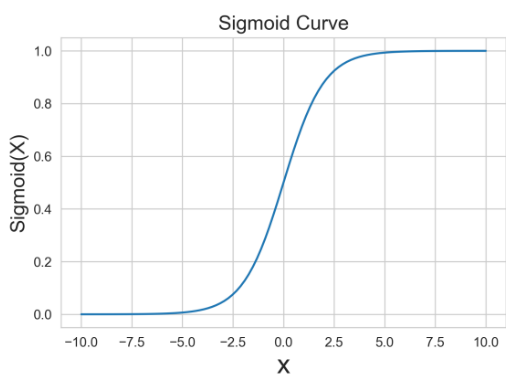

Figure 4.9: Sigmoid Activation Function

4.8 Summary

This is one of a the most important chapters of this study. As the name of this chapter reflects here whole process of our study have been discussed. The structure provides an illustration of the flow of operations for this study. Next, the procedure for the collection of data and the preliminary processing of it will be described. Displayed for your perusal are an explanation of, as well as an illustration of, the graphical representation of the dataset. The latter part of this section provides an overview of the development and functioning of the suggested model, covering topics such as Data Splitting, Feature Scaling Model Training and Testing, and other related topics.

CHAPTER 05: RESULTS

5.1 Introduction

In this chapter the evaluation of our model is done. Here the illustration of graphical representation of stock price prediction vs observation is shown. Also, the accuracy of the model is determined in terms of RMSE, MAE and Loss Function.

5.2 Results:

Training prediction versus observation sets across 500 epochs are depicted in Figure 5.1. We may observe that the curves are nearly identical and that inaccuracies diminish as more epochs pass. The training prediction set is hued blue, while the training observation set is hued orange.

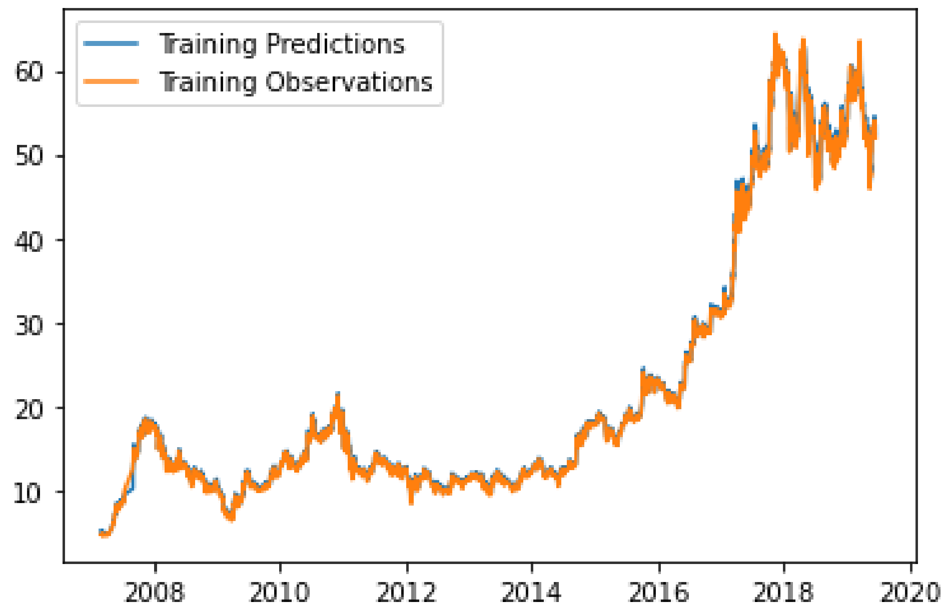

Figure 5.1: Illustration of Training Prediction vs Observation

The validation prediction vs observation over 100 epoch is presented in Fig 6.2. Here also the validation prediction set is hued blue, while the validation observation set is hued orange.

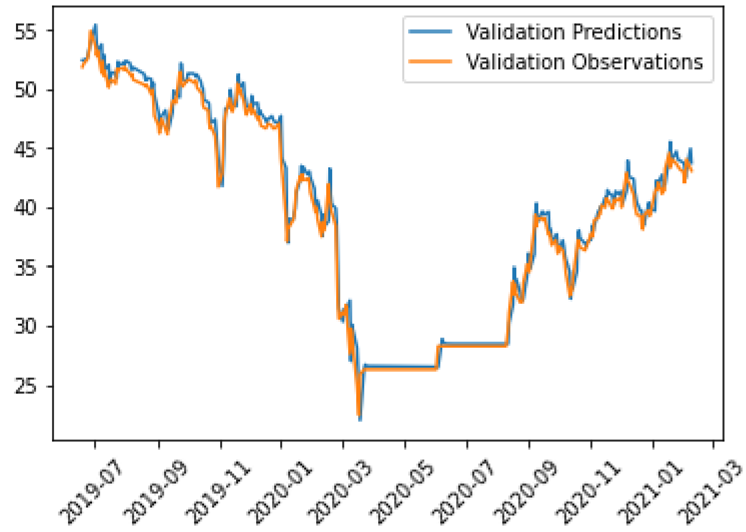

Figure 5.2: Illustration of Validation Prediction vs Observation

Figure 5.1 illustrates the testing of predictions against observation sets across a total of one hundred epochs. It's possible for us to notice that the curves are almost exactly the same, which demonstrates how accurate our model is. The training observation set is colored orange, whereas the training prediction set is colored blue.

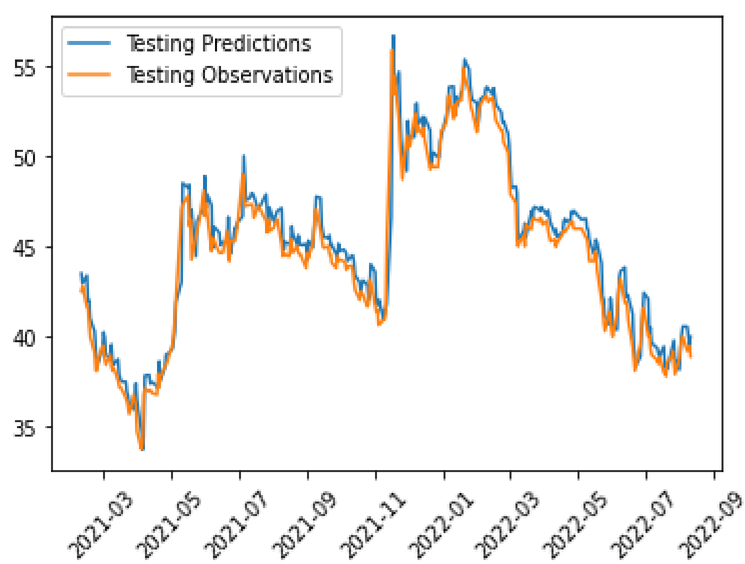

Figure 5.13 Illustration of Testing Prediction vs Observation

Finally, the integration of all three sets of results from training, validation, and testing, as well as observations, is represented in figure 5.4.

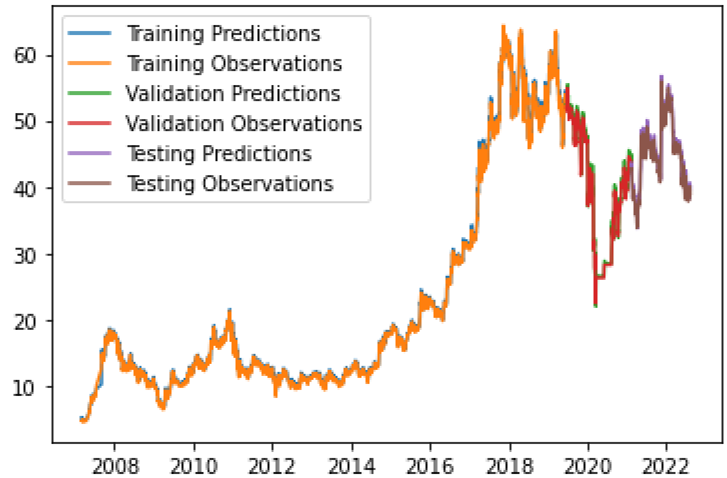

Figure 5.4: Illustration of Prediction vs Observation of Whole Model

The performance parameter of mean absolute error (MAE) is used to evaluate the efficiency of the model. MAE is a regression loss function. In this case, the loss is the mean of the absolute disparities between the actual and the anticipated values. MAE is not affected by outliers and given numerous samples with identical input feature values. The best prediction will be their median target value. The MAE is calculated according to:

$$MAE = \sum_{i=1}^{n} |y_i - x_i|$$

where, $\mathbf{y_i}$ is the prediction, $\mathbf{x_i}$ is the true value, and **n** is the total number of data points. The Root Mean Square Error (RMSE) is the residuals' standard deviation (prediction errors). Residuals are a metric of how far data points are from the regression line; RMSE is a measurement of how dispersed these residuals are. In other words, it indicates the degree of data concentration all around line of best fit.

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

The accuracy rate of our model is broken down into its component parts, Mean Absolute Error and Lose Function, as shown in the following table, 5.1.

Table 5.1 Results for Different Stocks

Company Name	**RMSE**	**MAE**	**Loss Value**
BRAC Bank Ltd.	0.6782	0.9096	1.4727
Grameenphone Ltd.	6.8404	2.4858	13.3004
Jamuna Oil Company Ltd.	4.2592	4.0155	19.3494
Square Textile	1.2548	1.3548	2.8104
Beximco Pharma	1.1237	0.3604	0.1985
Google	0.9293	0.6709	0.9922
Microsoft	2.3541	1.5769	5.6128
Tesla	2.2170	1.0470	4.9140

5.3 Analysis Results from Previous Contributions

The different techniques utilized to forecast the share price can be grouped into four groups.

Conventional Machine Learning Methods - Includes conventional techniques such as linear regression and logistic regression.

Deep Learning and Neural Networks - Numerous of these techniques employ RNNs and LSTMs, which are specialized RNNs.

Methods for Analyzing Time Series - This technique relies on forecasts and projections of discrete time data.

Table 5.2 compiles the various algorithms employed for the aforementioned categories.

Table 5.2: Comparison of the Performance of Various Algorithms for Forecasting Stock Prices

Category	Techniques	Metrics Used
Conventional ML	PLS Classifier [59]	Error Value = 0.81225 (average)
	SM Optimization [59]	Error Value = 0.79656 (average)
	SVM and ExtRa Based Sentiment Analysis [60]	SVM: + 0.003 (R^2 value)
		ExtRa: -0.02 (R^2 value)
Deep Learning	Sentiment analysis with LSTM [61]	MCC = 0.04092 Accuracy = 52.27%
	Sentiment analysis with Attention-based LSTM [61]	MCC = 0.04780 Accuracy = 54.58%
	LSTM [56]	RMSE = 0.0091, MAE=63, MAPE=2.23%
	CNN [62]	RMSE = 0.0087, MAE=61, MAPE=2.16%
Time Series	ARIMA [63]	Steps ahead (3 Times) RMSE: ~15%, MAPE: 20-25%, MAE: ≤15%
		Steps ahead (9 Times) RMSE: 15-20%, MAPE: 15-20%, MAE: 10-15%
	GAM using Fourier transformations [64]	Accuracy ~ 70%, MAPE = 1-5%
	Supervised Time series Learning [57]	K-fold cross validation: Perceptron NN = 75.48%, SVM = 75.48% Logistic Regression = 89.45%
		Train-Test split: Perceptron NN = 76.68%, SVM = 89.33%, Logistic Regression = 89.33%

Conventional ML

Merits

Traditional machine learning (ML) techniques, like SVM, produce comparatively higher accuracy because they operate well with high-dimensional datasets.

Demerits

These algorithms are extraordinarily sensitive to outliers.

Deep Learning

Merits

RNNs and LSTMs are the Deep Learning algorithms of choice for this assignment. During training, RNNs capture the meaning of the data, which is a benefit. Since they can correlate non-linear data from time series in the delay state, LSTMs perform well. [66]

Demerits

High number of training and memory needs are necessary.

Time Series

Merits

Time-series forecasting approaches, such as ARIMA, perform well with linear data and produce accurate short-term stock price forecasts. [67]

Demerits

The algorithm may not produce reliable stock price estimates over the long term.

5.4 Summary

Here the results of the proposed model are discussed. The model's output graph, representing a Prediction versus Observation perspective. It also includes a data Table 5.1 that calculates the model's accuracy in terms of MAE, RMSE, Loss Function. Then in Table 5.2 the comparison between different studies is shown. From there it’s clear that LSTM has superior capability while prediction stock market future movement.

CHAPTER 06: CONCLUSION AND FUTURE WORK

6.1 Conclusion:

Examining models by an LSTM neural network to forecast the returns of companies in the DSE and NASDAQ indexes was the aim of this thesis. I trained the model for a total of seven stocks and analyzed their accuracy using MAE and Loss Function. The accuracy of the model was not significantly different from what would be expected from a random prediction of a class or from a prediction that all days would be of a single class. Thus, we conclude that the predictive capacity of the model trained by the LSTM network was unsatisfactory and that more development is necessary to obtain greater precision. Theoretically, it should be simpler for a neural network to learn how to forecast stock returns than stock prices, as stock returns are typically more stable than market prices. In addition, the solution space for binary classification is substantially less than that for predicting the real stock price. For these reasons, we contend that performing binary predictions on stock returns should be a far simpler challenge than forecasting actual prices. Before going on to more difficult tasks, such as forecasting prices, we recommend further advancements in predicting returns, which may serve as direction for future researchers in the field.

6.2 Future Work:

In the future, more works can be done to improve the performance of stock prediction.

1. More Indicators should be imported: In this experiment, just three indications were considered. In reality, there are more indications used to evaluate companies when trading. Including additional indexes may enhance the accuracy of models' analyses.
2. Stack Models: In this instance, I utilized a single model. We could learn further by stacking models to determine whether it improves the accuracy of predictions.
3. Import Textual Information and use NLP: Some academics have used Twitter sentiment analysis [58] to anticipate stock market behavior. In addition to

deconstructing social media data, other qualitative indicators such as news, foreign and domestic policy change can be used to anticipate price trend.

4. Predict Exact Price Value: In the future, it may be possible to incorporate quantitative finance procedures with machine learning techniques in order to identify and forecast the actual price value.

Even though the majority of people have a negative view of using machine learning to anticipate stock prices because they believe the stock market is too volatile to anticipate, academics and traders from large corporations continue to investigate additional indicators and models to accurately predict the economic market. We might guess that machine learning approaches will give us with a promising future in studying and conquering the industry in the near future.

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