Forecasting Dhaka Stock Exchange prices Using Machine Learning Models: a Performance Analysis

Final Thesis Report
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Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
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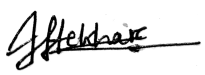

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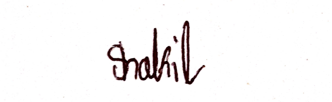

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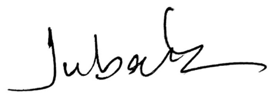

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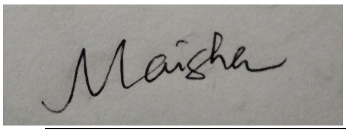

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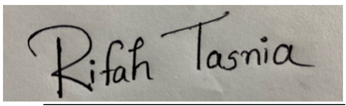

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Abstract

The financial markets have always been a focal point of interest for investors, analysts, and researchers. Predicting stock prices accurately has remained a challenging task. For many years, academics are analyzing the historical data to predict the prices; the most challenging and profitable use has been stock valuation forecasting. However, only a tiny portion of the elements which impact market movement can be measured. Examples of these factors include transaction volume, previous prices, and current prices. These variety of factors makes machine learning-based stock price prediction challenging and, to certain levels, questionable. Statistical and machine learning algorithms are used to predict short-term fluctuations in markets on an average market day, assuming there is ample historical data and factors available. This research uses a variety of machine learning techniques to present several comparison models for stock price prediction like LSTM, GRU and Nbeats and ARIMA. Historical data gathered from the official website of the Dhaka Stock Exchange (DSE) was used to train the models. Factors such as Date, Volume, Open, High, Low Close prices are included in the financial data. Conventional strategic metrics such as Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) R-Squared and Mean Absolute Error (MAE) were used for assessing the models. Furthermore, since stock prices are impacted by various other real - world factors other than numerical data, this research attempts to incorporate external factors like political situations, daily grocery prices and corruption to the existing numerical variables in stock prediction. Our research contributes to the developing repository of knowledge in machine learning of machine learning for financial forecasting with significant implications for investors, financial institutions, and policymakers who depend on detailed stock price predictions to make informed decisions. The opportunity for more study in this area is outlined in the thesis conclusion, along with the practical ramifications of the results for the larger financial sector.

Keywords:financial markets;investors; predicting stock prices;historical data; predict future values;forecasting; elements; market movement; prediction; statistical algorithms; LSTM; GRU; Nbeats; comparative models; ARIMA; Dhaka Stock Exchange (DSE); Mean Absolute Percentage Error (MAPE); Mean Squared Error (MSE); R-Squared error; Mean Absolute Error (MAE); financial forecasting; implications; investors; financial institutions; policymakers; informed decisions; practical ramifications; results; financial sector.

Dedication

We dedicate our work to our respected parents and fellow peers.

Acknowledgement

Firstly, all praise to the Great Allah for whom our thesis have been completed without any major interruption.
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Chapter 1

Introduction

1.1 Motivation

An economy's ability to support enterprises with long-term financing and to accelerate economic growth depends on having a strong market. Regulators that are too loose, speculative, and the historical bank domination of the financial sector pose serious problems for Bangladesh's capital market, despite its apparent signs of life. Previously, the speculative nature and lack of transparency in Bangladeshi capital market have been proven as major growth barriers. Despite of some tiny spikes in the interest graph in the 20th century, Dhaka stock exchange faced two major crashes in the market in 1996 and 2010-2011.
These backdrops have left a lasting scar and showed the need for improved risk management and forcasting system in the stock market. Although it's a hugely difficult task to comprehend with these fluctuations of the market trends , these forcastings provide valuable insights for the investors to anticipate any upcoming collapse. It is required to forsee the market trends for efficient decision making. So, considering

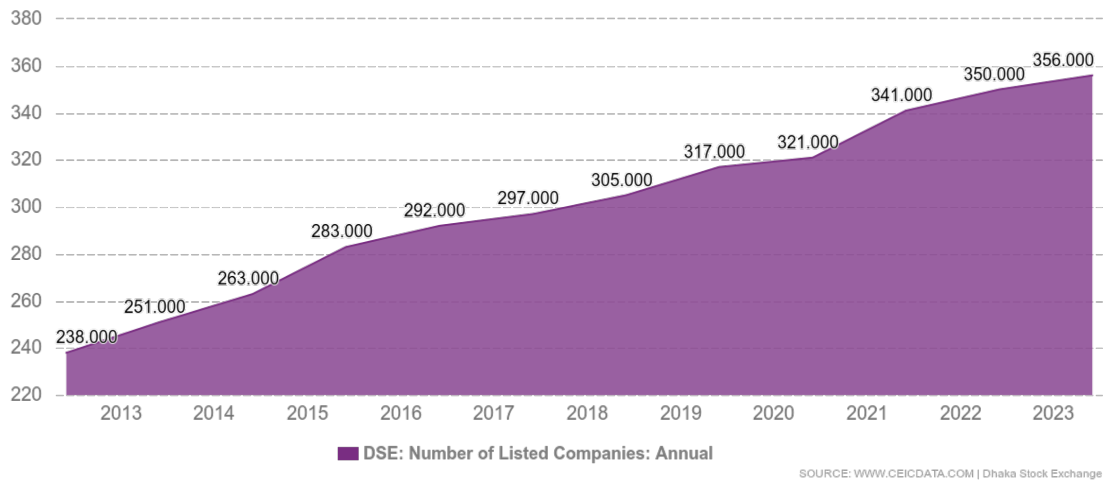

Figure 1.1: Number of companies over the years

those important implications, we take inspiration to come up with some useful findings in the field of forcasting and eventually contribute to the overall improvement of the national economy. Machine learning with it's power of adaptability and prediction can be a useful tool to use to anticipate the market. Time-series forcasting is a important area of research to reduce risks associated with the investments. The chances are high that, proper use of Machine learning and Deep learning can mitigate the loses of the investors in the long run. With a noble view to strengthening the investor's decision making of the Bangladeshi stock market and improving the predictive abilities in the larger financial market, this thesis sets out to predict the prices of Dhaka Stock Exchange(DSE) using machine learning models like LSTM, GRU and Nbeats.

1.2 Problem Statement

The search for consistency in trading leads to the investigation of forecasting techniques that aim to both reduce and exceed losses in this volatile market. An error made frequently by traders that keeps them from realising the full potential of profits is misjudging entry and exit points. Acknowledging this, it becomes necessary to apply accurate stock prediction methods, directing investors towards tactical choices that correspond with market patterns. Making decisions becomes more difficult in the stock market because of the constantly changing environment and abundance of important information that is readily available online. The thoughts and information shared online are having a greater and greater impact on investors. As a result, more advanced and intelligent forecasting methods based on technical or fundamental analysis are required. In this regard, looking forward to an impending stock price prediction method becomes essential. This technique is intended to serve as a safeguard against investing in businesses that might turn out to be unfeasible, in addition to serving as a tool for making well-informed decisions about which stocks to buy. We define our problem as a comparative analysis among some deep learning architectures (e.g. LSTM, GRU, NBEATS) by examining the performances of these algorithms in predicting stock prices . We aim to come up with a conclusion about which models are performing better and the implications of these results. The accuracy of these performances rely on various factors, this study aims to points out these particular factors and their weights on the overall performances of the mopdels. The main objective is to give investors the wisdom to wisely traverse the stock market landscape, optimising returns while lowering the hazards that come with making ill-informed investment decisions.

1.3 Research Objectives

1. **Quantitative Analysis of Social and Financial Development Tendencies:** Leverage established quantitative methods in social science research to analyze historical data, aiming to discern trends and patterns that influence both social and financial development.

2. **Time-Series Analysis Techniques:** Evaluate various time-series analysis techniques, recognizing their respective benefits and disadvantages, as techniques for building predictions from historical data. This exploration will inform the development of robust forecast models for future stock prices.

3. **Application of Python Scripting Language:** Implement Python scripting language for the development of efficient and fast-executing forecast models. This choice is driven by the need for a rapid execution environment, providing investors with timely predictions to formulate advantageous funding approaches.

4. **Optimization of Investment Strategies:** Formulate the most advantageous funding approach by utilizing forecast models derived from historical stock price data. The objective is to provide investors with a reliable reference for making informed decisions in the stock market.

5. **Maintaining Economic Stability:** Investigate the role of forecast models, implemented through Python scripting, in maintaining the economical stability of the share market. Assess the impact of predictive analytics on market dynamics and stability.

6. **Future Enhancements with Advanced Features:** Propose future work involving the enhancement of Python script code with more advanced features. This iterative approach aims to continually improve the accuracy and effectiveness of the forecast models.

7. **Implementation of Machine Learning Algorithms:** Implement a combination of machine learning algorithms, specifically LSTM, GRU, and Nbeats, for predicting future stock prices. After implementing these methods, we aim to move towards advanced techniques such as ARIMA, LSTM, bidirectional LSTM, and Prophet.

These research objectives collectively aim to contribute to the refinement of forecasting techniques, offering investors a reliable framework for decision-making in the complex and dynamic landscape of the stock market.

Chapter 2

Related Works

2.1 Stock Market Prediction Methods

predicting what stock prices will do next is a difficult task in finance. Investors and analysts have tried various methods over the years to make sense of the unpredictable stock market. This section explores the methods they've used.

2.1.1 Traditional Methods

Traditionally, analysts have used diverse strategies to anticipate stock movements. Time series analysis relies on historical data to spot recurrent patterns such as seasonal rises offering insights about future trends [36]. At the same time, the basic analysis focuses on the financial state of a business, thoroughly reviewing results and economic data to predict stock movements. [4]

2.1.2 Machine Learning and Deep Learning

The versatility of machine learning and deep learning makes it possible to be applied in situations where market circumstances are constantly changing. Nevertheless, they have their own difficulties, and in spite of their expertise, their forecasts are often exposed to the unstable character of the market.[33] [32] These researches provide valuable insights on the development of methodologies for predicting the stock market over time, from time series and fundamental analysis to the more modern incorporation of machine learning and deep learning. Although no strategy can guarantee results, these developing approaches provide traders and analysts a sense of direction in the unpredictable world of stock trading.

2.2 Machine Learning and Deep Learning in Stock Prediction

In this section, the discussion includes applications of Machine Learning(ML) and Deep Learning(DL) methods in prediction of stock market.

2.2.1 Machine Learning Algorithms

Machine learning has revolutionized stock prediction. By training with available historical data ML algorithms tries to capture trends of the stock market and eventually predict the future market movements [14]. The adaptability of ML models have proved to be one of the most useful features to keep pace with the dynamic nature of the stock market. According to a study conducted by Velu et al.(2023), supervised learning methods for classifying tweets and found that Support Vector Machine (SVM) outperformed Naïve–Bayes classification. Two-level polarity classification using manual sentiment analysis proved more effective than three-level polarity classification, especially on Microsoft (MSFT) stock, with high recall in identifying both positive and negative tweets. However, Naïve–Bayes classification exhibited poor recall for negative tweets across all stocks. Additionally, the study incorporated LSTM-RNN for stock price prediction and observed improvements with various sentiment analysis methods, particularly on Tesla (TSLA) and MSFT stocks. TSLA experienced a substantial reduction in Mean Absolute Percentage Error (MAPE) when manual sentiment was included. The study suggests future research avenues, including testing the proposed methods with more stocks, assessing model robustness in adversarial settings, and examining performance in various market scenarios. These areas offer important directions for further investigation based on the study's results. [44] The results of a paper which compares various ML techniques in the field of stockprice prediction to indicate that the two-stage model significantly improves accuracy compared to a single-pass model. The artificial neural network achieves the highest accuracy at around 74%, closely followed by support vector and random forest with measures exceeding 73%. Naive Bayes lags slightly but still performs at more than 67%. The two-stage setup enhances average accuracy to 72%. The paper suggests that this approach, which includes discretization of continuous data and the incorporation of multiple technical indicators, provides a distinct contribution to predicting stock price movements. The proposed method could be applicable for trading purposes, especially with further exploration of incorporating news and Twitter feeds for enhanced short-term directional predictions. [15]

2.2.2 Deep Learning

Deep learning, a subset of machine learning, has ushered in a new era in stock prediction by leveraging neural networks that mimic the intricacies of the human brain. Models like RNNs, LSTM, and GRU excel in capturing long-term dependencies in stock data. They specialize in handling time-series data, a fitting characteristic for stock market predictions.

Empirical studies in this domain reveal exciting breakthroughs. For instance, one study introduces an innovative approach that uses deep convolutional neural networks to organize price activities as bell-shaped curves, identifying market sentiments of greed and fear [13]. It's demonstrated that combining structures and time causality in model architecture can result in substantial financial gains and effective trend reversal identification in financial markets.

In essence, while machine learning and deep learning have substantially enhanced stock prediction capabilities, they aren't a crystal ball. They navigate the complexities of market data but can't eliminate all uncertainty, signifying the importance of prudence in stock market dealings.

Moreover, some studies focus on financial market forecasting using deep learning models, particularly long short-term memory networks (LSTM). While most research utilizes raw financial time series data, this study introduces a novel approach, employing deep convolutional neural networks to organize price activities as bell-shaped curves and identify market sentiments of greed and fear. The research also considers time causality when predicting trend reversal behaviors, addressing the challenge of capturing rapid market changes. The study includes two experimental stages, evaluating the accuracy and profitability of the proposed models, with impressive results. The models outperform control groups, particularly the EGC model, showing substantial annualized returns and improved profit-to-loss ratios. Statistical significance tests confirm the models' superiority over traditional approaches, highlighting their ability to identify trend reversals effectively in financial markets. The study demonstrates that combining structures and time causality in the model's architecture can result in significant financial gains, presenting a promising avenue for financial market forecasting. [31]

2.3 Time Series Forecasting Models

According to a study conducted by Semenoglou et al.(2023) which explores nine different data augmentation methods, including upsampling and time series combinations, and assesses their impact on forecasting accuracy, the time-series forcasting techniques have a significant effect on the applications of data augmentation [43].

This study [26] focuses on analyzing the daily share prices of the Chittagong Stock Exchange (CSE) within the period of January 2019 to December 2019, encompassing 241 trading days. The research takes random sampling and various statistical tests to select an appropriate ARIMA model for forecasting future daily share prices. In the natural language processing (NLP) and other types of sequential data tasks, the sequence processing models performed better. For both time-series data and other set of ordered elements, the sequence processing model is a very useful tool to understand and generate sequences of data.

2.4 Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) are an invaluable tool for analysts and investors due to their exceptional capacity to identify patterns in consecutive data. Their use in identifying patterns and adding outside variables to forecasts has produced some impressive results. They may have trouble with extremely long-term dependency, and they are unable to anticipate all unforeseen developments in the market, therefore these are their limitations.

By using the advantages of each component, hybridising Recurrent Neural Networks (RNN) with other models can improve stock price prediction. Combining an RNN with a Hidden Markov Model (HMM), for instance, can improve prediction accuracy by lowering the sensitivity to starting parameters and lowering the possibility of being trapped at local maxima. This hybridization strategy may provide a more reliable and efficient way to capture complicated [40]

Investors often use RNNs as part of their predictive toolkit, combining them with other techniques to make well-informed decisions in the ever-evolving landscape of stock trading.

2.5 Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)

Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are two useful tools having the power to capture long-term dependencies in data. LSTM and GRU are advanced types of recurrent neural networks (RNNs) which are designed with the capability to handle sequenced information with finesse.

LSTM have the ability to remember information over extended sequences, making it perfect for capturing long-term patterns in stock data. A paper compiled by Lanbouri et al.(2020) focusing on High Frequency Trading (HFT) and presents a model that uses Long Short Term Memory (LSTM) and technical indicators to forecast stock prices one-minute, five-minutes, and ten-minutes ahead. Using SP500 intraday trading data, the study calculates technical indicators and trains a regression LSTM model. The model's execution is based on historical price data, technical analysis indicators, and strategies. The experiment results indicate the method's effectiveness in predicting stock prices shortly before their occurrence. [20]. To determine the implications of LSTM , a study thorough conducted by Borovkova et al.(2019) introduces an hybridization of LSTM networks to predict intraday stock prices, incorporating a wide range of technical analytical indicators as input. As a whole, the study presents the superiority of the model's predictive performance compared to benchmark models and simplistic approaches. [11] Both LSTM and GRU have gating mechanisms which is used to decide what information to keep and what to forget. This helps in preventing the vanishing gradient problems, which can hinder learning in traditional RNNs. GRU and LSTM are adaptive learners. They can adjust their learning rates based on the complexity of the data, which is essential for modeling the ever-changing stock market.

This is a study which focuses on the prediction of stock prices using advanced machine learning techniques, particularly LSTM networks. It recognizes the pivotal role of stock markets in the global financial landscape and emphasizes the importance of stock price prediction for both large and small capitalizations in various markets [23].

The results suggest that LSTM outperforms ANN, achieving an accuracy of 97%, compared to ANN's 94%. The combination of LSTM and ANN algorithms aims to reduce risk and increase company profits. This research underscores the significance of advanced machine learning techniques in stock price prediction, offering potential benefits for investors and companies in optimizing their financial strategies.

While exploring through the implications of LSTM in existing literature, a thorough study consucted by Yildirim et al.(2021) provides us with some significant insights. In this research paper, the authors address the challenges and opportunities presented by the foreign exchange (Forex) market, characterized by high risks and high-profit potential. They emphasize the unique nature of Forex, where traders profit by predicting the direction of currency exchange rates. The study focuses on leveraging the effectiveness of LSTM, a popular deep learning tool, for directional predictions in Forex. Two distinct datasets, macroeconomic and technical indicator data, are utilized to capture the essence of fundamental and technical analyses prevalent in the financial world.

The authors propose a hybrid model that integrates two different LSTMs corresponding to the aforementioned datasets. Experimental results involving the EUR/USD currency pair demonstrate the success of this hybrid model in forecasting directional movements over one, three, and five-day periods. A classifier is introduced with three classes: "no_action," "decrease," and "increase," providing a nuanced approach to predicting currency pair changes.

The introduction of the "no_action" class, representing negligible changes between two time points, allows the authors to define a unique performance metric, profit_accuracy. This metric, measuring the ratio of profitable transactions to the total number of transactions, aligns with the main objective of profiting from correct predictions of currency pair movements.

The study employs a balanced dataset to ensure unbiased results, containing nearly equal instances of increases and decreases. Comparative analysis with baseline models using either macroeconomic or technical indicator data indicates a slightly better performance of the macroeconomic (ME_LSTM) model. However, combining features into a single LSTM does not significantly enhance accuracy. In contrast, the proposed hybrid model consistently outperforms, achieving the best profit_accuracy for predictions across all periods.

The authors highlight several key contributions, including the demonstration that processing macroeconomic and technical indicators separately, rather than combining them, significantly improves prediction accuracy. The introduction of a "no-change" class enhances accuracy by addressing small changes between consecutive days. Furthermore, the study explores LSTM's capability to predict values for multiple days ahead, with a slight decrease in accuracy values for longer prediction periods. Lastly, experimentation with different training iterations reveals that more iterations enhance accuracy while concurrently reducing the number of transactions, emphasizing the importance of a balanced approach to optimizing profitability and risk management. A new dataset is also used to validate the suggested hybrid model, demonstrating its strong performance.. [29]

2.6 Bi-directional Long Short Term Memory (BiLSTM)

Long Short-Term Memory (LSTM) is a specific kind of recurrent neural network (RNN) architecture model that helps to overcome the restrictions and boundaries of gradients that vanish in traditional RNNs. Moreover, it allows in capturing of long dependencies in any type of sequential data. The main aim of a directional LSTM is that it is capable of processing input data that can move in both directions- forward and backward. LSTM is considered a more advanced type of RNN.

BiLSTMS are basically LSTM but with a bidirectional architecture. The components of BiLSTMs are mainly considered of two kinds of LSTMs. While the other LSTM analyzes the backward direction, one LSTM handles the forward direc-

tion. The final output sequence is then created by combining the outputs of various LSTMs.
When in work, the outputs of both the forward and backward LSTMs are updated using a specific type of algorithm known as the Backpropagation Through Time (BPTT). This is a certain type of gradient-based observation that can extend back-propagation to sequences because of the temporal dependencies. Furthermore, in the case of Initialization, the initial state of the forward and backward LSTMs are selected differently. Usually, the backward LSTM of BiLSTM has the last element of the sequence as its initial hidden state. [30]

2.6.1 Common Applications of BiLSTM

BiLSTM is very commonly used for Natural Language Processing (NLP), speech processing, Bioinformatics, Time Series Analysis and so on.
Some of these have been described below in brief:

1. **Natural Language Processing (NLP)**:Parts of speech tagging comes in several forms, such as entity identification, sentiment analysis, machine translation, and so forth. BiLSTMs are widely used for such tasks as they can understand and synthesize the information from both the preceding and succeeding elements.

2. **Speech Processing**:As BiLSTMs are able to capture the relevant data from both the future and past sound units, these are widely used for speech recognition tasks.

3. **Bioinformatics**:For Bioinformatics discovery, such as analysis of DNA sequence and protein prediction in secondary DNA structure, BiLSTMs are commonly used.

2.6.2 Complications While Using BiLSTMs

The computation complexity of BiLSTM is much more complex and challenging when compared to regular LSTMs as they process the input sequences of both directions simultaneously. Moreover, even though BiLSTMs are quite powerful, it is suggested that this certain structure should only be in used depending on the nature of the input and task requirements. Therefore, use of it should be avoided if possible. [30]
BiLSTM is considered a very handy and sophisticated model as it can be connected with advanced neural network architectures such as CNN to create better scopes.

Therefore, it can simply be concluded that BiLSTM allows us to capture bidirectional information in sequential data which plays a very valuable role in many other applications.

2.7 Attention-based Models

In financial time series prediction, a shining star has emerged in the form of attention-based models. These models are akin to expert detectives with a unique ability to focus on the most critical clues in the data. A research focusing on stock price trend prediction, addresses the challenges posed by non-stationary and volatile stock prices. Despite some relatively large errors, the model consistently predicts the correct trend direction, showcasing its potential utility in assisting stock investors in decision-making. The study concludes that the attention-based LSTM model offers a promising alternative for accurate stock price trend predictions and practical applications in aiding investor decisions based on predicted trends. [21]
Attention based models possess the unique ability to selectively focus on relevant patterns, making them invaluable in the world of stocks. Their adaptability, efficiency, and capability to capture complex patterns and integrate external factors set them apart. By reducing noise and enhancing the signal, attention-based models have become an indispensable tool in the arsenal of investors and analysts in the dynamic world of stock trading.

2.8 Statistical Models

Multiple Linear Regression (MLR) is a statistical machine learning technique which is simpler than RNN models and also cost friendly. That being said ,a linear relationship between the variables is assumed by MLR.. But we know the stock market prices can depend on various economic, political, global etc. factors. Therefore, it is more common to see complex models like LSTM , CNN etc. Hybrid models can incorporate both RNN and MLR to predict the stock prices.
The performance of Apple INC's stock price was studied on a paper where Multiple Linear Regression model was used and the results were promising. They considered the open price of the stock as independent variable which eliminated the others factors to predict the price of the stock.[47] Another paper showed that BP neural network is more accurate than MLR as it predicted more accurately the prices of the stocks.[38] The linear relationship in MLR model often fails to cope with the complexity of stock predictions.
For simpler data sets, MLR model is ideal as it can provide more straightforward results with minimum complexity. MLR also serves as a base of more complex

models which can be joined to create hybrid models for best predictions.

2.9 Advanced Forecasting Models

In the ever-evolving landscape of stock market prediction, advanced forecasting models have emerged as a ray of hope for investors and analysts seeking more accurate insights. In this section, we introduce two such innovative models: N-BEATS and Prophet, and explore their unique capabilities and contributions to stock market prediction.

2.9.1 N-BEATS: Neural Basis Expansion Analysis for Time Series Forecasting

N-BEATS stands as a pioneering advancement in the realm of forecasting models. It is characterized by its neural basis expansion analysis, a concept that promises to revolutionize time series forecasting. N-BEATS takes a different approach by leveraging fully connected neural networks. Its innovation lies in its simplicity – N-BEATS is designed to be both efficient and highly effective.
The architecture of N-BEATS is identified by its flexibility in Time Series forecasting. In a research paper published in 2020, some components of N-BEATS architecture such as stacks, blocks, interpretable layers, gating mechanism etc. were introduced. This architecture allows N-BEATS for customization making it much more flexible. Each stack consists a backcast and a forecast sub network which generates a set of time series representing the past and future respectively. The generic blocks helps the model to capture different patterns. The outputs from the generic blocks form a linear combination and the interpretable layers allows the user to choose specifically according to functions which makes this model very adaptable. [17]
Studies have demonstrated the effectiveness of N-BEATS in stock market prediction. It is able to capture the short-term as well as the long-term dependencies of data which has been proven invaluable. LSTM, GRU and TFT models gave more accurate prediction compared to N-BEATS model in a research where the performance of various neural networks on auto sector stocks was analyzed. N-BEATS had the maximum number of errors than others. [46]
N-BEATS has potential because of its ability to balance between complexity and flexibility. Its adaptability to changing market conditions and its efficiency in processing vast datasets have made it a frontrunner in advanced forecasting. Combining N-BEATS with other traditional models in order to solve the complexity of stock market prediction looks promising.

2.9.2 Prophet: Forecasting at Scale

Prophet is another pioneering model that has gained recognition for its unique approach to time series forecasting. Developed by Facebook, Prophet focuses on providing users with a straightforward and intuitive tool for forecasting. Its innovation lies in its adaptability to handle seasonality, holidays, and special events.

One of Prophet's notable features is its ability to generate uncertainty intervals for forecasts. In the world of stocks, uncertainty is a constant companion. Like N-BEATS, Prophet is also flexible and simple. Prophet has the ability to detect abnormal patterns and label them as holidays which can be useful in stock market. It can also perform well during irregularities which is very common in stock market data. In a recent research, Facebook Prophet was used for stock prediction. The results concluded that Prophet is quite useful in case of predicting stock price for a long period of time. [35] The LSTM , ARIMA etc. models do not work well on inconsistent datas as they are only suitable for short term. For irregular data sets, Prophet are more effective. But there are some limitations while using Prophet because it is not as complex as other models. Moreover, it is not ideal for short term predictions.

In advanced forecasting models, N-BEATS and Prophet are two of the most promising and innovative architectures. They introduce novel concepts and capabilities that hold great promise for stock market prediction. N-BEATS, with its neural basis expansion analysis, excels in handling diverse time series data, while Prophet, with its adaptability to seasonality and provision of uncertainty intervals, offers a user-friendly and intuitive solution.

2.10 External Factors and Predictive Variables

Stock market prediction is not confined solely to historical stock data and market-specific factors. Researchers and analysts have increasingly recognized the significanceof various external factors on stock prices. In this section, we delve into the influence of external variables such as economic indicators, news sentiment, and global market trends and the innovative research that has incorporated these variables into predictive models. Sirigano et al. entifies a universal relation between bid and ask depths and the probability of a price decrease, providing evidence for common structure across different assets and time periods. Since deep learning has expertise in image, text, and speech recognition, it is often assisted by multi-layer neural networks. When the neural network is compared with a linear model it demonstrates a significant increase in accuracy, around 5 percent to 10 percent, compared the effects of using nonlinear neural networks. [9]

2.11 Comparative Studies

Since the stock market is a very dynamic system, there has been rapid experiments incorporating various models and techniques. To have a better and overall idea of these aspects, we tried to look for the comparative studies conducted in this field

2.11.1 Machine Learning vs. Traditional Methods

Comparative studies often put machine learning against traditional methods, shedding light on the advantages of modern approaches. Gencay et al.(2001) compared the performances of machine learning algorithms such as neural networks and support vector machines with traditional time series forecasting methods like ARIMA. The findings of this research showed that machine learning algorithms often outperformed traditional methods, particularly in capturing complex and nonlinear patterns in stock data. [2] [37] Taleongpong et al.(2020) shows that cutting-edge machine learning model offers better accuracy than current delay prediction systems in forecasting key performance indicators. [24] The anlaysis offers insights into the challenges and opportunities of using ML in Predictive Models and serves as a valuable resource for future research in this domain. [12] In case of stock price prediction, a study evaluates the effectiveness of two techniques, Artificial Neural Network (ANN) and Random Forest (RF), for predicting closing prices of stocks for five different sector companies. The evaluation is based on metrics like Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Bias Error (MBE). The results indicate that ANN outperforms RF in terms of better prediction results for stock prices, as observed from the comparative analysis of these error metrics. [25] Again a research study mentioned the capabilities of multiple linear regression model (MLR) for predicting stock prices through an incremental process. It is comparatively a less expensive model where the relationship between the variables are analyzed. Through this statistical technique of machine learning, predicting the stock prices seems quite promising . [18]

2.11.2 Development of Deep Learning methods

The presence of deep learning, marked by the rise of neural networks like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), has redefined stock price prediction. Huang et al. conducted a comprehensive comparative study exploring the effectiveness of deep learning models against traditional models. Their research showed that deep learning models, particularly LSTM, excelled in capturing long-term dependencies in stock data. These findings hinted at the superiority of deep learning in handling sequential data. [3] In some studies, methodical analysis is con-

ducted on the application of deep learning networks for stock market prediction and analysis. High-frequency stock market prediction could benefit from deep learning's ability to extract characteristics from unprocessed data without requiring knowledge of predictors beforehand. The research delves into diverse deep learning algorithms, network configurations, activation functions, and techniques for data representation, offering an unbiased evaluation of their benefits and limitations.
Additionally, the studies notice a significant improvement in covariance estimation when the prediction model is applied to covariance-based market structure analysis. High-frequency traders can benefit from these discoveries because they can improve the prediction of stock return and covariance, which in turn helps anticipate the total market return and risk. This is relevant when trading indexes of stocks derivatives. While the studies do not offer definitive proof of deep learning's superiority, they highlight promising avenues for future research. For instance, incorporating additional factors such as trading volume and derivative prices into the input data, especially at higher frequencies, may yield more effective predictions. They invite researchers to further investigate the complex relationships between stock prices and various factors, paving the way for advancements in high-frequency trading strategies and market analysis. [8]
There are some other methods being developed discovering newer horizon in the landscape of forcasting such as the Bag-of-Future (BoF) approach, highlighting its advantages and challenges. The BoF method is noted for its simplicity, interpretability, and competitive performance on various evaluation metrics for time series forecasting. It emphasizes the ability to provide continuous representations and insights into the series, while also mentioning that it may struggle with abrupt changes in sequences. The method's performance is compared to other benchmark methods, and further extensions and tests on longer forecast horizons are considered for future research. [42] Another research explores the use of Long Short-Term Memory (LSTM) technology for predicting future trends in the stock market. The paper emphasizes the increasing popularity of machine learning, especially LSTM, in stock forecasting due to its reliance on current stock values informed by historical data. The results summarize several studies employing various machine learning techniques for stock market prediction. For instance, a 2019 study by P. Chaitanya & K. Srinivas found that ARIMA was more efficient than ANN and SVM. Other studies highlight the use of SVM with higher accuracy on small and large datasets, the effectiveness of sentiment analysis on Twitter data, and the positive results of LSTM in stock market prediction. The conclusion underscores the importance of calculated risk in the stock market, emphasizing the use of algorithms and expert strategies for analysis and prediction. [41]

2.11.3 Ensemble Methods and Hybrid Models

The comparative studies suggests that ensemble methods and hybrid models holds strong potentiality while predicting the stock trends . A study highlights the potential of PCA-DNN classifiers in achieving the highest classification accuracy and superior trading strategy performance, offering promising avenues for future research. [16]
Debashish et al. focused on addressing the nonlinearity of the stock market, based on a study conducted on the pharmaceutical sector of Bangladesh. The positive results suggest potential benefits for investors. The research also highlights that while the hybrid approach is promising, stock price predictions in markets like the DSE are influenced by various external factors, including interest rates, foreign direct investment, currency rates, political events, and other variables. [7] In this paper, Banik et al. addressed the challenge of forecasting stock market movements, which has historically been difficult due to the noisy and time-varying nature of financial data. [5] However, the authors recognize that machine learning techniques can be effectively applied to predict stock market behavior. The study focuses on stock market prediction to assist investors, acknowledging the losses they may incur due to uncertain investment objectives and unpredictable market conditions.
The hybrid model in this research combines the strengths of ANN and RS to enhance prediction accuracy and generate decision rules for stock trading. The research employs data discretization using RS equal binning and attribute reduction with RS Johnson's reducer algorithm. The performance of the models is assessed using a confusion matrix to evaluate their accuracy in predicting whether stock prices will fall or rise.

2.11.4 Context Matters

Among some crucial points shown by these comparison analysis, a important aspects to be noticed is that the potential of a specific model is mostly dependant on the particular factors and contexts. Ding et al. stated the importance of considering these particular factors while choosing from these predictive models.[13]

2.12 Limitations of Existing Literature

Although the there has been made significant advancements in the studies related to stock prices, there are still some limitations which need to be addressed to ensure broader scope of development. Among these limitations, the most important one is related to the available data from DSE. Bose et al. figured out some of these issues. The historical data available in various sources are not enough easily accessible for the practitioners . Besides, there has been constant weakness and inconsistency in the available data which eventually hampers the quality of the studies. In addition to that, the lack of reliable datasets are restricting the potential scopes of research. [6] Another important issue noticed in the studies conducted is these researches do not provide a overall general conclusion , rather they are limited to specific situations and timespan of the market which is a major setback to include the dynamic mechanism and trend of the stock market. [13]

Chapter 3

Dataset Preparation

The initial stage of any machine learning project is data preparation, which is usually a challenging process. When there are no existing benchmark data for the particular problems at hand, this challenge becomes more difficult. Right now, building a data set comes with a number of difficulties. We will go into the specifics of each strategy and discuss the decisions we made in this regard.

3.1 Data Collection

Stock exchanges around the world have compiled with vast amounts of datasets. As previously stated, the DSE and CSE are the two major stock markets in our nation. Furthermore, we have decided to focus our research entirely on DSE. The DSE website offers data archives for more than 500 trading companies that are involved in the stock market.

3.2 Data Pre Processing

First and foremost, there were certain important pre-processing tasks that needed to be completed before we could begin working with the dataset. First, we prepared our data for precise analysis by transforming the date column into a datetime format.
Then, we created a new dataframe and randomly selected 100 companies from the trading codes column, which basically lists companies who engage in stocks. But few of the company names were missing from this dataframe, so we cleaned it up by removing any extra spaces and commas between the values.
Then, We selected fifteen stock companies that would be the focus of our work from this list. Let's get into the specifics of training and testing. Our training set consisted of every price with dates from January 2010 to January 2021, with the remaining data which are from February 2021 to December 2022, making up our

test set. All stock prices were rescaled to fall between zero and one (the lowest and highest values) in order to standardize and make our data comparable. It's important to remember that each company keeps its own distinct scale.
Now, we're all set to go for the following stages of our project with our training and test sets prepared.

Chapter 4

Methodology

4.1 Workflow

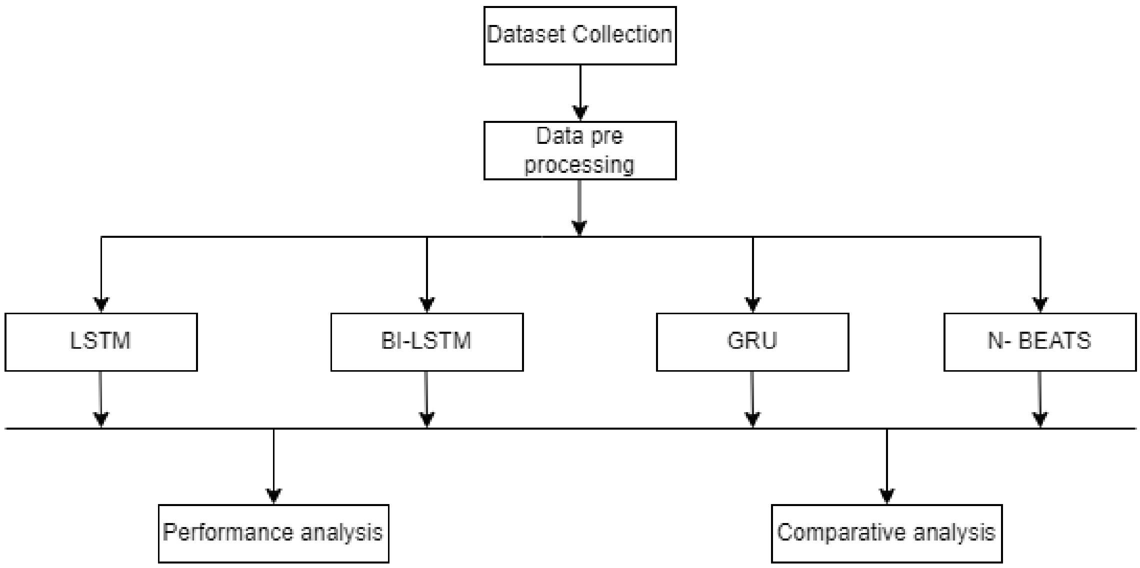

Figure 4.1: Work Flow Diagram

The study consists of several processes though which the entire research progressed. The following diagram represents the steps we iterated to complete the study.

4.2 LSTM

Traditional Recurrent Neural Networks (RNNs) face challenges because of the vanishing gradient issue with short-term memory, especially when managing larger information sequences. Fortunately, advanced versions of RNNs have emerged to overcome this limitation by retaining crucial information from earlier parts of the sequence and carrying it forward. The most well-known variants are GRU (Gated Recurrent Units) and LSTM (Long Short-Term Memory). These modifications suc-

cessfully tackle the issue of long-term reliance in RNNs, where the model can predict words more accurately based on current information but finds it difficult to predict words stored in long-term memory. However, typical RNNs tend to perform worse as the sequence length rises.
LSTM, on the other hand, excels in preserving information for an extended period by default. It finds applications in processing time-series data, as well as in tasks involving prediction and classification. The incorporation of LSTM has significantly improved the efficiency of RNNs, especially when dealing with long-term dependencies in sequential data analysis.
Let's start with a quick review of a basic Recurrent Neural Network (RNN) structure. An RNN is made up of an input layer, a hidden layer or layers, and an output layer, just like a Feed Forward Neural Network, as shown in Figure 4.2.

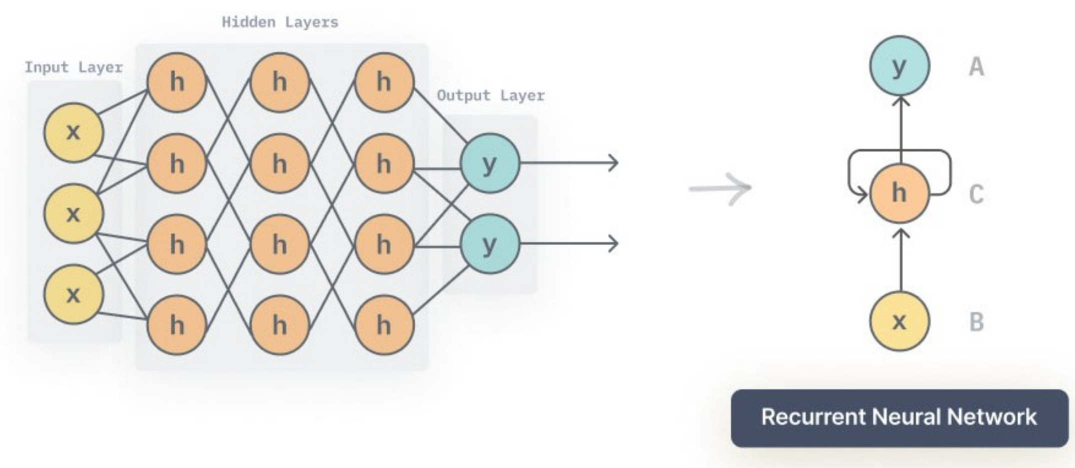

Figure 4.2: Basic RNN structure

However, Recurrent units are incorporated into the hidden layer of RNN, which makes it unique and allows the algorithm to process sequential input efficiently. This is accomplished by periodically passing and combining the input of one timestep with a hidden state from an earlier one. In essence, RNN leverages these recurrent units to handle sequential data in its hidden layer, employing a mechanism of incorporating information from past timesteps into the current computations.
Indeed, both RNNs and LSTMs employ recurrent units for learning from sequential data. However, the inner workings of these recurrent units differ significantly between the two. The two main functions of a standard RNN's recurrent unit diagram, when seen in a simple manner (without taking into account weights and biases), are merging the previous hidden state with the new input and passing the outcome via the activation function.
The recurrent unit receives the computed hidden state at timestep t, which is then

merged with the input at timestep t+1 to compute the new hidden state at timestep t+1. This procedure repeats until the predetermined number (n) of timesteps is reached, iterating from t+2, t+3, and so on to t+n. In contrast, A more complex method is used by LSTM (Long Short-Term Memory), which incorporates numerous gates to decide which information to keep and discard. LSTM also introduces a cell state that functions as a long-term memory component.
The architecture comprises the sub-networks with recurrent connections that make up the memory blocks. These memory blocks control information flow and preserve their state across time by using non-linear gating units.

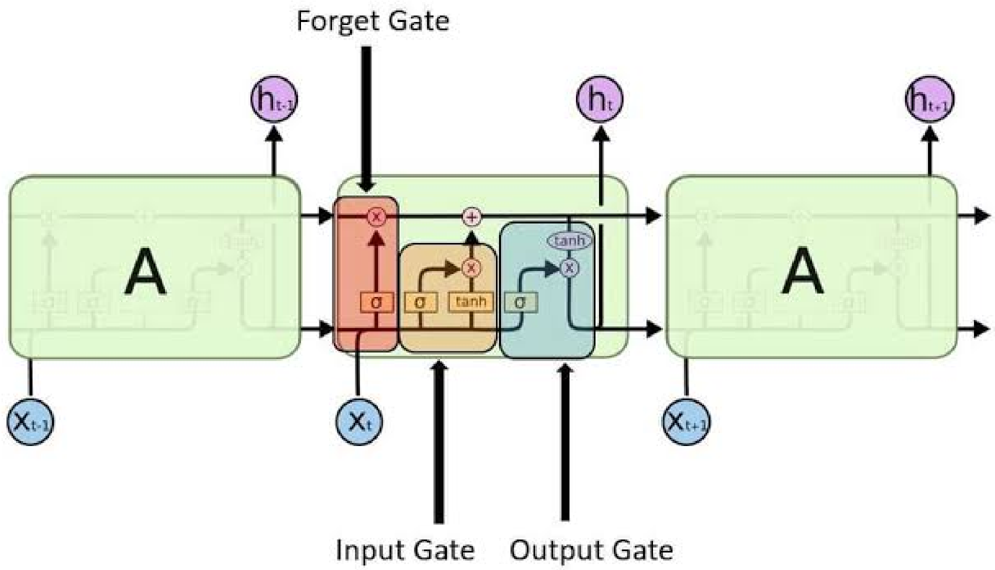

Figure 4.3: LSTM architecture

The LSTM architecture is illustrated by the Figure 4.3 where it consists of various numbers of memory cells arranged in a chain form and four neural networks. A LSTM unit contains a cell and three gates which are an input gate, an output gate and a forget gate. These gates regulate the data that enters and exit the cell which makes LSTM to effectively process time series data with indeterminate durations. The detailed process of how the gates store information is discussed below.
Input Gate: The first gate is the input gate which is essential in determining which input values to affect memory modification. The sigmoid function allows for the passage of either 0 or 1 when making binary decisions. The tanh function is utilized to assign weights to the provided data simultaneously to enable the assessment of their importance in a scale of -1 to 1.

$$it = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$Ct = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

Forget Gate: Which data should be erased from the memory block determines the forget gate. The gate is managed by a sigmoid function which analyzes each cell state value and takes into account both the current input and the previous state to produce a value in the range of 0 to 1.

$$ft = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Output Gate: The output gate decides which data from the memory block should be released. It depends on the input and memory of the block and employs a sigmoid function to determine whether it allows through values of 0 or 1. Additionally, the tanh function which operates on a scale from 0 to 1 determines the range of values that can pass through. The tanh function multiplies the input values by the sigmoid output after the weights representing the relative importance of each of the given values which are allocated on a scale from -1 to 1.

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = O_t \cdot \tanh(C_t)$$

4.3 GRU

The architecture of GRU and Long Short-Term Memory (LSTM) are quite similar. Compared to LSTM, GRU is a relatively recent development, and it stands out for possessing a simpler architecture containing an update gate and a reset gate. GRU has no an output gate in comparison to LSTM, a difference that is illustrated in Figure 4.4

Due to their simplified design, GRUs typically provide quicker and more straightforward training than their LSTM counterparts since they rely on fewer parameters. Like LSTMs, these GRU gates also sigmoid activated, which restricts their values to the interval (0,1). One important part that controls the retention of relevant data from the prior state is the reset gate. In a similar way the amount to which the new state practically repeats the prior one can be monitored with the assistance of an update gate.

The hidden state (H_t), in particular, is managed by the Reset Gate in short-term

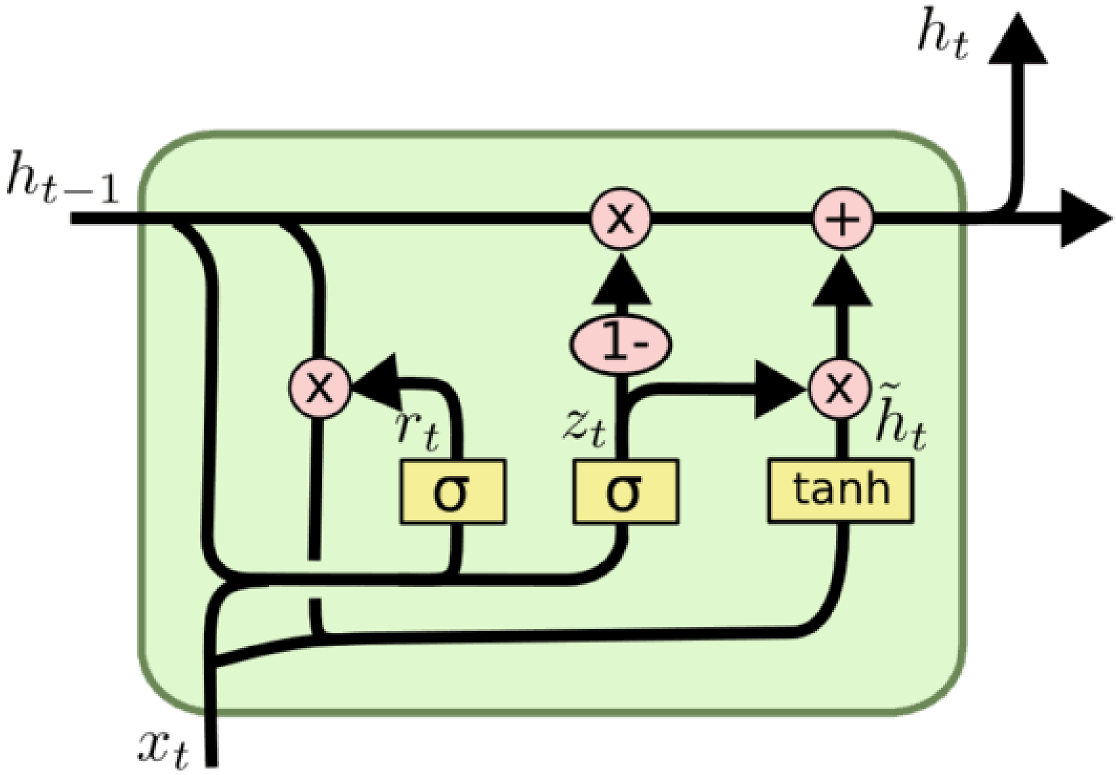

Figure 4.4: Structure of GRU

memory. This essential function is captured in the equation regulating the Reset gate.

$$rt = \sigma(x_t * U_f + H_{t-1} * W_f)$$

The sigmoid function will help to limit the value of rt to the interval between 0 and 1. The weight matrices connected to the reset gate are shown as U_r and W_r in this instance.
Similarly, we provide the appropriate equation for the Update gate, which we introduce for long-term memory, below.

$$u_t = \sigma(x_t * U_u + H_{t-1} * W_u)$$

4.4 N-BEATS

Neural Basis Expansion for Time Series or N-BEATS presents neural basis expansion analysis for unparalleled efficiency which makes the mode a revolutionary in forecasting. N-BEATS uses fully connected neural networks, that is why it is less complicated and more effective than older methods. It uses a distinctive design which ultimately makes it capable of independently recognising the patterns of stock markets along with other wide range of applications. It is renowned for its remarkable adaptability by using the features like stacks, blocks and interpretive layers.

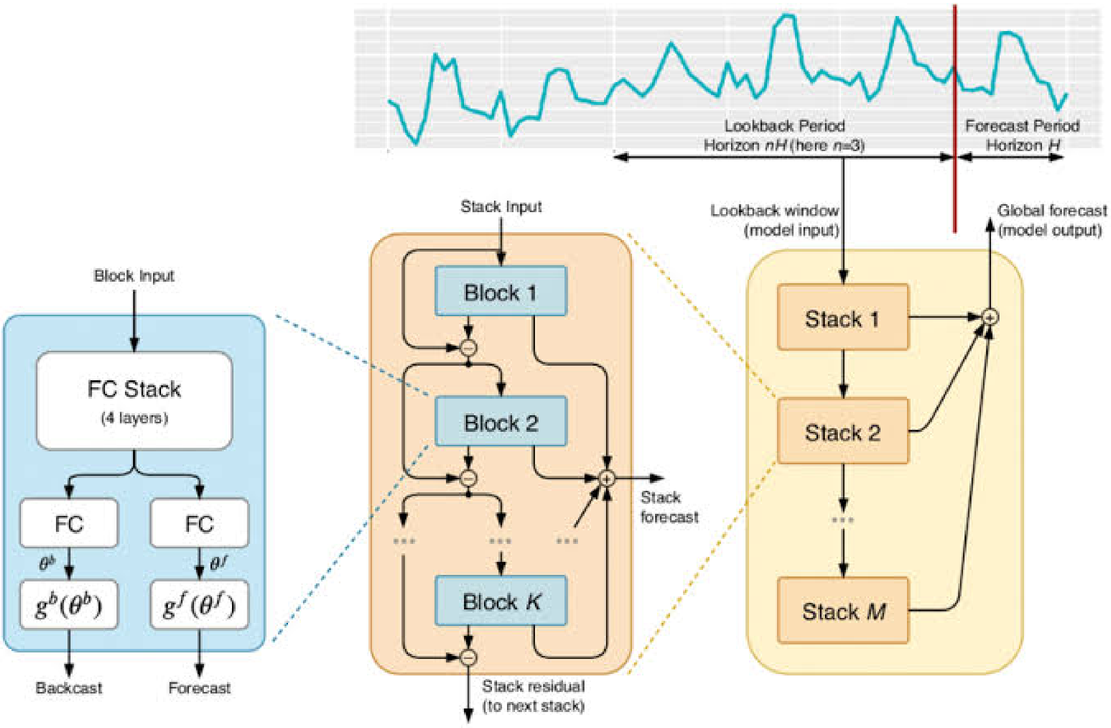

Figure 4.5: NBEATS Structure

The detailed process of how the blocks works are discussed below.

Trend Sub-block: The goal of the trend sub-block is to forecast the local trend of any given time series. It uses harmonic functions and a fully linked neural network to identify underlying patterns. The equation for the trend sub-block is:

$$\hat{y}^{(l)}_{t+h|t} = g(x_{t-L+1:t}, \theta^{(l)}_t) + \sum_{i=1}^{d} w^{(l)}_i \cdot h_i(x_{t-L+1:t})$$

Where the predicted value for l th horizon at that particular moment $t + h$ is $\hat{y}^{(l)}_{t+h|t}$ A fully connected neural network with parameters $\theta^{(l)}_t$ is applied to the input window $x_{t-L+1:t}$ and is called $g(x_{t-L+1:t}, \theta^{(l)}_t)$. Weights for the d harmonic functions $h_i(x_{t-L+1:t})$ are represented by $w^{(l)}_i$.

Seasonality Sub-block:

The seasonality sub-block captures the periodic patterns of a given time series. Weights and harmonic functions are used in the prediction process. The equation for the seasonality sub-block is:

$$\hat{y}^{(l)}_{t+h|t} = \sum_{i=1}^{d} w^{(l)}_i \cdot h_i(x_{t-L+1:t})$$

Where the predicted value at that moment $t + h$ for l th horizon is $\hat{y}^{(l)}_{t+h|t}$. Weights

for the d harmonic functions $h_i(x_{t-L+1:t})$ are represented by $w_i^{(l)}$.
The N-BEATS model consists of multiple fully connected blocks stacked together, offering adaptability to different time series patterns. It doesn't rely on recurrent or convolutional layers, ensuring computational efficiency.

4.5 Implementation Process

In this section, Our aim is to demonstrate how well our stock prediction algorithm works at precisely identifying and forecasting the predefined closing prices of ten specific companies. The setup begins by importing essential libraries, including NumPy, pandas, and matplotlib. We initiate the process by loading the dataset and specifying the target variable for the problem at hand.
To kickstart the procedure, we employ the read csv() function from pandas to seamlessly import the CSV file into Python. After thorough data processing, as delineated in section 3, the subsequent phases involve extracting necessary features for data analysis, partitioning the dataset into testing and training sets, training algorithms for price prediction, and ultimately visualizing the data. Initially, our LSTM model undergoes training using the training dataset, encompassing data up to 2022, which serves as a testing set for fifteen chosen companies.
A cell, an information door, an entrance door, and a door with a view make up a typical LSTM unit. These inputs collect values across variable time periods and control the flow of data into and out of the cell. The capacity of LSTM to learn temporal dependencies that are specific to a given situation is one of its fundamental strengths. Crucially, the length of time that each LSTM unit collects data—whether it be substantial or brief—is dictated by the activation function found in the recurrent components.
It's vital to underscore that the cell state undergoes substantial amplification by the output of the neglected entrance, fluctuating between 0 and 1. Feature scaling is applied to ensure data values fall within the 0 to 1 range. The RNN is constructed for the dataset, initialized through a sequential repressor. The architecture involves the incorporation of the first LSTM layer and subsequent layers, integrating dropout regularization to eliminate undesirable values. The final step includes adding the output layer. The RNN is compiled by introducing the RMSprop Optimizer and defining the loss using metrics like mean absolute percentage error, mean absolute error, mean squared error, and r2 score.
Improving our prediction approach involves incorporating shifting and lagging techniques. Essentially, we adjust the timing of our predictions, a widely used practice in signal processing. Lagging occurs when we initiate our prediction earlier, resulting in a persistent lagged prediction. The duration of this persistence is equivalent to the

displacement in our prediction, leading to values represented as NaN. For example, we trail it by 10 days, the final 10 day forecasts will be NaN. Conversely, shifting occurs when we change our prediction to begin later. Initial values for shifted forecasts are set to NaN up to the displacement in our prediction. For example, the original 10 day projections will become NaN if we move it by 10 days.
The Gated Recurrent Units (GRU) Model was implemented in a manner akin to that described for the LSTM Model. Nonetheless, the SGD optimizer was employed. Interestingly, the earlier version of the GRU only had 50 units; whereas, the present version has a dense GRU network with 100 units.
Using the training dataset, we carefully train our model until the January 2021, evaluating the start of our journey into the world of N-BEATS. This set, strategically chosen for its diversity, acts as a rigorous testing ground for our predictions involving fifteen selected companies. Let's now examine the N-BEATS model's construction. Like an LSTM unit, the N-BEATS model has a complete structure with what is called a forecast sub-network, which is similar to the LSTM cell. The main features of this construction are elements similar to an information door, an entrance door, and a door with a view. Like the temporal dance an LSTM unit does, each of these elements is essential to coordinating the complex data flow inside the model. N-BEATS deviates from conventional approaches by strengthening the output via the so-called "neglected entrance" rather than relying on complex cell states. This mechanism is the foundation of our ability to forecast, carefully bouncing between 0 and 1. Careful feature scaling is used to ensure consistency in our data format, limiting the values to the discriminating range of 0 to 1. Like the model's unique feature, the generic blocks skillfully capture the subtle subtleties of the stock market's moods.
The next step involves carefully compiling the N-BEATS model and using the RMSprop Optimizer to add even more computational efficiency. The r2 score, mean absolute error, mean squared error, and mean absolute percentage error are the evaluation metrics that we use to systematically evaluate the effectiveness of the model.

Chapter 5

Result and Analysis

5.1 Performance Metrics

In this section, we evaluate the performance of three different models—LSTM, GRU, and NBEATS—using four commonly used metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R2) Score.

5.1.1 Mean Squared Error (MSE)

The Mean Squared Error (MSE) is a measure of the average squared difference between predicted and actual values. It is calculated using the following formula:

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

For assessing overall accuracy,It is crucial to use the Mean Squared Error (MSE), which offers a comprehensive measurement of the average squared difference between expected and actual data. More effectiveness is thought to be shown by lower mean square error (MSE) levels, which signify a closer match between expected and observed outcomes.

5.1.2 Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) represents the average absolute difference between predicted and actual values. It is calculated using the formula:

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

The information about mistake sizes is provided by the Mean Absolute error (MAE), which quantifies average absolute differences; lower MAE values are favored.

5.1.3 Mean Absolute Percentage Error (MAPE)

The Mean Absolute Percentage Error (MAPE) measures the average percentage difference between predicted and actual values. The formula is given by:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|y_i - \hat{y}_i|}{|y_i|}\right) \times 100$$

The average percentage variance is represented by the Mean Absolute Percentage Error (MAPE), which offers a measure of precision. Lower values of MAPE indicate better accuracy.

5.1.4 R-squared (R2) Score

The R-squared (R2) Score indicates the proportion of the variance in the dependent variable that is predictable from the independent variable(s). It is calculated as:

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

where $\bar{y}$ is the mean of actual values.
As a coefficient of determination, the R2 Score evaluates the percentage of predictable variation in stock prices; values nearer 1 indicate a better fit. These metrics provide a comprehensive overview of the models' performance, considering aspects like squared errors, absolute errors, percentage errors, and overall model fit.

5.2 Performance Analysis

The suggested LSTM, GRU and NBEATS models, developed using Python, forecasts the prices of fifteen stocks, including ABBANK, ACTIVEFINE, AFTABAUTO, PIONEERINS, SONALIANSH, ACI, BATASHOE, BEXIMCO, BRACBANK, DESCO, GP, OLYMPIC, SQURPHARMA, SINGERBD and PENINSULA. We use important indicators to evaluate the forecasting accuracy and predictability of stock prices for fifteen selected companies using performance matrics. Collectively, the abovementioned metrics determine how reliable and efficient our forecasting model is; higher R2 scores and lower MSE, MAE, and MAPE values are thought to indicate more accurate forecasts. The accompanying graphics show the visual representation of these forecasts. In particular the plots shows the expected values of these fifteen company shares, a representation of our algorithm for stock price prediction over a specified period of time.

5.2.1 LSTM

The degree of accuracy varies when LSTM performance data for the selected companies are analyzed. With outstanding R-squared (R2) Score (0.94, 0.95 and 0.95 respectively) and low MSE and MAE values (2.30 and 1.10, 0.91 and 0.64, 8.29 and 2.17 respectively), ACTIVEFINE [5.2], PENINSULA [5.15], SINGERBD [5.13] stands out for its remarkable accuracy. BEXIMCO [5.8], PIONEERINS [5.4] and GP [5.11] shows exceptional accuracy with near perfect R2 score of 0.97, 0.96 and 0.97 along with relatively low MSE and MAE values(18.33 and 3.10, 39.03 and 4.05, 30.83 and 4.29 respectively). ACI [5.6] and BATASHOE [5.7] also shows excellent accuracy, especially with their pretty high R2 Score of 0.92 and 0.94, with the MAE value (4.08 and 19.43) are also being comparatively lower.

Figure 5.1: Predicted vs Actual values of ABBANK from LSTM

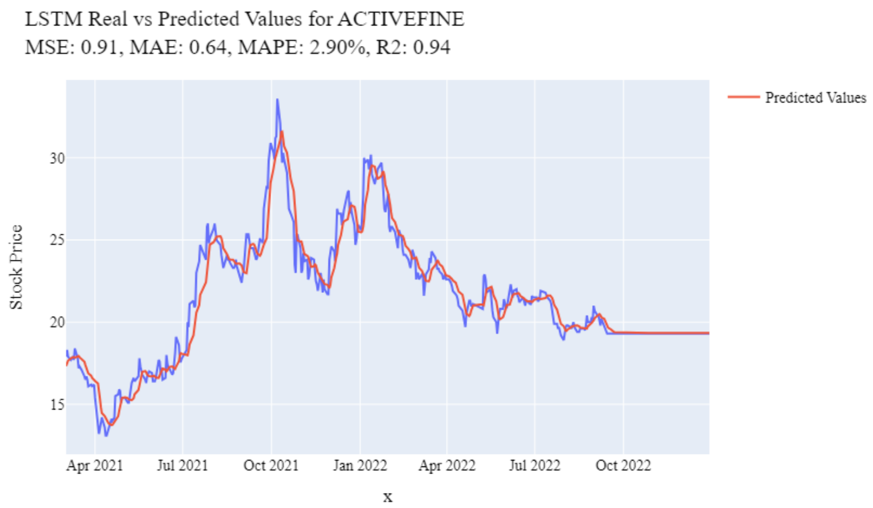

Figure 5.2: Predicted vs Actual values of ACTIVEFINE from LSTM

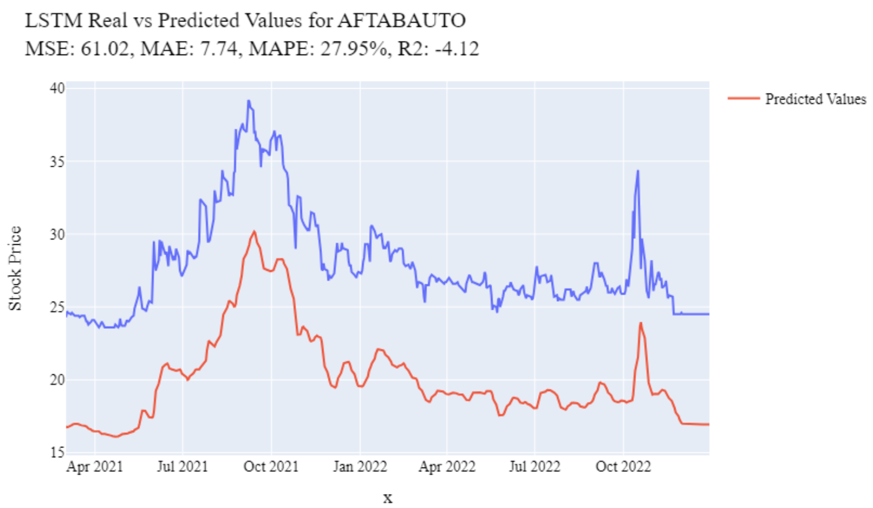

Figure 5.3: Predicted vs Actual values of AFTABAUTO from LSTM

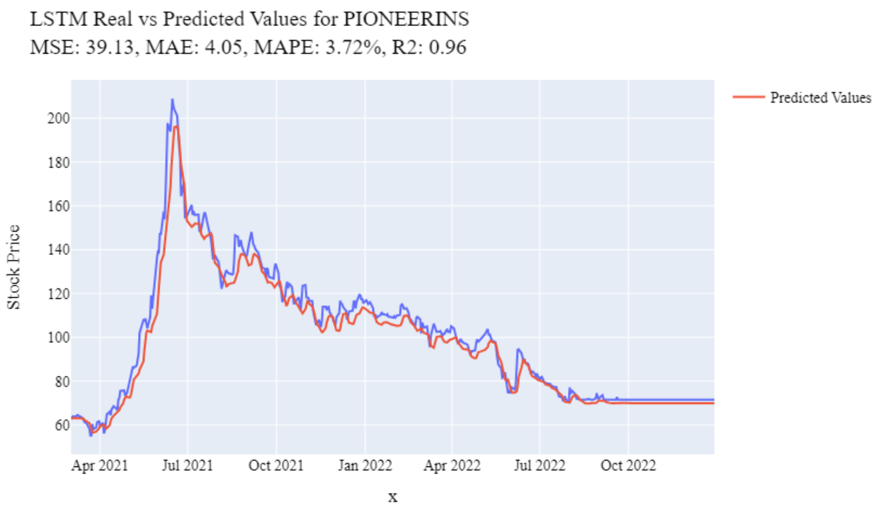

Figure 5.4: Predicted vs Actual values of PIONEERINS from LSTM

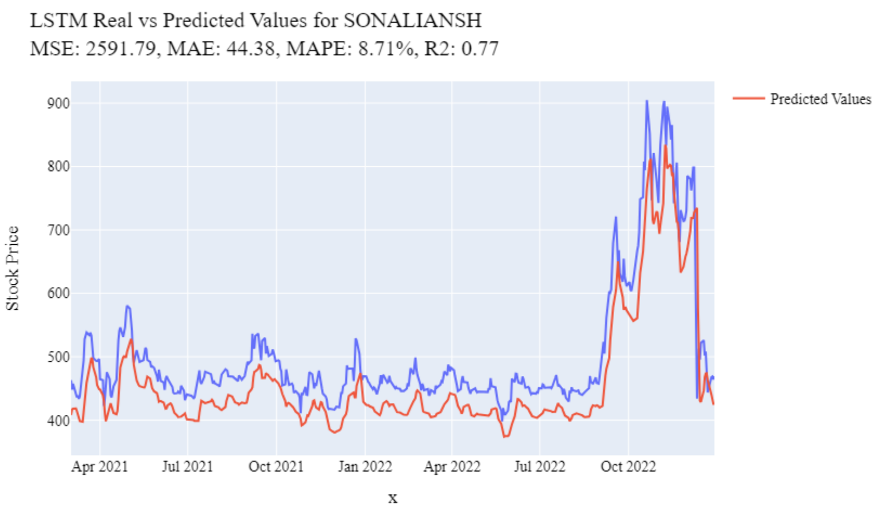

Figure 5.5: Predicted vs Actual values of SONALIANSH from LSTM

Figure 5.6: Predicted vs Actual values of ACI from LSTM

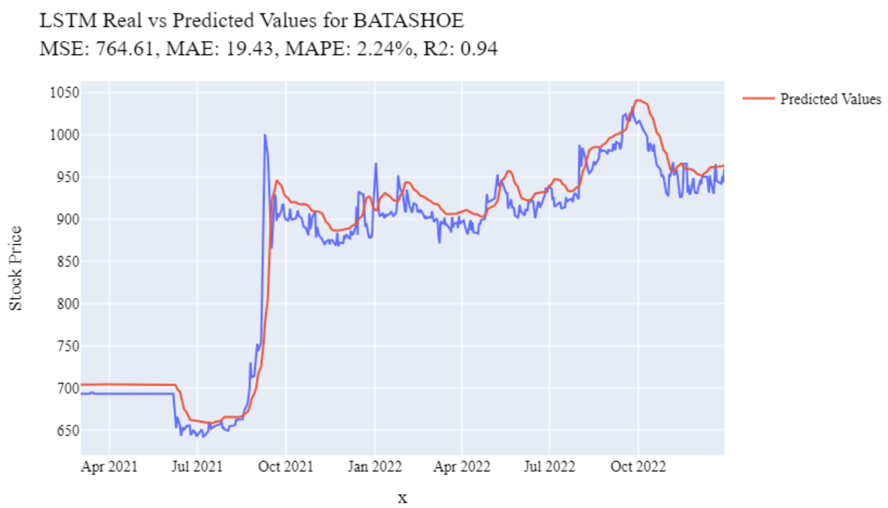

Figure 5.7: Predicted vs Actual values of BATASHOE from LSTM

Figure 5.8: Predicted vs Actual values of BEXIMCO from LSTM

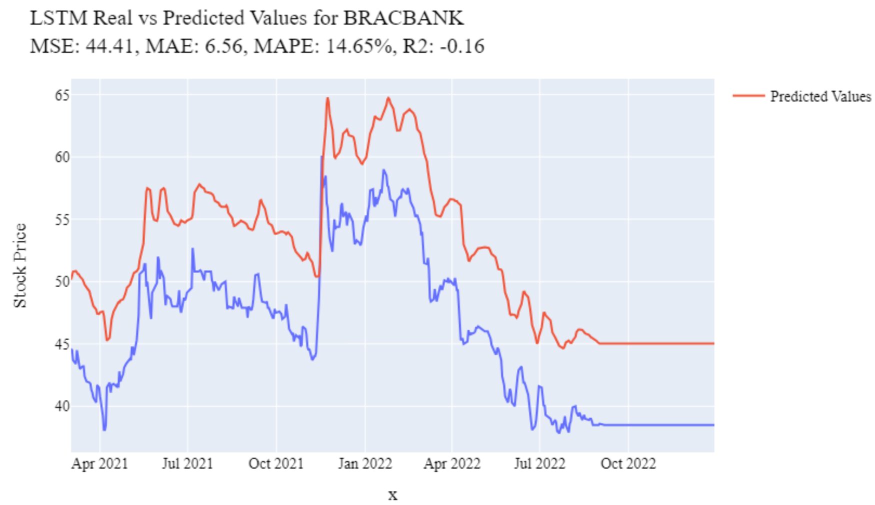

Figure 5.9: Predicted vs Actual values of BRACBANK from LSTM

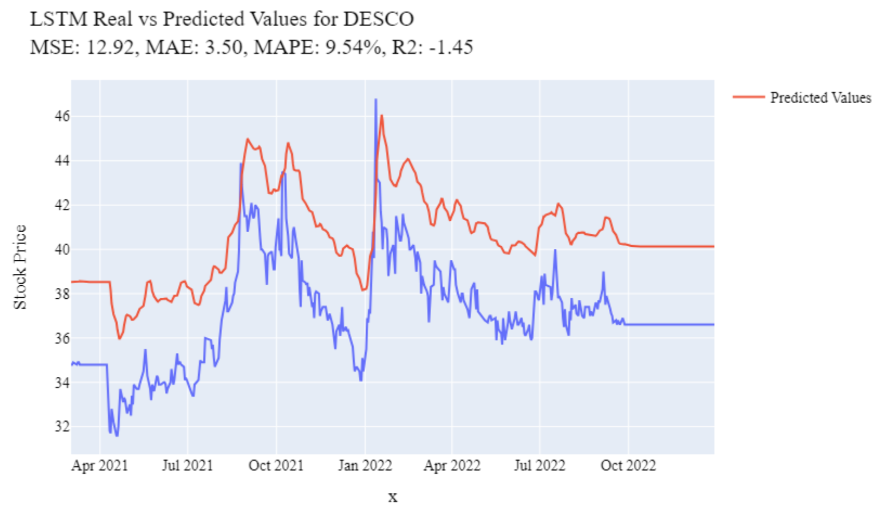

Figure 5.10: Predicted vs Actual values of DESCO from LSTM

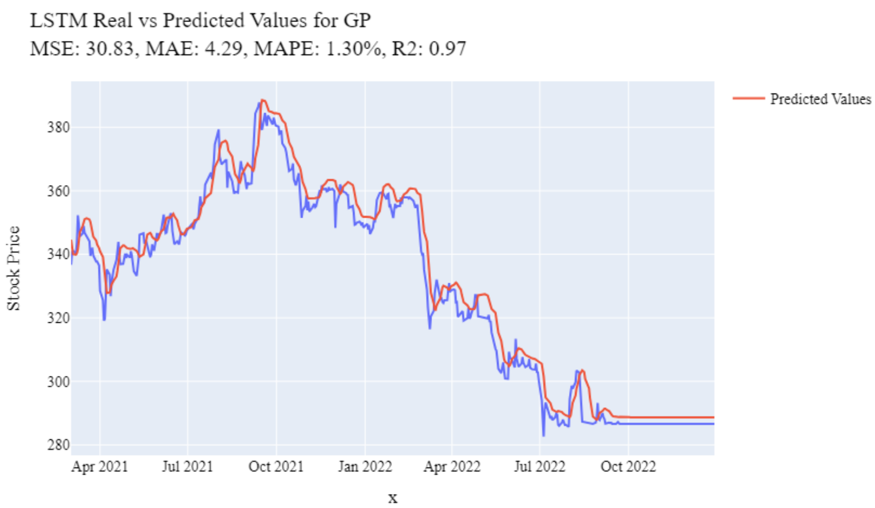

Figure 5.11: Predicted vs Actual values of GP from LSTM

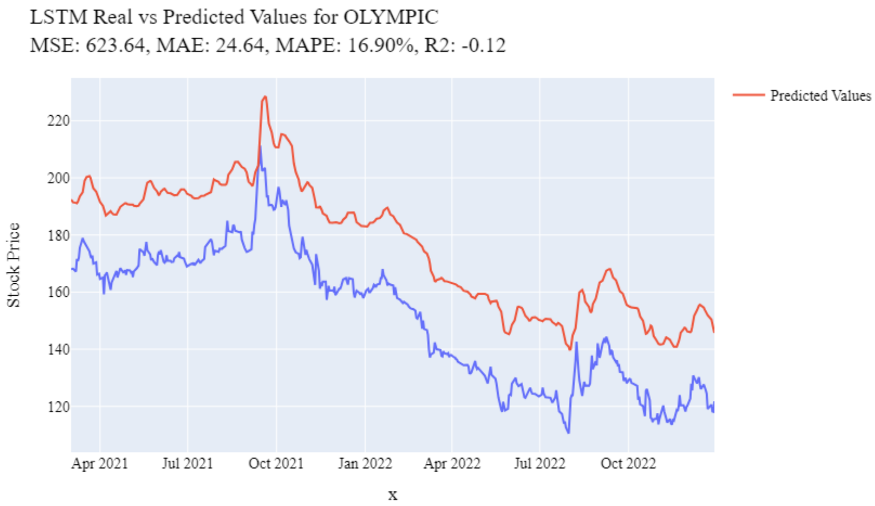

Figure 5.12: Predicted vs Actual values of OLYMPIC from LSTM

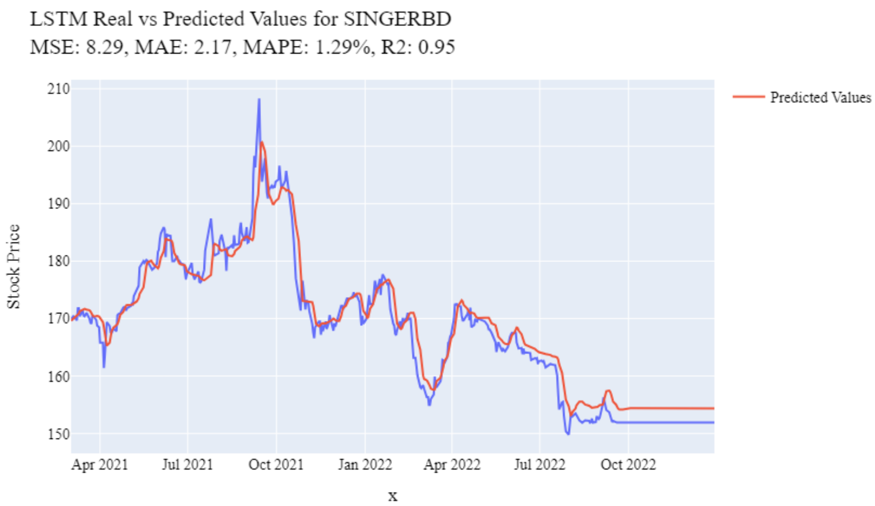

Figure 5.13: Predicted vs Actual values of SINGERBD from LSTM

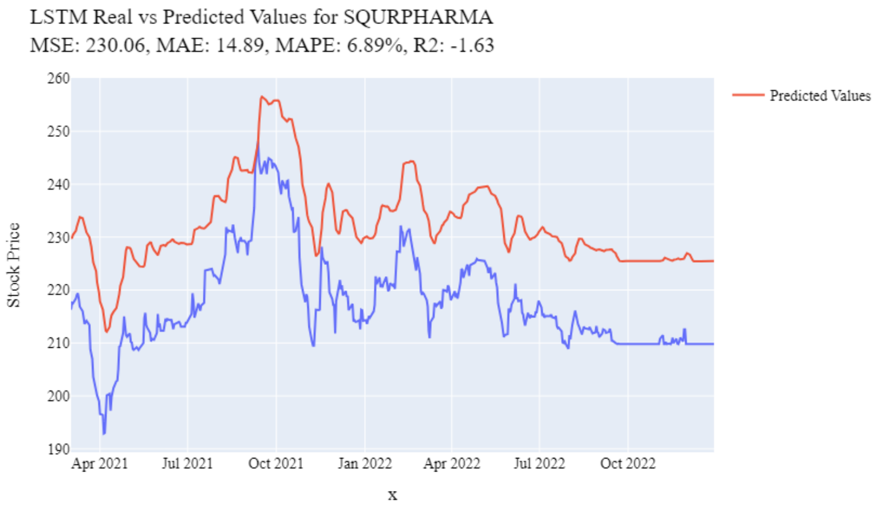

Figure 5.14: Predicted vs Actual values of SQURPHARMA from LSTM

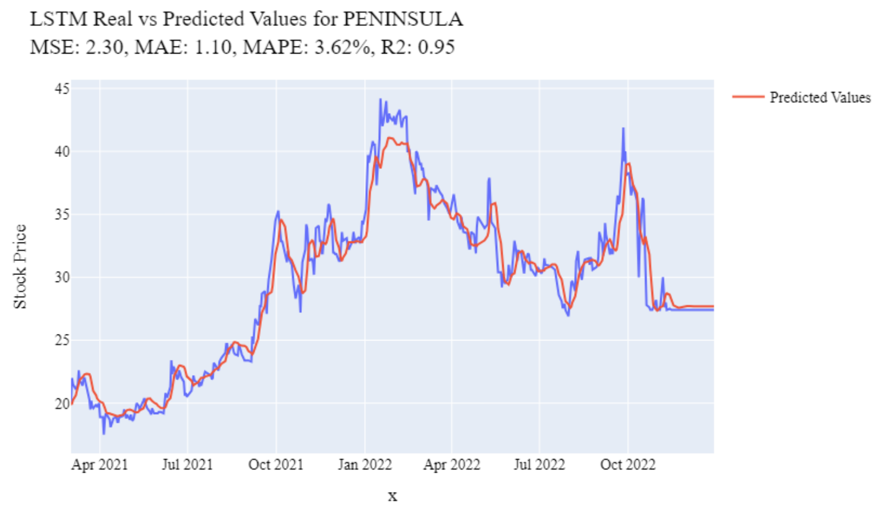

Figure 5.15: Predicted vs Actual values of PENINSULA from LSTM

With comparatively high R2 Score of 0.77, SONALIANSH [5.5] exhibits dependable accuracy despite slightly elevated MAE value (44.38). Despite its nagetive R2 score BRACBANK [5.9] demonstrate moderate accuracy With low MAE value of 6.56. With very lower MSE and MAE values, DESCO [5.10] exhibits decent accuracy; however, the model's trustworthiness is compromised by comparatively negative R2 Score (-1.45). Moreover, OLYMPIC [5.5], SQURPHARMA [5.14], ABBANK [5.1] and AFTABAUTO [5.3] also faces difficulties as seen by their higher MSE values and negative R2 Score. It is noteworthy that LSTM exhibits remarkable performance in the cases of ACTIVEFINE, BEXIMCO, SINGERBD, PENINSULA, PIONEERINS, GP, ACI and BATASHOE where its forecasting abilities stand out. This demonstrates how well the model captures complex patterns in stock data. Even while its performance varies slightly amongst firms, it regularly shows that it is effective at producing trustworthy forecasts.

5.2.2 GRU

Analyzing the GRU performance metrics for the selected companies also reveals varying degrees of accuracy.The results are somewhat similar to LSTM. With an almost perfect R-squared (R2) score of 0.97 and low MSE and MAE values (1.09 and 0.72 respectively), BRACBANK [5.24] stands out for its remarkable accuracy. Like LSTM , ACTIVEFINE [5.17] and PENINSULA [5.30] shows excelent accuracy for GRU with R2 score of 0.96 and 0.97 along with very low MSE and MAE values(0.52, 0.49 and 1.29, 0.80 respectively). GP [5.26] also shows excellent accuracy, especially with its exceptional R2 score of 0.99, with the MAE (2.64) and MSE (14.59) are also being lower. BEXIMCO [5.23] and ACI [5.21] also performed well with R2 of 0.98 and 0.95 respectively. Their MSE and MAE values are comparatively low (16.18, 3.06 and 24.03, 3.38 respectively).

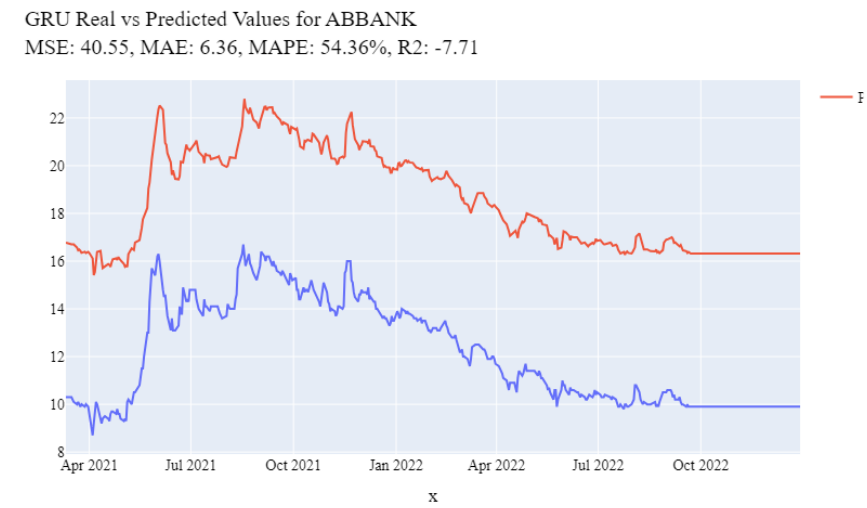

Figure 5.16: Predicted vs Actual values of ABBANK from Gru

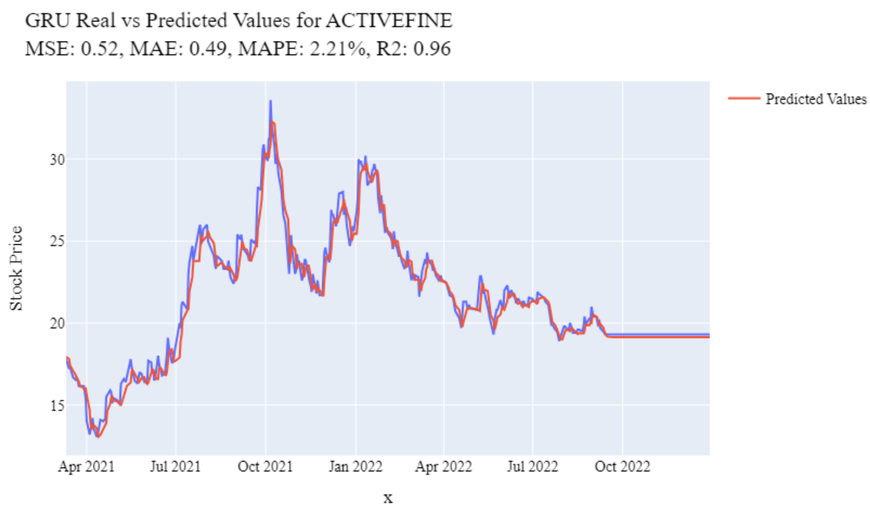

Figure 5.17: Predicted vs Actual values of ACTIVEFINE from Gru

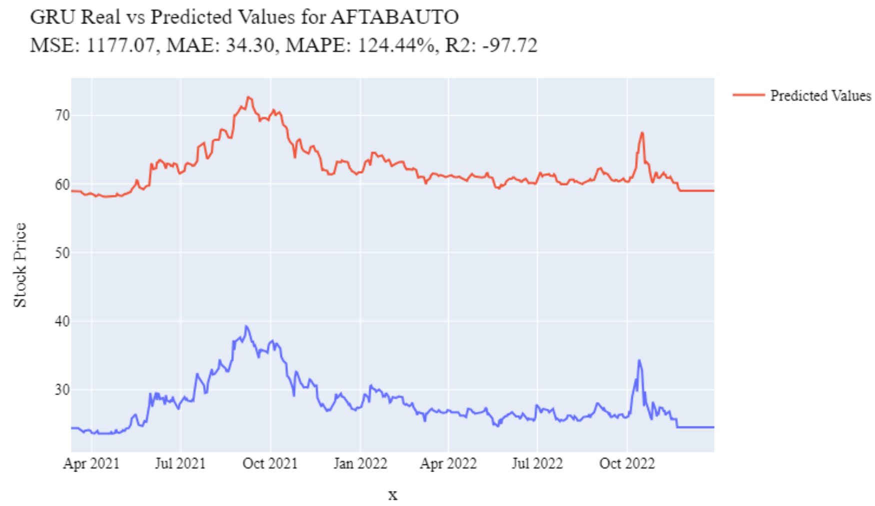

Figure 5.18: Predicted vs Actual values of AFTABAUTO from Gru

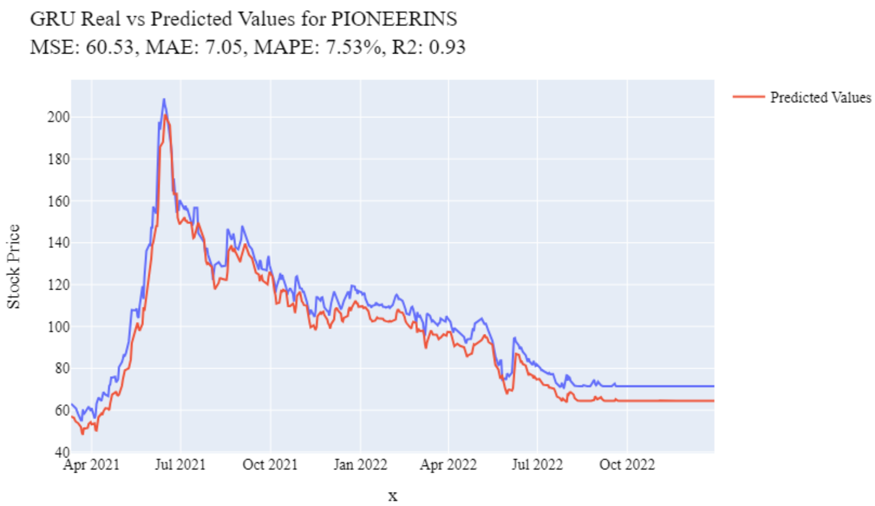

Figure 5.19: Predicted vs Actual values of PIONEERINS from Gru

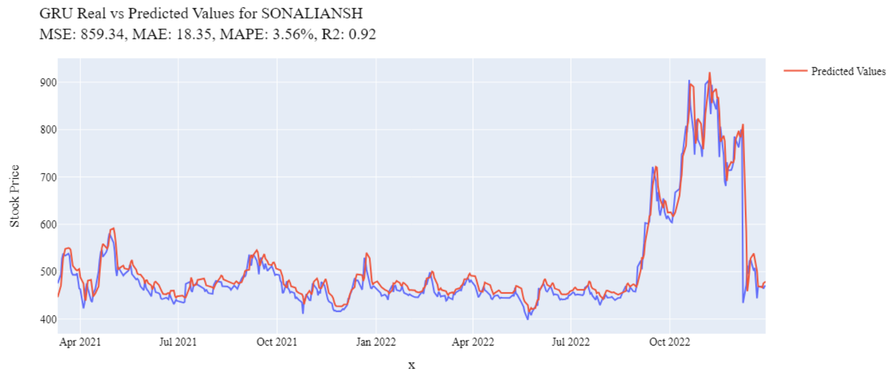

Figure 5.20: Predicted vs Actual values of SONALIANSH from Gru

Figure 5.21: Predicted vs Actual values of ACI from Gru

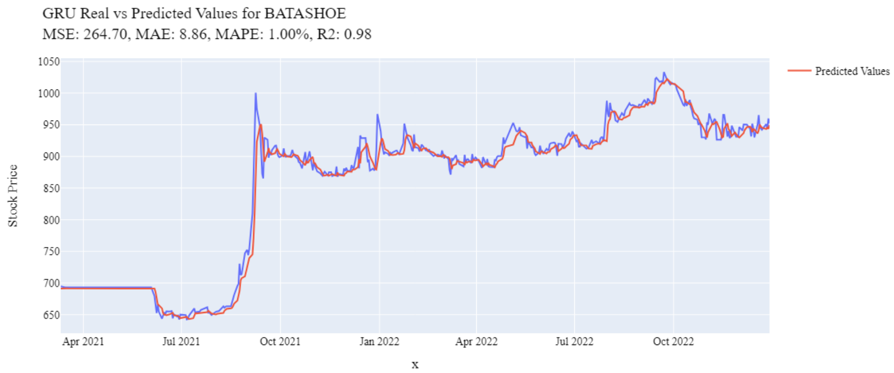

Figure 5.22: Predicted vs Actual values of BATASHOE from Gru

Figure 5.23: Predicted vs Actual values of BEXIMCO from Gru

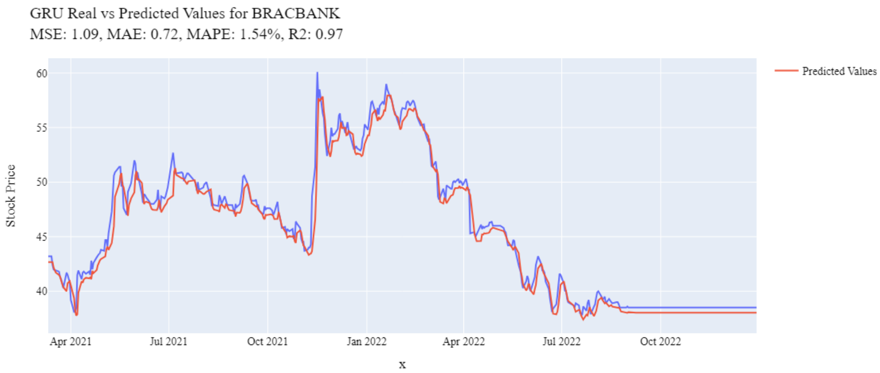

Figure 5.24: Predicted vs Actual values of BRACBANK from Gru

Figure 5.25: Predicted vs Actual values of DESCO from Gru

Figure 5.26: Predicted vs Actual values of GP from Gru

Figure 5.27: Predicted vs Actual values of OLYMPIC from Gru

Figure 5.28: Predicted vs Actual values of SINGERBD from Gru

Figure 5.29: Predicted vs Actual values of SQURPHARMA from Gru

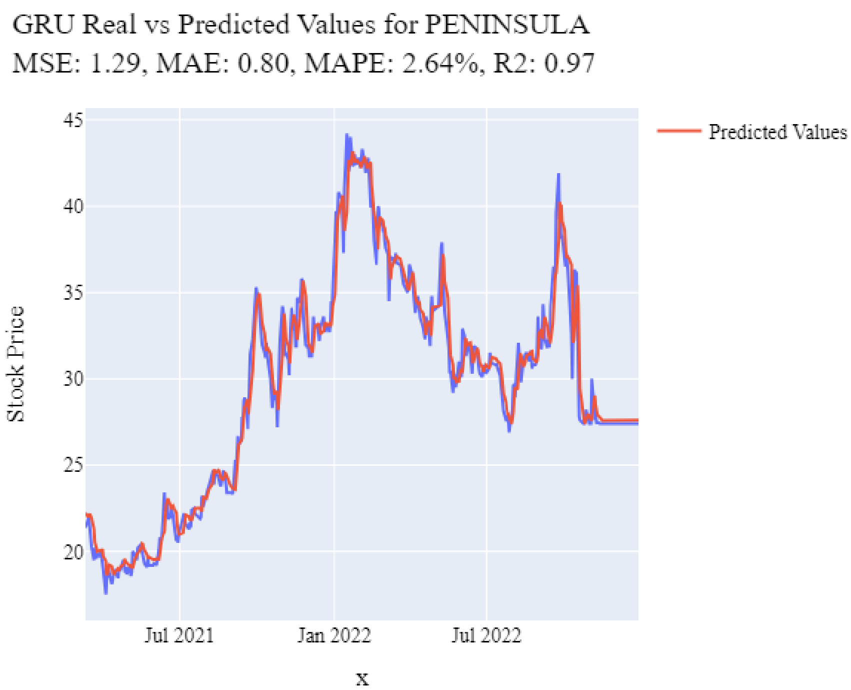

Figure 5.30: Predicted vs Actual values of PENINSULA from Gru

With an impressive R2 score of 0.93, PIONEERINS [5.19] shows dependable accuracy. Despite slightly elevated MSE value (60.53) and MAE value (7.05), it trails closely behind. With R2 Scores of 0.98 for BATASHOE [5.22] and 0.92 for SONALI [5.20] demonstrate great accuracy, despite somewhat elevated MSE and MAE values. With very lower MSE and MAE values, OLYMPIC [5.27] exhibits decent accuracy. However, the model's trustworthiness is compromised by comparatively lower R2 score (0.73) . With a negative R2 score of -0.74 SINGERBD[5.28] doesn't show good accuracy. With -7.71 R2 along with significantly lower MSE and MAE values (40.55,6.36), ABBANK [5.16] exhibits poor accuracy. However, with a negative R2 score of -4.79, SQUAREPHARMA [5.29] exhibits very low accuracy with relatively higher MSE and MAE values (515.09 and 22.58). DESCO [5.25] also showed low accuracy with -17.51 R2. But the poorest performance was seen in AFTABAUTO [5.18] in terms of accuracy with an R2 of -97.72 and an extremely high MSE value of 1177.07. Despite that GRU also exhibits remarkable performance in the cases of BRACBANK, ACTIVEFINE, PENINSULA and GP, where its forecasting abilities stand out. Which confirms its accuracy is notably high affirming its potential utility in specific contexts.

5.2.3 NBEATS

The precision of NBEATS model performance data varies among the selected companies, indicating fluctuations in accuracy. This observation underscores the need for a comprehensive examination to understand the diverse dynamics influencing NBEATS model efficacy within specific organizational contexts. With remarkable R-squared (R2) Score (0.69, 0.67 and 0.75 respectively) and MSE (3413.89, 325.21, 10.30) and MAE values (52.41,17.76,3.01 respectively) - SONALIANSH [5.35], GP [5.41], PENINSULA [5.45] stands out for its remarkable accuracy. Because PENINSULA has the best result in the case of all 4 matrices while having the lowest MSE (10.30), it gives the most accurate result. After these, the predicted result that is comparatively good is for BATASHOE [5.37] with an R2 score: of 0.37. However, its MSE is pretty high being 7862. 15, MAE being comparatively better with 87.57. Besides these, the rest of the predicted results are not satisfactory as have a negative value when it comes to R2. For example- (-0.60, -0.21, -0.06, -0.09) have the closest value to 0 (ideal range being 0-1) and MSE(23.52, 1099.68, 486.45, 757.72), MAE(4.80, 32.92, 21.65, 27.19) of ACTIVEFINE [5.32], PIONEERINS [5.34], ACI [5.36], BEXIMCO [5.38] respectively.

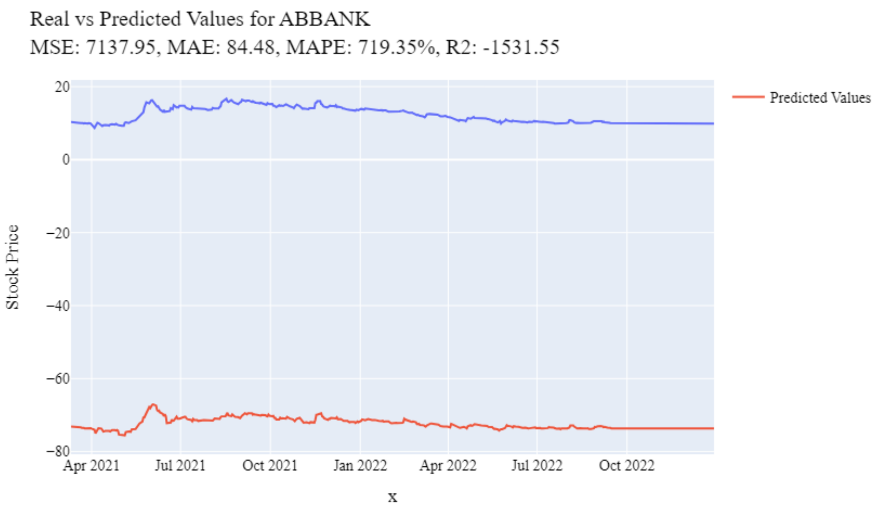

Figure 5.31: Predicted vs Actual values of ABBANK from Nbeats

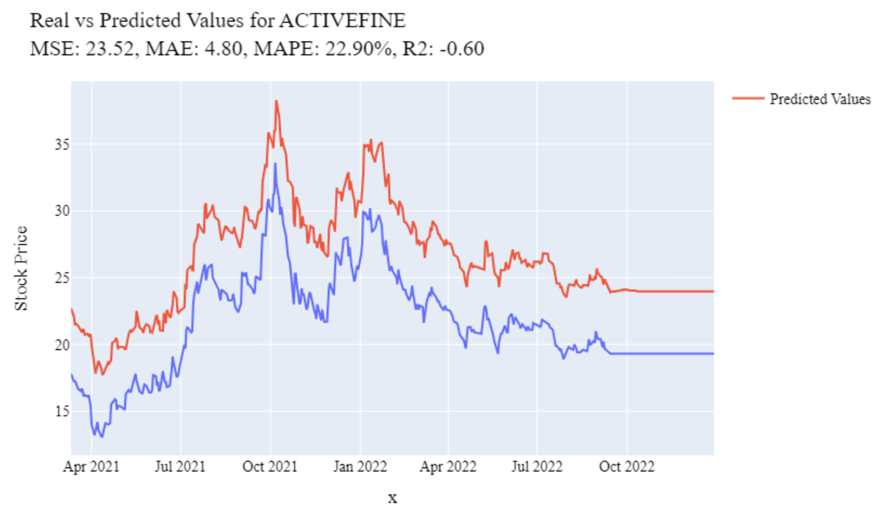

Figure 5.32: Predicted vs Actual values of ACTIVEFINE from Nbeats

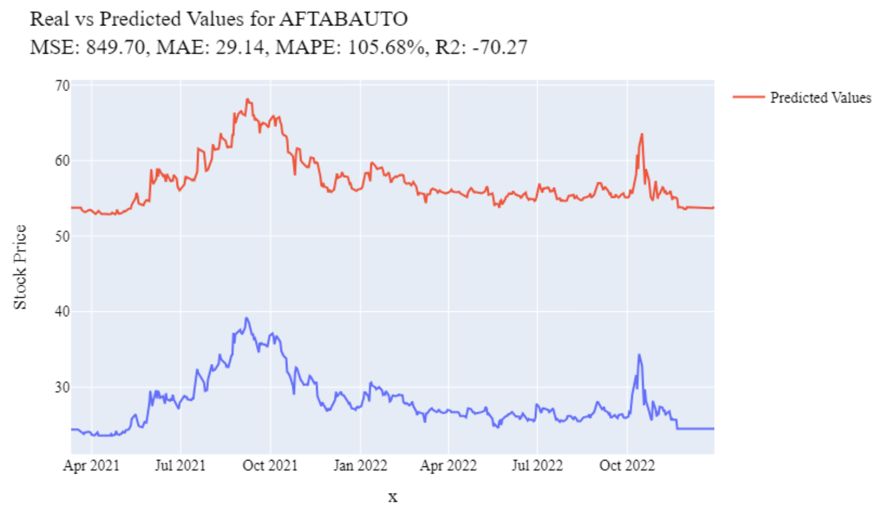

Figure 5.33: Predicted vs Actual values of AFTABAUTO from Nbeats

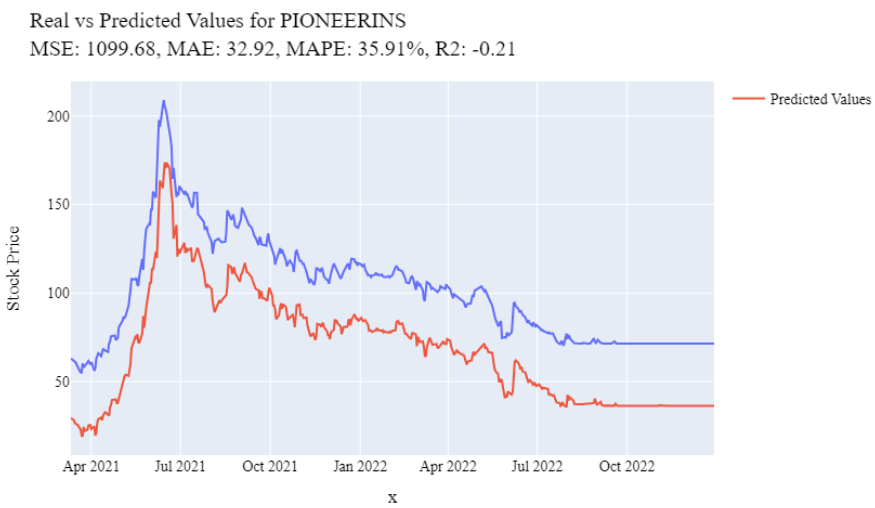

Figure 5.34: Predicted vs Actual values of PIONEERINS from Nbeats

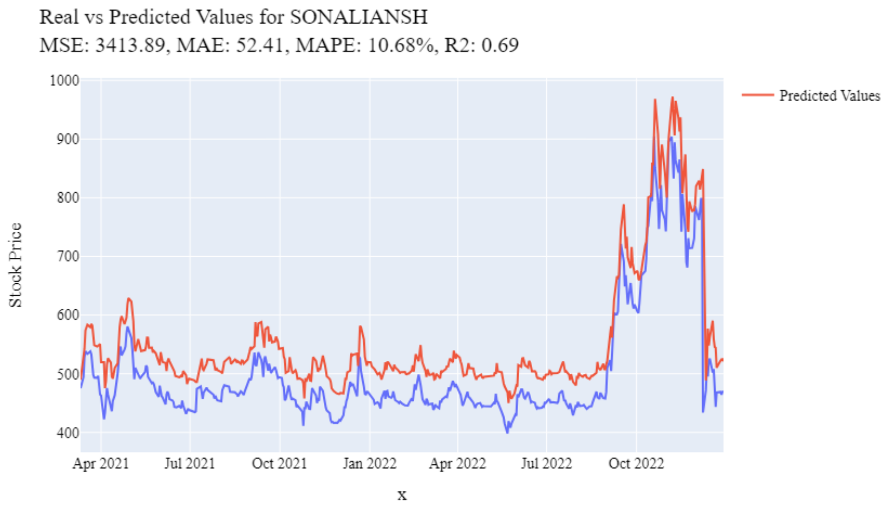

Figure 5.35: Predicted vs Actual values of SONALIANSH from Nbeats

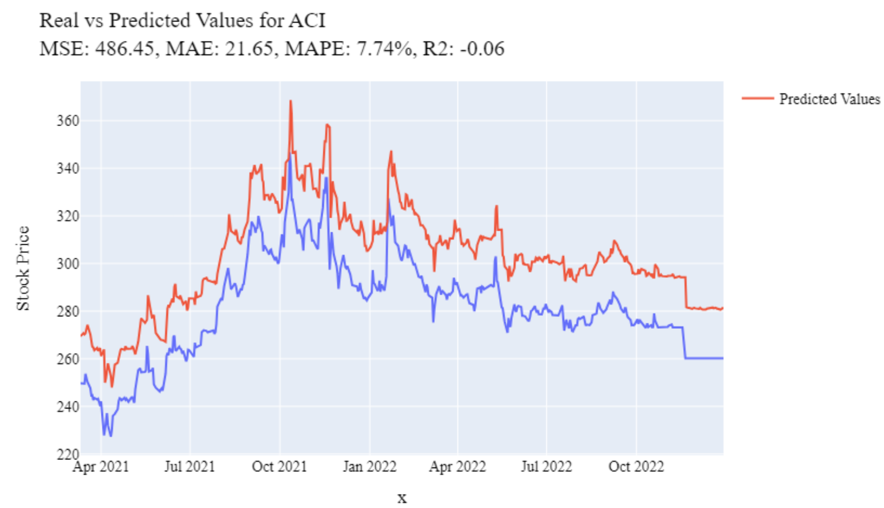

Figure 5.36: Predicted vs Actual values of ACI from Nbeats

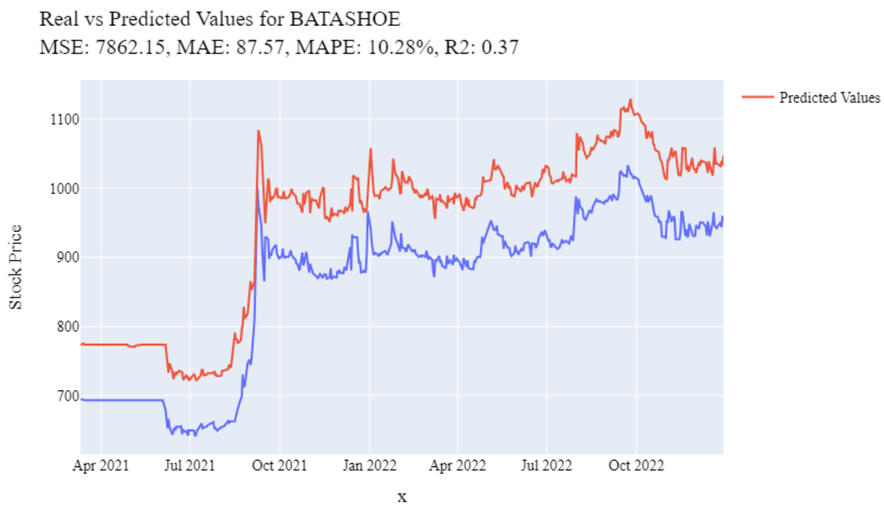

Figure 5.37: Predicted vs Actual values of BATASHOE from Nbeats

Figure 5.38: Predicted vs Actual values of BEXIMCO from Nbeats

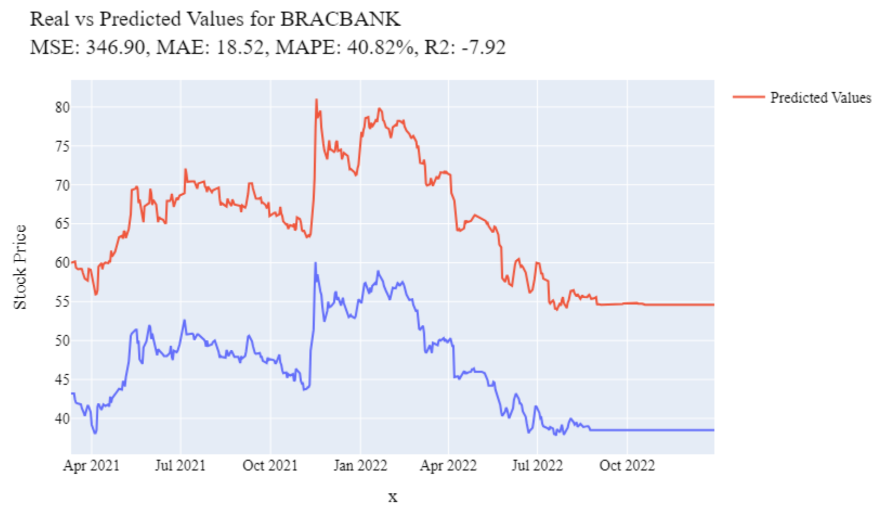

Figure 5.39: Predicted vs Actual values of BRACBANK from Nbeats

Figure 5.40: Predicted vs Actual values of DESCO from Nbeats

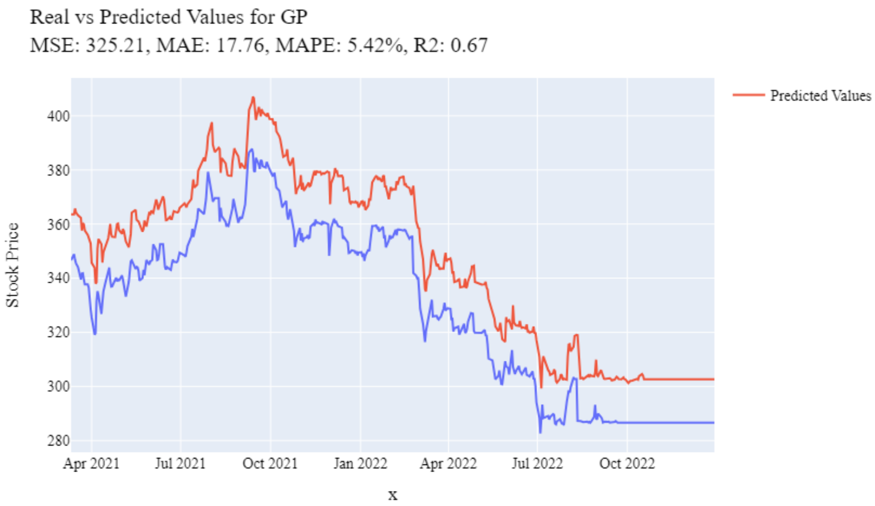

Figure 5.41: Predicted vs Actual values of GP from Nbeats

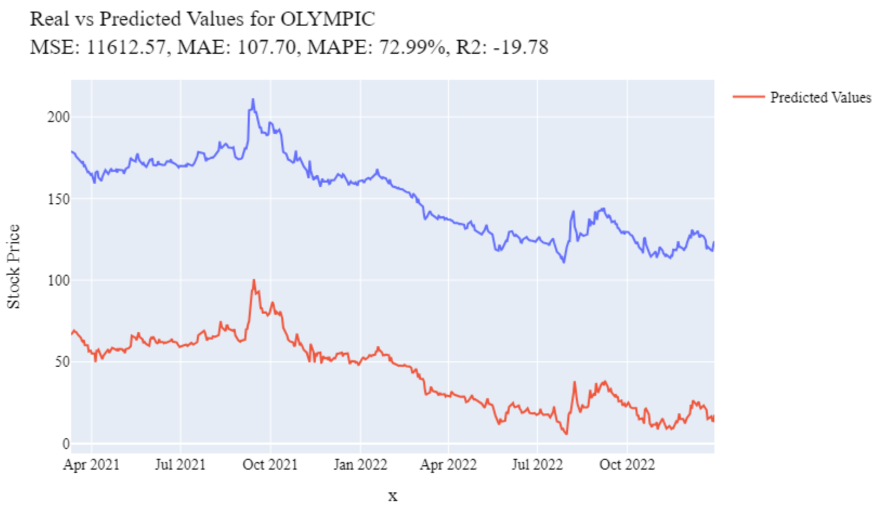

Figure 5.42: Predicted vs Actual values of OLYMPIC from Nbeats

Figure 5.43: Predicted vs Actual values of SINGERBD from Nbeats

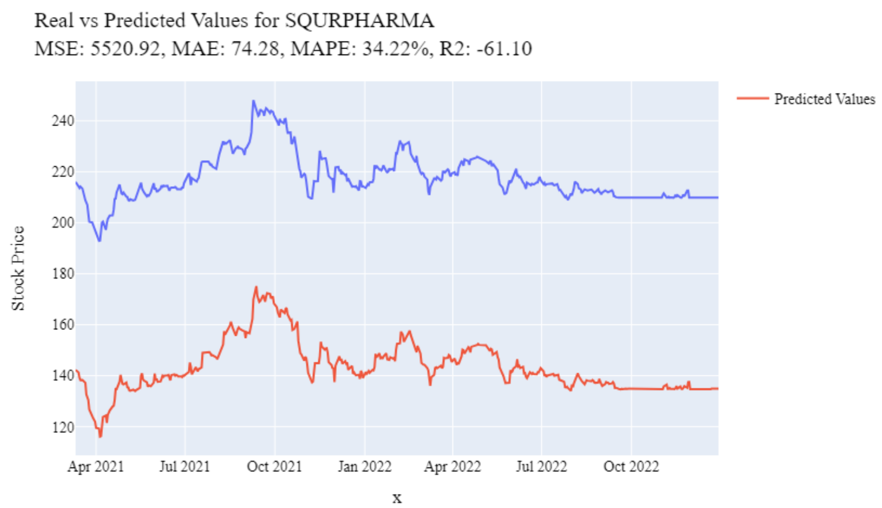

Figure 5.44: Predicted vs Actual values of SQURPHARMA from Nbeats

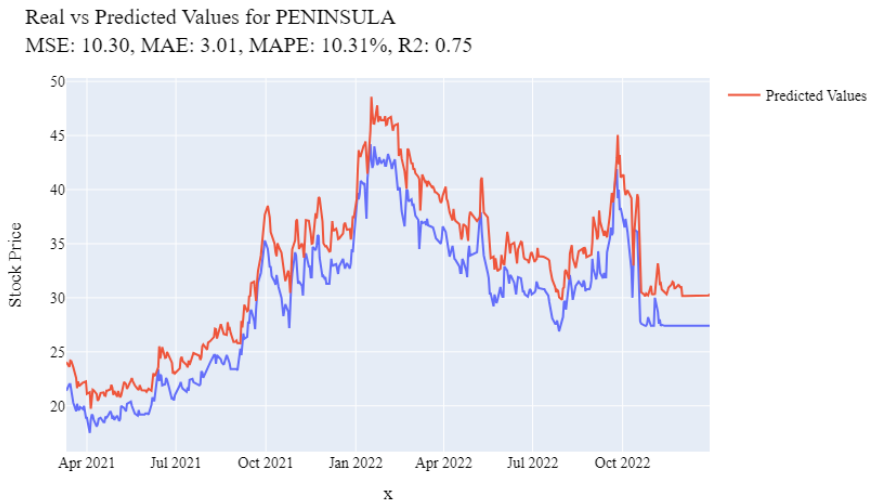

Figure 5.45: Predicted vs Actual values of PENINSULA from Nbeats

Companies like ABBANK [5.31], DESCO [5.40] show the most disappointing results as they provide R-squared (R2) Score -1531.55 and -1526.24 respectively with quite high MSE(7137.95, 8035.87)and MAE(84.48, 89.64) results as well. The rest of the predicted results have very low accuracy when compared to these NBEATS results. Moreover, when further compared, the accuracy levels are not up to the mark when compared with the previous results of LSTM and GRU. However, it is indeed noteworthy that NBEATS shows the best analysis results in the case of SONALIANSH [5.35], GP [5.40] and PENINSULA [5.45]. Therefore, it can be concluded that NBEATS requires more accuracy of results to achieve further refinement and dedicated efforts.

5.3 Discussion

The above plots provide a comprehensive idea on the predictive performance of the models. While some models have generated convincing prediction plots for some of the companies, there are some unusual prediction graphs too which is necessary to address. For example, figures 5.24, 5.39, 5.22 demonstrate some sudden spikes in the stock prices which is also well predicted by the model. This kind of prediction may seem abnormal to some extent but in time-series forecasting, these are quite familiar phenomenon. This kind of sudden rise of price or random price hikes are very common in time series predictions especially in stock market prediction and cryptocurrency price prediction tasks. Our data includes the closing price of the previous day which is equal to the price of a particular day's opening price. This input of yesterday's closing price helps to predict the sudden spike of the data as this study focuses on short term prediction. For long term forecastings, multimodal

data consisting of various factors is required since other factors are important. But some companies show seasonality in prices, in those cases long-term predictions can be done. Even though the prices will not be accurate but the declines or rises can be predicted accurately. For example, we notice some common trends in the stock prices on most of the plots 5.36, 5.35, 5.21, 5.6 from april to july prices are low and tends to go down but in october prices tend to go up for most of the companies. This type of seasonality comes handy in longterm prediction. Since our methodology mainly focuses on the real-time prediction, the closing price of the previous day is regarded as one of the most significantly weighted variables.
Neural Network is a popular method to predict stock market prediction and other time series forecasting [1], [10], [28] . Recent works suggest that memory gates in RNN variants [19], [22], [27] and Stack Residuals from the models like Nbeats [34], [39], [45] contribute to real-time Stock prediction and other time series forcasting.

5.4 Comparison and Final Analysis

Different patterns show up when the LSTM, GRU, and NBEATS models for stock price prediction are compared. The GRU model performs well and consistently across a range of companies, with ACTIVEFINE, BRACBANK, GP and PENINSULA standing out for their high accuracy, but struggles with ABBANK, AFTABAUTO and DESCO as seen by a negative R-squared (R2) Score. On the other hand, the LSTM model shows excellent accuracy for f ACTIVEFINE, BEXIMCO, SINGERBD, PENINSULA, PIONEERINS, GP, ACI and BATASHOE. However, the NBEATS model shows inconsistent results, performing well for PENINSULA but moderate to poorly for almost every other company, which raises questions about its capacity to precisely capture specific stock movements. The following plots shows the accuracy for different companies for performance metrics MSE [5.46], MAE [5.47], MAPE [5.48] and R2 score [5.49]. For R2 score, we have shown only from 1 to -10 despite it having very large negative values to have a more clear plot. Overall, LSTM come across as more accurate model than GRU for this particular dataset where NBEATS shows significantly less accuracy than the RNN variants. All aspects considered, each model has its advantages and disadvantages. However, in order to maximize accuracy, careful thought and possible improvements are essential, particularly in situations where certain models exhibit limitations.

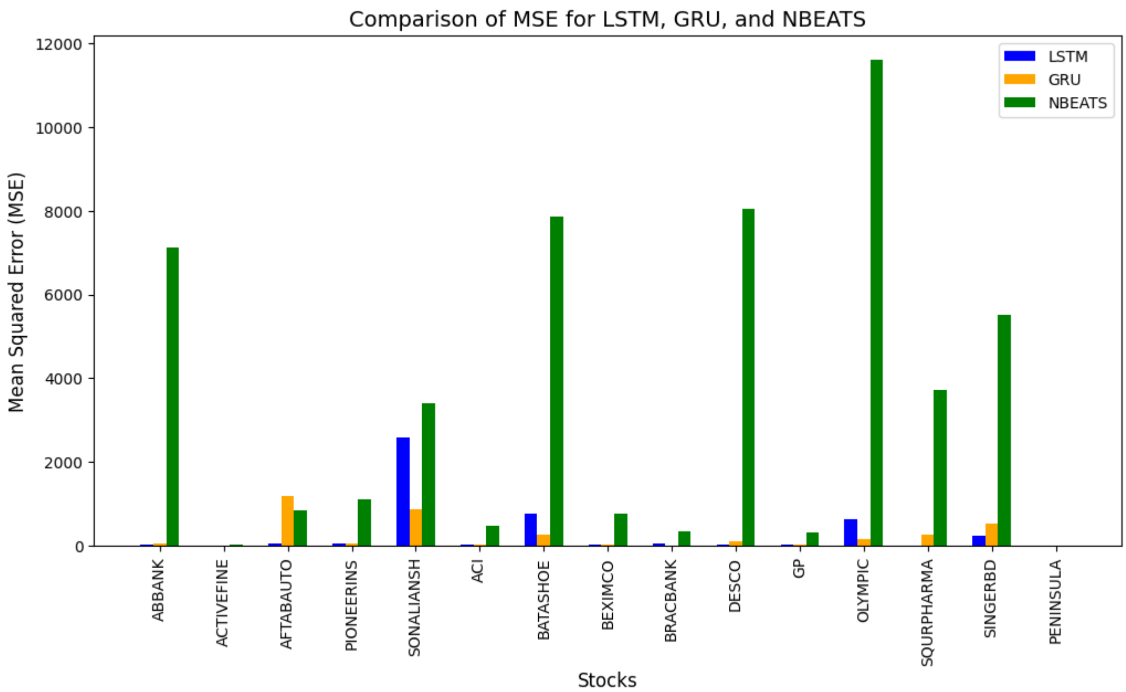

Figure 5.46: MSE comparison

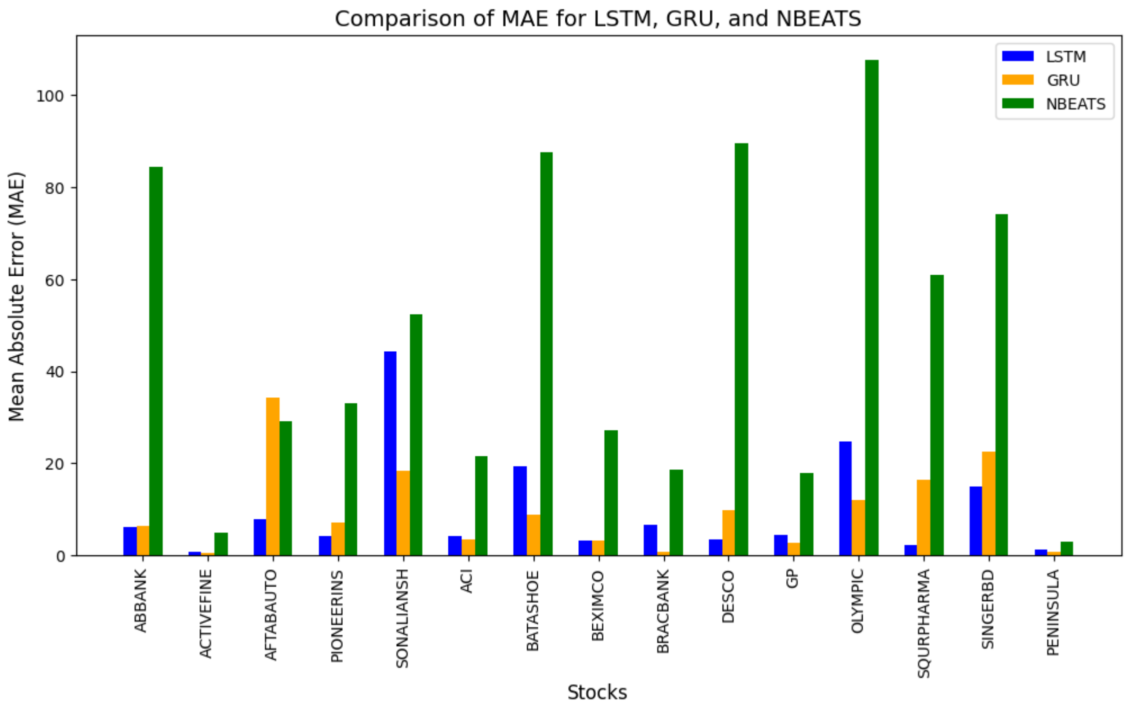

Figure 5.47: MAE comparison

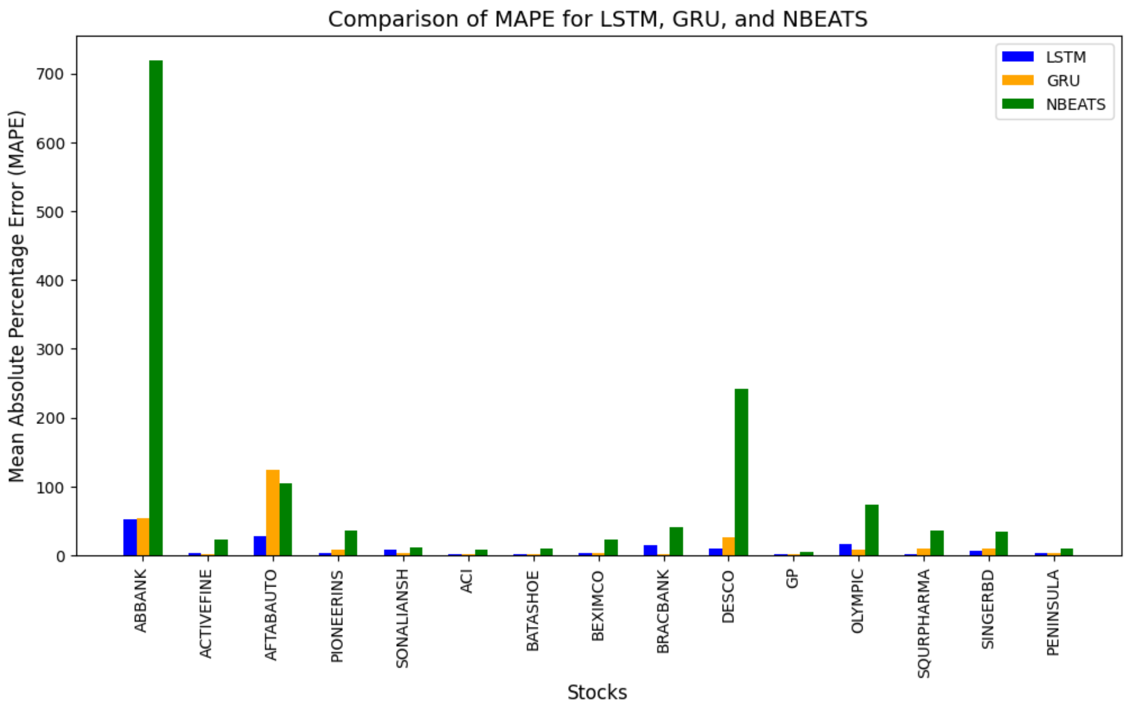

Figure 5.48: MAPE comparison

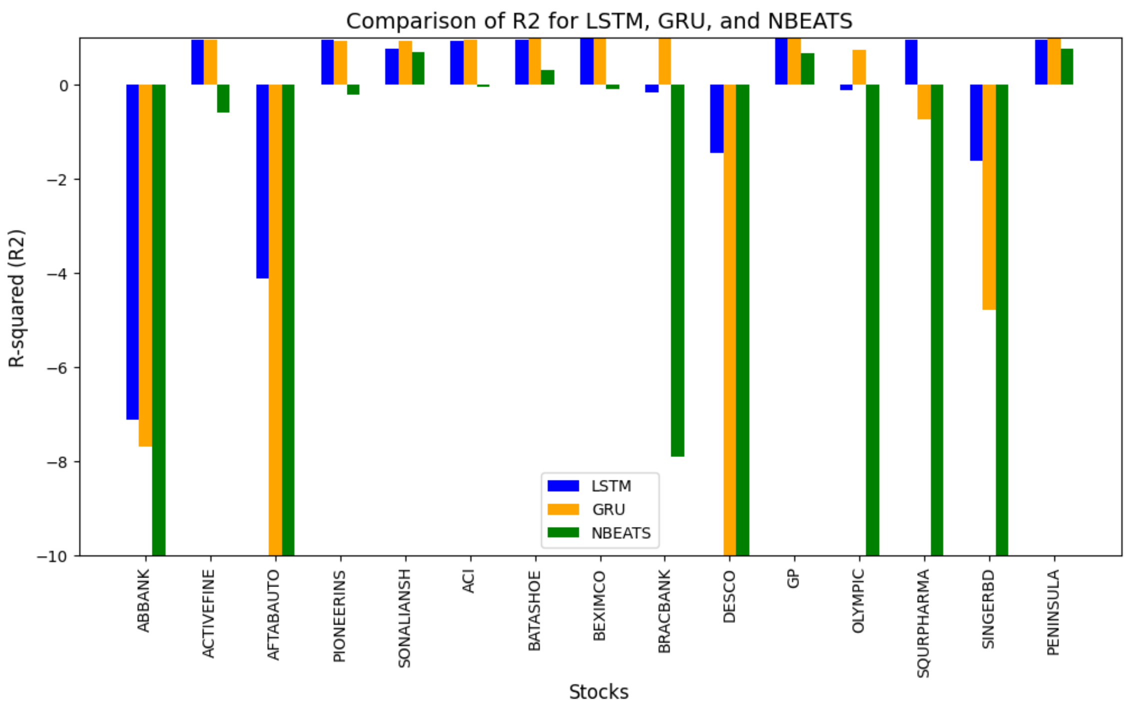

Figure 5.49: R^2 comparison

The comparative assessment of the LSTM, GRU, and NBEATS models according to their performance metrics is shown in this table [5.1].

Company	**LSTM**	**GRU**	**NBEATS**
ABBANK	Low	Low	Low
ACTIVEFINE	High	High	Moderate
AFTABAUTO	Moderate	Low	Low
PIONEERINS	High	High	Moderate
SONALIANSH	High	High	Moderate
ACI	High	High	Moderate
BATASHOE	High	High	Moderate
BEXIMCO	High	High	Moderate
BRACBANK	Moderate	High	Low
DESCO	Moderate	Low	Low
GP	High	High	Moderate
OLYMPIC	Moderate	Moderate	Low
SQURPHARMA	Moderate	Moderate	Low
SINGERBD	High	Moderate	Low
PENINSULA	High	High	High

Table 5.1: Stock Price Prediction Model Accuracy Comparison

The kind of training data, the importance given to various evaluation measures, and the particular project needs should all be taken into consideration when choosing between GRU and LSTM. When deciding which of GRU or LSTM to use for a given application, factors like computational efficiency, training speed, and the capacity to capture temporal dependencies in diverse ways all play a role.

5.5 Incorporating External factors

Since stock prices are very dynamic and there are so many factors affecting significantly the prices, We looked for studies which included these external factors in Machine learning forcasting. But while there were some analysis on these factors, these were not incorporated with ML models.

5.5.1 Dataset preparation

To include these factors to this research, a simulated dataset with simulated factors data is used which contains simulated values of the external factors like political stability, grocery prices and corruption. For higher values (ranging from 0-1) political stability and corruption, the stock price drops in real world scenerio and for higher grocery prices, the stock drops. So we incorporated these factors to understand how our model performs on these contexts. To achieve the goal, we the new columns

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	date	trading_coc	last_traded	high	low	opening_pı	closing_pri	yesterdays_	trade	value_mn	volume	Political_st	Grocery_pr	Corruption
2	12/30/2010	ACI	373.5	374	368	368	372.6	372.5	135	6.5451	17600	0.8666569	399.98989	0.2551706
3	12/30/2010	BATASHOE	630	688	630	685	652.9	666.7	155	13.5248	20500	0.8666569	399.98989	0.2551706
4	12/30/2010	BEXIMCO	311.7	315	310.7	313	311.5	310.8	4637	420.0111	1345400	0.8666569	399.98989	0.2551706
5	12/30/2010	BRACBANK	859.5	884	851	864.75	856.25	853.25	3410	349.4749	403250	0.8666569	399.98989	0.2551706

Figure 5.50: Updated dataset with external factors columns

were merged to the actual stock dataset from DSE [5.50] . Now the new dataframe is consists of three new features related to real world factors.

5.5.2 Model implementation

The models implemented earlier namely LSTM, GRU and NBEATS were implemented with the same configuration for all 15 companies with the added variables to analyze the impactof these features on the performances of the models.

5.5.3 Result

To analyze the results , the performance metric used here was Mean Squared Error (MSE).

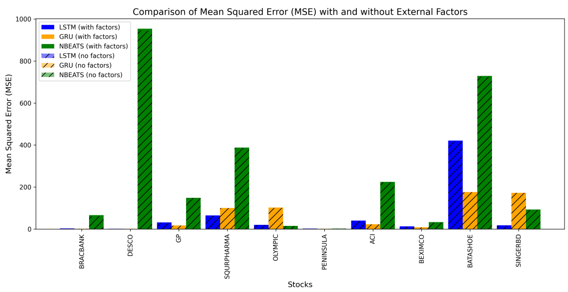

Figure 5.51: MSE Comparison with external factors

Coming to the results, the models show no significant improvement from the MSE data of the actual plot and the validation loss is increasing indicating the model is over fitting towards training data.

Analysis

Based on these results we can state that, the used dataset had some internal biases in data representation. The issues include incomplete data, lack of real world impact and under-representation of relevant data with historical and sampling bias. another possible reason to impact is model optimization. The tuning and optimization we made may not be optimized enough to catch the impact of the factors.

Scopes for Future Works

The future works may include some advanced models with hybridization techniques, feature engineering, incorporate more impactful real world factors to come up with more convincing prediction.

5.6 Comparison with existing works

Here, we review several research papers and present a comprehensive overview of stock price prediction methodologies. The focus is on understanding the various criteria that contribute to the performance and precision of these models. The selected criteria include the data sources employed, the choice of models, the evaluation metrics used, and the achieved accuracy. The following table (5.2) provides a side-by-side comparison of key aspects across different research papers and our own research.

Research Papers	**Data Source**	**Models Used**	**Performance Metrics**	**Accuracy**	**External Factors**
Gencay et. al (2018)	Kaggle, Yahoo Finance, Bloomberg	ARIMA, N-BEATS	MSE, MAPE	81%	✗
Banik et. al (2014)	Yahoo Finance, Alpha Vantage	LSTM, MLP	RMSE, MAE, MAPE, R2	70%	✗
Debashish et. al (2016)	Delhi Stock	RNN, MLP	f-1 score, MAPE, R2	77%	✗
Borovkova et. al (2019)	Kaggle	LSTM	RMSE, MAE	67%	✗
Lanbouri et. al (2020)	Kaggle	RNN, MLP	RMSE, MAE, MAPE, R2	78%	✗
Our Research	Dhaka Stock Exchange	LSTM, GRU, N-BEATS	MSE, MAE, MAPE, R2	73%	✓

Table 5.2: Comparison of Stock Price Prediction Research

The table aims to facilitate a holistic understanding of the strengths and limitations of each approach.

Chapter 6

Conclusion

Our research presents a performance analysis for forecasting structure for stock price that uses a combination of company data, price, and volume as input variables.The three ML models that we have trained and tested for this study are LSTM, GRU, and NBEATS. Comparative assessments for the dataset were based on historical data collected from the DSE stocks, spanning through a period of 2010 to 2022. Notably, the LSTM model demonstrated greater accuracy compared to other models. This enhanced precision shows how well the method can spot complicated patterns in stock data. Even though there are some encouraging outcomes of our research, it is required to address some of the limitations and shortcomings of our methodology. The one major restriction that we have found is the fact that different companies have varying access to historical data. Finding correlations between companies with very different data histories was challenging due to the uneven dataset listed on stocks. As a result, we had to reduce the study's overall scope by only manually picking fifteen companies. It is also important to keep in mind that stock time series are typically non-stationary, which ultimately makes precise forecasting even more challenging. Despite the impressive accuracy shown by our models LSTM, GRU, and NBEATS among others, the complexity generated by stock price volatility may not be fully captured by these models. To overcome the limitations that we have faced, we hope to increase our forecasting capacity in our future research through the use of more advanced forecasting models like ARIMA, SARIMA, and Prophet. These models are widely recognized for their efficiency in time series analysis and offer unique qualities that can improve the accuracy found by our existing LSTM, GRU, and NBEATS models. The addition of the well-known pattern and seasonality-detecting ARIMA and SARIMA models will enable an in-depth knowledge of the dynamics of stock prices. Adding Prophet to our tools will also improve our ability to forecast as Prophet is intended to handle abnormalities and breaks in time series data. We hope to be able to spot nuances in the data with this larger repertory that our current models might not be able to fully capture. Furthermore, we intend to do a comparative analysis of these models to come up with more comprehensive insights into the benefits and drawbacks of each, helping in determining the most efficient approach for forecasting any time series data.

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