PREDICTING NEPAL'S STOCK MARKET USING MACHINE LEARNING ALGORITHMS

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PREDICTING NEPAL'S STOCK MARKET USING MACHINE LEARNING ALGORITHMS

The Master Research Project Presented

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DECLARATION

I declare that this Dissertation/Research Project, in its entirety, is my own work. It has not previously been presented in whole or part, for any other award. Neither has it been published in whole or in part elsewhere and presented here without the proper use of references. Neither has it been commissioned in part or whole to be written by another party or individual on my behalf.

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ABSTRACT

The thesis explores the application of machine learning techniques for predicting the Nepal Stock Exchange (NEPSE) Index, focusing on the performance of three machine learning models: Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). It aims to pinpoint the most effective algorithm by analyzing historical stock data and economic indicators. The research highlights the complexities of predicting stock market movements in emerging economies like Nepal and seeks to provide a scientific basis for the use of advanced analytics in financial forecasting.

Findings from the study reveal the significant potential of machine learning in understanding and forecasting market trends. The Gated Recurrent Unit (GRU) model performed the most accurately and reliably among the tested algorithms, showcasing its exceptional capacity for forecasting NEPSE Index movements. This variance in model performance emphasizes the importance of selecting the right algorithm for market predictions, suggesting that a particular model may offer superior insights for forecasting the NEPSE Index. This insight is crucial for investors and analysts seeking to navigate Nepal's volatile stock market as it provides a data-driven approach for making informed investment decisions.

The thesis contributes to the academic field of financial market prediction and practical investment strategies in emerging markets. By comparing different machine learning models, it offers valuable conclusions about their applicability and efficiency in real-world scenarios. The study's implications extend beyond Nepal, offering a model for how machine learning can enhance market analysis and investment strategies in similar financial environments worldwide, thereby bridging the gap between theoretical research and practical financial decision-making.

Keywords: NEPSE Index, Machine Learning, Feedforward Artificial Neural Network, Long-Short Term Architecture, Gated Recurrent Unit, Root Mean Squared Error, Mean Absolute Error

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ABBREVIATIONS

ML	: Machine learning
AI	: Artificial Intelligence
NEPSE	: Nepal Stock Exchange
EMH	: Efficient Market Hypothesis
ANN	: Artificial Neural Network
LSTM	: Long-Short Term Memory
GRU	: Gated Recurrent Unit
GDP	: Gross Domestic Product
MSE	: Mean Square Error
RMSE	: Root Mean Square Error
MAE	: Mean Absolute Error
EMA	: Exponential Moving Average
MACD	: Moving Average Convergence/Divergence
RSI	: Relative Strength Index
MFI	: Money Flow Index
ATR	: Average True Range
ReLU	: Rectified Linear Unit

CHAPTER I
INTRODUCTION

1.1 Research Context

Stocks are the most widely used financial instrument ever created for accumulating wealth (Poterba, 2000). The advancement in technology has made it possible for anyone to open a trading account and own the stocks (Tamrakar & Sahu, 2018). However, the market's unpredictability has led to substantial losses for many investors (Kolte, et al., 2023). Because of this, stock market predictions have become an important topic and have attracted researchers' attention for decades. The basic principle of stock market prediction is that historical information available to the public can be used to predict possible stock returns in the future (Al-Radaideh, et al., 2013). This information includes a variety of components, including economic indicators (such as interest rates and currency rates), sector-specific information (such as rates of industrial output growth and consumer prices), and information particular to individual companies (such as income statements and dividend yields) (Kolarik & Rudorfer, 1997).

The stock market behaviors have been captured using a variety of modeling techniques, with the two predictive spheres of technical analysis and fundamental analysis receiving most of the attention (Chowdhury, 2021). Technical analysis, which aims to forecast future stock prices, relies on the principle that previous market activities disclose crucial information and insights into the psychological factors influencing stock values. It is based on the idea that stock prices reflect collective psychology, serving as an intermediary for various public sentiments, ranging from anxiety, anticipation, and pessimism to assurance, excessive optimism, and greed (Drakopoulou, 2015). The moving average (MA), autoregressive integrated moving average (ARIMA), and more recently artificial intelligence-based procedures are just a few of the analytical methods that fall under this category (Sivasamy & Peter, 2018).

The fundamental analysis focuses on monetary policies, government initiatives, and economic benchmarks like GDP, exports, and imports for market prediction (Nazir, et al., 2010). This strategy excels in forecasting economic conditions, though it may not always provide exact market prices. Mathematical methods have been used in the field of basic analysis, with vector autoregression (VAR), a multivariate modeling method, serving as a notable example (Stock & Watson, 2001).

This study focuses on applying machine learning to forecast the NEPSE index. This method falls within the category of technical analysis of the stock market. The underlying presumption in this situation is that forecasts can be generated using market information and stock values do not adhere to a random walk in which subsequent changes have zero association (Lo & MacKinlay, 1988). The NEPSE index is predicted using Artificial Neural Networks (ANN), Gated Recurrent Unit (GRU), and Long-Short Term (LSTM) algorithms.

1.2 Statement of the Problem

Stock market fluctuations can have a substantial influence on both the economies and individuals. A decline in share price can severely disrupt an economy’s functioning. A prime example is the stock market crash of 1929, which served as the key reason for the great depression in the 1930s (Romer, 1990). Conversely, when stock prices are high, companies are more inclined to initiate Initial Public Offerings (IPOs) to raise capital. Rise in mergers and acquisitions are also witnessed during this period. This heightened investment activity contributes to notable economic growth (Regmi, 2012).

With the advancement of technology, the stock market has become more accessible, allowing more individuals to participate in trading activities. However, this increased accessibility has not simplified the market's complexity. The inherent unpredictability of stock markets leads to significant financial risks, as noted by Asgharian (2023). The challenge, therefore, lies in developing models that can make educated estimates and informed predictions based on historical and current data (Al-Radaideh, et al., 2013). To address this challenge, various mathematical models have been developed and tested for their effectiveness in stock market prediction.

Pele (2011) presented a statistical approach to the predictability of stock market crashes, emphasizing the role of mathematical modeling in understanding and predicting market phenomena. Yoo, Kim, and Jan (2005) discussed the importance of incorporating event information into prediction models for more accurate stock market forecasting, highlighting the need for accurate event weighting methods and stable automated event extraction systems.

Machine learning, especially neural networks, has been at the forefront of these developments. Selvamuthu, Kumar, and Mishra (2019) conducted a study on the Indian stock market, demonstrating the efficacy of artificial neural networks in predicting stock market trends. Their research, focusing on tick data, highlights the potential of neural network models in analyzing and forecasting complex financial market behaviors.

In the context of Nepal's stock market, the complexity of market dynamics, influenced by diverse factors such as economic indicators and company-specific information, presents significant challenges for prediction. This complexity is compounded by the limited research on designing machine learning models for Nepal's market, a largely uncharted territory in financial modeling. Menon, Singh, and Parekh (2019) emphasized the potential of neural network models in stock market prediction, highlighting their capability to extract meaningful trends from intricate market data. Such a capability is particularly pertinent for the Nepalese market, where conventional prediction methods may not fully capture the nuances of its market behavior.

This research aims to address the challenges of predicting NEPSE by applying and evaluating the most effective machine-learning algorithms. This endeavor will not only contribute to the growing field of machine learning applications in stock market forecasting but also provide valuable insights for investors and analysts. By harnessing the power of advanced predictive models, this study seeks to navigate the complexities of NEPSE and potentially lead to more informed investment strategies, offering a significant tool for financial decision-making in a market characterized by its unique challenges.

1.3 Research Objectives

This study is focused on forecasting the Nepal Stock Exchange (NEPSE) index using advanced machine learning algorithms and aims to compare the predictive accuracy of these algorithms.

The general objective of the research is to investigate and evaluate the effectiveness of machine learning models in Nepal's stock market forecasting. By utilizing advanced machine learning algorithms, it aims to expand both theoretical and practical knowledge in the field of financial forecasting.

The specific objectives of the study are outlined as follows:

- To apply machine learning algorithms, specifically Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), for the prediction of the NEPSE index.
- To conduct a thorough comparative analysis of these algorithms and determine their effectiveness in the prediction.
- To contribute to the academic literature on financial market forecasting by demonstrating the application of sophisticated analytical methods in the context of an emerging market.

This comprehensive approach aims to produce a nuanced understanding of the capabilities of various machine learning models in stock market forecasting. This will provide important direction for future research and practical application in the field of financial analytics.

1.4 Research Hypothesis

In the process of developing hypotheses for this research, examining pertinent literature is crucial to establish a solid foundation and rationale for the empirical evaluations.

Research by Ryo et al. (2016) indicated that ANNs have shown promising results in financial market predictions due to their ability to model complex non-linear relationships within data. This insight leads to the first hypothesis:

- **H1: Artificial neural networks have better accuracy than long short-term memory and gated recurrent units in predicting Nepal’s stock market.**

A study by Fischer and Krauss (2018) demonstrated the effectiveness of LSTM models in stock market predictions, highlighting their superior capability in handling time-series data, which is intrinsic to stock market analysis. Based on this evidence, the second hypothesis is proposed:

- **H2: Long short-term memory has better accuracy than artificial neural networks and gated recurrent units in predicting Nepal’s stock market.**

According to a study by Cho et al. (2014), GRUs have been effective in modeling sequential data with fewer parameters than LSTMs, potentially offering more efficient computations without compromising performance. This forms the basis for the third hypothesis:

- **H3: Gated recurrent units have better accuracy than long short-term memory and artificial neural networks in predicting Nepal’s stock market.**

These hypotheses will be tested to provide a comprehensive understanding of the most effective machine-learning techniques for stock market prediction in Nepal.

1.5 Significance

The significance of this research, focused on predicting Nepal's stock market using machine learning algorithms, extends beyond mere academic interest. The study offers substantial practical implications in the realm of financial decision-making. By employing advanced machine learning models such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), the study aims to deliver an in-depth and nuanced analysis of stock market movements. This approach represents a critical shift from traditional analysis methods to more sophisticated, data-driven techniques.

The application of machine learning models in this research underscores a notable evolution in stock market forecasting. These models, with their enhanced accuracy and reliability, are uniquely suited to capture the intricate dynamics of the stock market, a domain heavily influenced by investor psychology and market sentiment (Drakopoulou, 2015; Chowdhury, 2021; Sivasamy & Peter, 2018). The use of advanced machine learning models is particularly vital given the dynamic and often unpredictable nature of stock markets.

A key component of this research is the comparative analysis of ANN, LSTM, and GRU models. This comparison will not only shed light on the strengths and weaknesses of each model but also offer a comprehensive assessment of their collective forecasting capabilities. Such an analysis is crucial in determining the most effective tool for predicting the stock market, providing valuable insights into the practical applicability of these models in real-world scenarios.

Furthermore, this research addresses existing limitations in current research methodologies, thereby contributing to both academic knowledge and practical applications in the financial sector. By delivering nuanced and empirically validated insights, the study stands to benefit a broad spectrum of stakeholders, including investors, financial analysts, and researchers. The findings of this research are particularly relevant for those interested in emerging markets like Nepal, where traditional models and global market trends may not fully encapsulate local market behaviors.

In essence, this research is poised to offer significant contributions to the field of financial forecasting. By enhancing the understanding of stock market dynamics in emerging economies and providing more precise predictive tools, it aims to facilitate informed and strategic investment decisions. This will influence both academic discourse and real-world financial practices.

1.6 Limitations

Despite the rigorous design and comprehensive execution of this research, it is important to recognize certain limitations that may impact its scope and applicability. A primary constraint of this study is its geographical focus solely on Nepal's stock market, utilizing data spanning from 2073/06/01 BS to 2080/05/31. This specific focus means that the findings and insights derived from this research may not be directly transferable or universally applicable to stock markets in other countries, where market dynamics and influencing factors can vary significantly.

Another limitation lies in the research methodology, which predominantly employs a quantitative approach. The analysis is based primarily on historical data and certain economic indicators, potentially overlooking the influence of more qualitative aspects such as news, social media discussions, and market rumors. Even though these elements can significantly impact stock markets, they are not extensively incorporated in this study. Furthermore, financial markets are subject to a wide array of external variables, including trader sentiment, company filings, and unforeseen global events like the COVID-19 pandemic, which are not comprehensively accounted for in this analysis.

Finally, the constraints of time and resources have also impacted the research. Being time-restricted and self-funded, the study relies heavily on secondary data sources. The absence of direct interactions with market regulators and stockbrokers has limited the depth of understanding regarding the impact of new regulations and market practices on stock market. This represents a notable gap in the study, as such interactions could have provided richer, more nuanced insights into the functioning of Nepal's stock market.

In summary, while the research offers valuable contributions to the understanding of stock market dynamics using machine learning algorithms, these limitations must be considered when interpreting the findings and considering their applicability to other contexts or future research endeavors.

1.7 Organization of the Thesis

The organization of the report is systematically structured into five key chapters, each dedicated to a specific aspect of the research on applying machine learning algorithms in predicting Nepal's stock market.

- Chapter I: Introduction - This chapter sets the foundation of the research. It outlines the background, articulates the problem statement, discusses the significance of the study, and acknowledges its limitations. The introduction section contextualizes the research within the broader domain of stock market prediction and machine learning.
- Chapter II: Literature Review - In this chapter, a comprehensive review of existing literature is presented. It explores theoretical concepts and previous research works related to the application of various machine learning algorithms for stock market prediction. This chapter is instrumental in establishing a conceptual framework for the study and identifying gaps in existing research which this study aims to address.
- Chapter III: Research Methodology - This chapter describes the methodological approach of the study. It details the data sources, the selection criteria, and the machine learning models employed for analysis. This chapter is critical for understanding how the research was conducted and the rationale behind the chosen methodologies.
- Chapter IV: Data Analysis and Result - Here, the implementation of machine learning algorithms and their evaluation is discussed. This chapter provides insights into the accuracy of the algorithms used and their effectiveness in predicting the NEPSE. The evaluation of these models is central to understanding their practical applicability and efficiency.
- Chapter V: Discussion, Conclusion, and Implications - The final chapter summarizes the findings of the research. It identifies the most effective model among those tested and offers implications for future research in this area. This chapter not only concludes the study but also provides a pathway for further investigation.

CHAPTER II
LITERATURE REVIEW

2.1 Introduction

Financial markets have always been the center of economic activity because of the potential for significant gains or losses. One big part of these markets is the stock market, where people buy and sell shares of companies, they own (Setiawan, et al., 2021). Figuring out when the stock market will go up or down has been a key interest of both investors and scholars (Narayan & Reddy, 2016). The recent development of machine learning algorithms has provided a potential way to reveal the deep patterns buried in complex market movements and historical data (Sadia, et al., 2019).

This section endeavors to lay the foundation for a robust and informed investigation into predicting the stock market using machine learning algorithms. Through an exploration of theoretical underpinnings, examination of empirical findings, and formulation of conceptual frameworks, the literature review contributes to the understanding of stock market dynamics and presents a wider discussion on the potential of machine learning algorithms in financial forecasting.

2.2 Theoretical reviews

The theoretical review is a cornerstone of research to frame the study within the context of established theories and principles. This section aims to illustrate established theories and principles related to this research.

2.2.1 Stock Exchange

The term "stock market" refers to a platform of marketplaces and exchangers with frequent buying and selling activities involving shares that are publicly issued (Hiransha, et al., 2018). There are two unique phrases used in the context of the stock market: "stock exchange" and "stock market," both of which refer to the official trading of assets. According to Ben Moews et al. (2019), a stock exchange is defined as a place where traders can buy and sell shares of one or more companies. There can be numerous stock exchange marketplaces on a national and international scale.

The only stock exchange in Nepal is called the Nepal Stock Exchange (NEPSE), where investors and traders can trade shares of different listed firms (Chalise, 2020). It plays a crucial role in the nation’s financial ecosystem by offering a transparent and well-organized capital market supporting Nepal's economic growth and creating investment opportunities (Baral, 2019).

2.2.2 NEPSE Index

The NEPSE Index represents the barometer of the Nepalese stock market, encapsulating the overall performance of the shares listed on the exchange. As Nepal's only stock exchange, NEPSE plays a pivotal role in the country's financial market, providing a platform for the trading of stocks, bonds, and other securities. The NEPSE Index is not just a financial indicator but also an indicative of broader economic trends and challenges, including the impact of global economic crises and the nation's political landscape (Joshi, 2023). A study by Bim Prasad Panta (2020) noted a correlation between macroeconomic factors like GDP growth, inflation rates, interest rates, and foreign direct investment and the movements of the NEPSE Index, indicating the sensitivity of the market to the overall economic health of the country.

2.2.3 Efficient Market Hypothesis

The concept of an "efficient market" was introduced by E.F. Fama in 1965 as “a market with a great number of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where current important information is almost freely available to all participants”. This perspective assumed that any new information about the market would rapidly disseminate, leading to prompt incorporation into security prices. The idea underlying this hypothesis is that, in an efficient market, it is not possible to predict future share prices using past data (Fama, 1976). This means both the technical and fundamental analysis wouldn’t result in significantly better returns for investors. The EMH is correlated with the concept of a random walk, which suggests that the future trajectory of prices cannot be foreseen (Bonga, et al., 2023).

2.2.4 Traditional Market Prediction Techniques

Financial markets have witnessed a significant evolution in prediction models, adapting to the increasing complexity and intricacies of market dynamics. These models have transitioned over time from relatively simple techniques to more sophisticated ones, paralleling the evolution of financial markets themselves (Lo, 2004).

One of the earliest and most fundamental techniques in market prediction is the use of smoothing techniques, which help in identifying underlying trends in market data. The moving average method, for example, smooths out short-term fluctuations to highlight longer-term trends by averaging a series of data points (Bollerslev, 1986). Similarly, exponential smoothing, another crucial method in this category, assigns exponentially decreasing weights to older data points, thereby making the model more reactive to recent market changes (Hyndman, et al., 2008).

Curve fitting is a technique that uses historical data to predict future market trends. This method involves identifying the best-fitting curve that represents the relationship between different variables, effectively predicting cyclical behaviors in financial markets (Campbell, 1991). Linear regression models, another traditional prediction method, are used to understand relationships between variables by fitting a linear equation to observed data. These models work well in scenarios where relationships are linear and relatively uncomplicated (Fama & French, 1989). However, their inability to capture the complexities of financial time series data has been a significant limitation.

The limitations of linear models in capturing the dynamics of financial markets have led to an increased focus on non-linear models. These models are adept at capturing more complex and intricate patterns within the market data, as they do not assume a linear relationship between variables. Non-linear models have been essential in understanding asymmetric information and volatility clustering common in financial time series (Hsieh, 1991; Engle, 2001).

Another traditional method worth noting is the Autoregressive Integrated Moving

Average (ARIMA) model. ARIMA is particularly effective in analyzing time series data for forecasting by describing autocorrelations in data. It has been widely used for its ability to model various time series with a degree of accuracy (Box & Jenkins, 1976).

Furthermore, technical analysis, a methodology for forecasting the direction of prices through the study of past market data, primarily price and volume, has been a long-standing tool for stock market prediction. Techniques under technical analysis, such as chart patterns and indicators like the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD), have been widely employed by traders and analysts (Murphy, 1999).

2.2.5 Machine Learning

Academics first used the term "artificial intelligence" in 1956 at a conference held at Dartmouth University. This incident represented the very start of a fresh field of study into the replication of intelligent human behavior by machines (Cordesch, 2007). It is an integration of many different fields, including biology, computer science, logic, psychology, and philosophy (Duan & Xu, 2012).

A computer cannot gain intelligence on its own. The knowledge must be given either in a form that the computer understands, or the computer must be capable of learning on its own. Additionally, an intelligent computer system must be able to continuously improve its knowledge through real-world applications (Young, et al., 2018). The process of training computers to gain human skills like learning, judging, and decision-making to emulate intelligent behavior is known as machine learning (Xu, et al., 2021). The core idea behind ML is the use of an algorithm whose performance is improved by the process of learning from data (Liu, et al., 2020). It has shown impressive results in the fields of speech recognition, machine translation, text generation, computer vision, and the creation of intelligent robots.

2.2.6 Machine Learning in Financial Forecasting

The field of financial forecasting has seen a major shift towards computational and data-driven methods with the introduction of machine learning in finance. ML applications have been successfully implemented in areas such as risk management, market forecasting, and credit scoring, significantly enhancing the accuracy and efficiency of these processes (Shi, et al., 2022).

In the specific realm of stock market prediction, the impact of ML has been transformative, moving away from conventional forecasting methods to more dynamic, algorithm-based approaches (Kumar & Thenmozhi, 2006). This evolution reflects the ability of ML techniques to process and analyze complex datasets more effectively than traditional models (Huang, et al., 2005). They excel at uncovering subtle patterns and correlations that might elude conventional methods, providing a comprehensive perspective on potential market movements (Brooks, 2008).

Additionally, firms in tech-centric regions like Silicon Valley are applying ML to make financial products more accessible, thereby reducing entry barriers for individuals engaging with financial markets. This trend is not only about enhancing financial operations but also about broadening financial inclusivity and literacy (Zhang & Lu, 2021).

2.2.7 Machine Learning Algorithms

Financial forecasting can be tagged as data-intensive, noisy, non-stationary, unstructured, and hidden relations (Solanki, et al., 2022). In addressing these challenges, algorithms specifically, ANN, GRU, and LSTM have gained prominence. These algorithms are known for being able to learn order dependence on sequence prediction problems (Choe, et al., 2021).

Artificial Neural Networks are the most used machine learning algorithms for stock market prediction because of their accuracy in time series data (Selvamuthu, et al., 2019). They adapt well to varying patterns in financial data, offering a significant advantage over traditional linear models in terms of predictive accuracy (Zhang, et al., 2020). The ability of ANNs to identify trends and market sentiment has attracted particular interest. Such insights are critical for understanding the behavior of the stock market. (Patel, et al., 2015).

LSTM networks, a specialized form of neural networks, address the need for retaining information over extended periods. This makes LSTM network suitable for sequence prediction problems such as stock market forecasting. Comprising of cell, input, output, and forget gates, LSTM controls data flow in and out of the cell. The cell is the core unit, which memorizes values across different time intervals. A critical factor for considering the LSTM model is that it can capture long-term dependencies of time series data. Because of this ability, LSTM networks have proven to be highly effective in financial market predictions, particularly in identifying complex temporal patterns within stock data (Fischer & Krauss, 2018).

GRUs are also known for retaining information over extended periods and have gained prominence for their efficient structure and performance. They offer a more streamlined architecture compared to LSTMs, maintaining comparable performance with less computational complexity. This efficiency makes them a valuable tool for predicting stock market trends, while also capturing and analyzing temporal relationships in market data (Cho, et al., 2014; ArunKumar, et al., 2022).

2.2.8 Evaluation Metrics

Evaluation metrics are essential tools used to assess the performance of predictive models. They provide insights into model's accuracy, reliability, and overall effectiveness (Hyndman & Koehler, 2006). However, the choice of the right evaluation metric is crucial for validating models and facilitating informed decision-making (Armstrong & Collopy, 1992).

Among these metrics, Mean Absolute Error (MAE) stands out for its straightforward approach to measuring the average error. It calculates the average absolute difference between predicted and actual values, providing a clear indication of prediction accuracy (Géron, 2021). MAE is particularly valued for its interpretability, as it remains on the same scale as the data. Chai and Draxler (2014) highlight MAE's utility in reflecting model performance in a directly understandable way, while Willmott and Matsuura (2005) note its effectiveness in evaluating forecasting models across various disciplines.

Mean Squared Error (MSE) is another essential metric that quantifies the average of squared errors. It squares the errors and is generally useful in scenarios where large errors are particularly undesirable. MSE's sensitivity to outliers is both a strength and a limitation (Chai & Draxler, 2014). Root Mean Squared Error (RMSE) builds on MSE by taking its square root, which maintains the emphasis on larger errors while returning the scale of error to the original data units. This balance of sensitivity and interpretability makes RMSE a valuable tool (Hyndman & Koehler, 2006; Armstrong & Collopy, 1992).

The coefficient of determination, R-squared (R^2), measures the proportion of variance in the dependent variable that is predictable from the independent variables. In machine learning for stock market prediction, R^2 provides an overview of the model's fit to the data (Heckman, et al., 2010). Gujarati (2009) elaborates on the importance of R^2 in regression models while cautioning against over-reliance on it, especially in cases of overfitting.

2.3 Empirical reviews

As financial markets continue to evolve, the integration of technology, particularly machine learning, has garnered significant attention for its potential to enhance predictive capabilities. This review focuses on synthesizing and analyzing a collection of previous studies that have explored the application of machine learning algorithms to forecast stock market movements.

2.3.1 Evaluating the Efficient Market Hypothesis

The efficient market hypothesis has been the subject of extensive empirical studies. While Fama (1970) argued that stock prices reflect all available information, subsequent studies have revealed nuances. For instance, Lo and MacKinlay (1988) found evidence against the random walk hypothesis, a cornerstone of EMH. Malkiel

(2003) found that market anomalies, such as the January effect, challenge the EMH, while (Jegadeesh & Titman, 1993) demonstrated momentum effects that contradict the hypothesis. Research by Shiller (1981) on stock price volatility indicated deviations from market efficiency. Furthermore, Grossman and Stiglitz (1980) argued that if markets were perfectly efficient, there would be no incentive for investors to gather information, therefore creating a paradox. Behavioral economists, like Kahneman and Tversky (1979), have also highlighted cognitive biases in investor behavior, which are inconsistent with EMH. These studies suggest that while markets may be generally efficient, anomalies and predictable patterns do exist, raising questions about the absolute validity of the EMH.

2.3.2 Machine Learning in Stock Market Forecasting

Moghaddam et al., (2016) explored the potential of Artificial Neural Networks (ANN) in forecasting the NASDAQ index. They constructed and validated two distinct networks for predicting the NASDAQ index. Their study incorporated short-term and historical stock prices, as well as daily data. The approach adopted by the researchers involved utilizing input parameters spanning the previous four to nine working days. Interestingly, the output of the model was found to be independent of the number of days used as inputs for the prediction process. This study underscores the potential of ANN as a predictive tool for stock market dynamics, particularly showcasing its prowess in handling intricate relationships within data. However, ANN can also have significant disadvantages like vanishing gradient problems and over fitting (Moon, et al., 2019).

The use of a Gated Recurrent Unit (GRU) can overcome the problem of overfitting and vanishing gradient (Rahman, et al., 2019). A 2019 study by Saud and Shakya examined the performance of various optimization techniques, including momentum, RMS Prop, and Adam, in relation to the accuracy of stock price predictions made using Gated Recurrent Units (GRUs). The two stocks they concentrated on were traded on NEPSE. The study's findings showed that the GRU model using the Adam optimization technique had better accuracy and maintained consistent prediction performance (Saud & Shakya, 2019).

Long short-term memory (LSTM) is regarded to be better than other algorithms in sequential tasks like predicting the stock market (Hao & Gao, 2020). Zou and Qu (2020) conducted a study utilizing the daily prices and volumes of the top 10 S&P 500 stocks. The statistical data was collected between 2004 and 2013. The dataset was divided into three portions: 70% for training, 15% for development, and 15% for testing purposes. After evaluating four distinct models, it was discovered that the Long Short-Term Memory (LSTM) model performed better than the others. This advantage was ascribed to LSTM's better capacity to forecast financial time series since it can identify long-term dependencies in the time series data.

Shahi et al. (2020) conducted a comparative study to predict stock prices through the gated recurrent unit (GRU) and long short-term memory (LSTM) models. They integrated financial news sentiments alongside stock features as input for stock market prediction. The authors theorized that adding sentiment data from financial news to the predictive process would improve the performance of deep learning models in stock market prediction.

2.3.3 Robustness of Evaluation Metrics

The robustness of evaluation metrics in machine learning is a critical area of research as these metrices help to compare and determine the best fit models. Because of this, several studies have been done to contribute towards identifying suitable metrices for regression tasks such as stock market prediction. Two of the most used evaluation metrices for regression are Mean Absolute Error (MAE) and Mean Squared Error (MSE). The robustness of MAE in financial modeling is evident through its ability to provide a direct and interpretable measure of average prediction error. Baumgärtner et al. (2022) emphasized the practicality of MAE, particularly its weighted version, in complex financial models where errors have varying degrees of impact.

Kelotra and Pandey (2020) delved into the robustness of evaluation metrics, including MSE, emphasizing their reliability in financial predictions. Similarly, Chai and Draxler (2014) has provided an insightful analysis of the selection between RMSE and MAE. They concluded that neither is inherently superior, but their effectiveness depends on the error distribution within the data. Gelman et al. (2019) highlighted the usefulness of R^2 in Bayesian regression models, a perspective crucial for stock market predictions where Bayesian methods are increasingly applied.

Liu, Ayitelieke, and Yu (2022) focused on integrating Support Vector Regression (SVR) and Random Forest (RF) through bagging techniques, revealing significant improvements in R^2 and MSE metrics. Their findings highlight the effectiveness of these metrics in evaluating the robustness of integrated learning models. (Liu, Ayitelieke, & Yu, 2022).

Jiang's (2021) review of deep learning models for stock market prediction emphasized the evolving nature of evaluation metrics. Although the review didn't specifically focus on MAE, MSE, RMSE, or R^2, it highlighted the growing importance of robust and adaptable metrics in assessing the performance of advanced deep learning models in stock market predictions (Jiang, 2020)

2.3.4 Historical Analysis of NEPSE

While studying the behavior of NEPSE, one significant area of focus has been the relationship between NEPSE's performance and macroeconomic variables. Devkota & Dhungana (2019) found a correlation between NEPSE indices and various economic indicators such as GDP, inflation rates, and foreign investment. Another critical aspect examined by researchers is the impact of political stability on NEPSE. Studies have highlighted how political events and stability in Nepal significantly affect investor confidence and, consequently, market performance (Ojha, 2019).

The resilience and vulnerability of NEPSE during financial crises have also been the subject of empirical investigation. For example, the global financial crisis of 2008 and its impact on NEPSE was analyzed by Khadka & Budhathoki (2013), who noted a delayed but notable effect on Nepal’s stock market, indicating both resilience and eventual susceptibility to global economic trends.

2.3.5 Traditional Forecasting in NEPSE

Traditional methods for predicting the Nepal Stock Exchange (NEPSE) prominently featured statistical models and fundamental analysis techniques. These approaches were primarily centered on in-depth analyses of company financial statements to predict stock prices (Kadel & Patodiya, 2023). Additionally, some researchers have also incorporated analyses of broader market trends and essential economic indicators, which are key to forecasting market movements (Gurung, 2004)

Time-series analysis, including moving averages, was commonly employed to understand and predict market trends by smoothing out short-term fluctuations (Vaidya, 2020). Moreover, exponential smoothing techniques were also applied to assign progressively decreasing weights to older data, enhancing responsiveness to recent market changes. While effective in certain aspects, these techniques often face limitations in handling the complex dynamics of the stock market (Maskey, 2022). Nonetheless, these traditional methods laid a foundational understanding of stock market behavior, essential for the evolution of more sophisticated predictive models (Khanal & Shakya, 2016).

2.3.6 Application of Machine Learning in NEPSE

The application of machine learning (ML) in the Nepal Stock Exchange (NEPSE) represents a significant advancement in financial market analysis. Recently, research has started to focus on the implementation of sophisticated algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest in the context of NEPSE. For instance, a study by Pun and Shahi (2018) demonstrates the effectiveness of Support Vector Regression and ANN in capturing complex market patterns in NEPSE, leading to more accurate predictions of stock prices.

The application of machine learning models like Regression Analysis and Decision Trees to predict the future performance of stocks listed on NEPSE is found to be effective in certain market conditions (Er.HariK, 2018). A notable study by Zhao (2021) compared the efficacy of traditional time-series models with ML techniques, indicating a significant improvement in prediction accuracy when using ML models.

Despite these advancements, the application of ML in NEPSE is not without challenges. Issues such as data quality, market volatility, and model overfitting remain areas of concern. Saud & Shakya (2021) discussed these challenges, emphasizing the need for more robust models and comprehensive data analysis to enhance the reliability of ML applications in NEPSE.

2.4 Research Gap

There is a significant research gap in the field of AI-driven financial forecasting, especially when it comes to developing nations like Nepal. While existing studies, as highlighted by Hiransha et al. (2018) and Bollen (2011), have explored the potential of machine learning in stock market predictions globally, there's a notable scarcity of in-depth research focusing on markets like NEPSE. This gap is significant as it overlooks the unique economic and market characteristics of these regions, which can greatly influence the performance and applicability of AI models like ANN, GRU, and LSTM.

Addressing this gap, the current research endeavors to comprehensively analyze and compare the effectiveness of these advanced machine learning algorithms in the Nepalese stock market context. Such a study is crucial not only for expanding the academic understanding of machine learning in financial forecasting but also for uncovering insights specific to less-explored markets. This approach aims to provide a nuanced understanding of how these AI models perform under different market conditions, contributing to the broader field of AI and its practical applications in diverse economic settings.

2.5 Conceptual Frameworks

The conceptual framework for forecasting the NEPSE Index through machine learning algorithms is structured around the integration and analysis of diverse datasets to predict stock closing prices. This framework is underpinned by the assumption that stock market behaviors in NEPSE, like other emerging markets, are complex systems influenced by a variety of factors. Three advanced machine learning models Long Short-term Memory (LSTM), Gated Recurrent Unit (GRU), and Gated Recurrent Unit (GRU) are employed to forecast the NEPSE index.

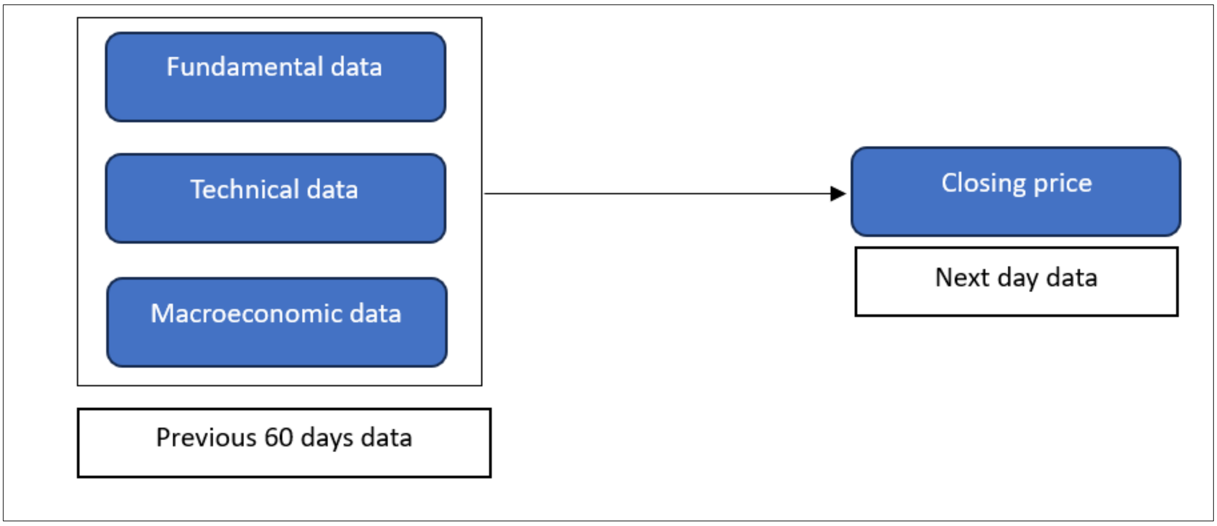

Figure 1 Conceptual framework

Source: Author’s own creation (2023)

These models are trained and evaluated using historical data, which includes the past 60 days' information to forecast the following day's closing prices. This approach aligns with the theoretical understanding that, despite intrinsic nonlinearities and the chaotic nature of the stock market, historical information can offer insights into future trends.

The framework for employing machine learning algorithms to forecast the NEPSE index has strategically excluded limited news data. This decision is informed by insights from Chaskar (2020), who highlighted the challenges of limited news data in achieving accurate stock market predictions. Such data, due to its volatile and unpredictable nature, may introduce significant noise into the predictive models. This can sometimes skew the results. Therefore, the framework focuses on leveraging more quantifiable and stable inputs like fundamental, technical, and macroeconomic data to enhance the reliability and accuracy.

CHAPTER III
RESEARCH METHODOLOGY

3.1 Introduction

The research methodology of our research describes a systematic approach undertaken for data preprocessing, research design, and model architectures along with tools and packages used. Subsequently, this section also describes different concepts like optimization and hyperparameters which are important for designing machine learning models.

3.2. Data

According to Ahangar et al. (2010), stock markets are intrinsically complex and exhibit characteristics such as noise, non-linearity, non-parametric behavior, and deterministic chaos. The complex nature of stock markets is the outcome of numerous interrelated factors, both at local and global levels. Various elements contribute to this complexity, including but not limited to global economic indicators, shifts in unemployment rates, influential countries' monetary policies, immigration regulations, natural calamities, and public health conditions. This enormous amount of information is presented in a variety of ways and distributed via several platforms (Pokhrel, et al., 2022).

The unorganized distribution of information makes it challenging to select the appropriate data for predicting stock prices. Scholars have developed several strategies to address this problem (Hoseinzade & Haratizadeh, 2019). There has been a trend, with some researchers relying solely on technical indicators, while others emphasize historical data (Jian & Kim, 2018).

This research considers fundamental, technical, and macroeconomic information for stock market prediction. The dataset used in this study spans from 2073/06/01 BS to 2080/05/31 BS, providing an extensive temporal snapshot for analysis. This section describes the data collection and processing methods employed to prepare the dataset for subsequent machine learning analysis.

3.2.1 Data Definitions

The data is collected in two datasets: the fundamental dataset which consists of historical NEPSE index data, and the macroeconomic dataset.

The data present on fundamental datasets are:

- Open: The initial price at which the NEPSE index starts at the opening of the trading day.
- High: The highest value that the NEPSE index reaches within the trading day.
- Low: The lowest value that the NEPSE index drops to during the trading day.
- Change: The value by which the NEPSE index has increased or decreased from the previous trading day's closing value.
- Percentage Change: The relative increase or decrease of the NEPSE index, expressed as a percentage, from the previous close.
- Turnover: The total volume or value of shares traded on the NEPSE during the trading day.

The data present on the macroeconomic dataset are:

- Total deposit/GDP: The ratio of the total bank deposits to the country's GDP.
- Total credit/GDP: The ratio of the total credit provided by banks to the GDP.
- Total credit/Total deposit: The proportion of total credit given out by banks to the total deposits held.
- Total liquid asset/Total deposit: The percentage of liquid assets banks hold against the total deposits.
- Weighted average interest on savings: The weighted average interest rate paid on savings accounts.
- Weighted average interest on fixed deposits: The average interest rate paid on fixed deposit accounts.
- Weighted average interest on credit: The weighted average interest rate charged on borrowed credit.

Technical indicators data are calculated using fundamental data and added to the dataset. These technical indicators provide insights into the momentum, strength, and volatility of the stock market, which are essential factors in prediction models. The technical indicators used in this study are:

- Moving Average Convergence Divergence (MACD): The MACD is a trend-following momentum indicator that shows the relationship between two moving averages of an index value. It identifies changes in the strength, direction, momentum, and duration of a trend. It is calculated by subtracting the 26-period exponential moving average from the 12-period EMA. MACD provides signals for potential buy and sell opportunities.

- MACD Signal: The MACD Signal is a derivative of the MACD and is used to identify potential buy or sell signals. It is calculated as the 9-day EMA of the MACD line itself. When the MACD crosses above its signal line, it is often considered a bullish signal, suggesting that the price of the asset is likely to experience upward momentum. Conversely, when the MACD crosses below the signal line, it is taken as a bearish signal, indicating potential downward price movement.

- Relative Strength Index (RSI): RSI for an index like NEPSE measures the speed and magnitude of recent changes to evaluate overbought or oversold conditions. It ranges from 0 to 100 and is typically used to identify whether the market is in an overbought (above 70) or oversold (below 30) condition, which might indicate a potential reversal in the index's trend.

- Money Flow Index (MFI): The MFI is a volume-weighted momentum indicator that measures the flow of money into and out of a security over a specific period (usually 14 days). Here, it is modified to use the total turnover of NEPSE instead of volume. This change offers a broader perspective on market sentiment as the turnover represents the total value of all traded shares within a specific period, capturing the overall activity of the market. This comprehensive measure reflects the collective investment flow in the NEPSE, providing a more accurate representation of market dynamics.

- Average True Range (ATR): The ATR is an indicator that measures market volatility by examining the range of changes in an index's value. It calculates the maximum of these three values: the difference between the current high and low, the absolute value of the current high minus the previous close, and the absolute value of the current low minus the previous close.

3.2.2 Data Collection

The fundamental dataset which comprises daily trading figures of the NEPSE index, including open, high, low, close, change, change percent, and turnover data is sourced from ShareSansar, a comprehensive financial portal. This fundamental data forms the backbone of the stock market analysis, capturing the inherent volatility and trend patterns within the specified period. The technical indicators were calculated based on this fundamental data.

Macroeconomic datasets were incorporated to account for the broader economic context influencing the stock market. This dataset includes Total deposit/GDP, Total credit/GDP, Total credit/Total deposit, Total liquid asset/total deposit, and interest rates (savings, fixed deposit, and credit), all of which were obtained from Nepal Rastra Bank monthly report. Remittance data, another significant economic indicator in the context of Nepal, was also included from ShareSansar.

Table 1 Data collection

Data	**Source**	**Frequency**
Fundamental:		
Open price	Share Sansar	Daily
High price	Share Sansar	Daily
Low price	Share Sansar	Daily

Close price	Share Sansar	Daily
Volume	Share Sansar	Daily
Macroeconomic:		
Remittance	Share Sansar	Monthly
Total Credit/ Total Deposit (%)	Nepal Rastra Bank	Monthly
Total Liquid Assets/Total Deposit (%)	Nepal Rastra Bank	Monthly
Weighted average interest rate – Saving (%)	Nepal Rastra Bank	Monthly
Weighted average interest rate – Fixed (%)	Nepal Rastra Bank	Monthly
Weighted average interest on credits (%)	Nepal Rastra Bank	Monthly
Technical indicator (Calculated):		
Moving average convergence divergence (MACD)	………..	Daily
MACD Signal	………..	Daily
Average true range (14 period)	………..	Daily
Relative strength index (14 period)	………..	Daily
Money flow indicator (14 period)	………..	Daily

Source: Author’s own creation (2023)

3.3 Research Design

Research design serves as a blueprint for detailing the research process. It includes the research's structural design, data collection and preprocessing strategies, model construction, and evaluation techniques.

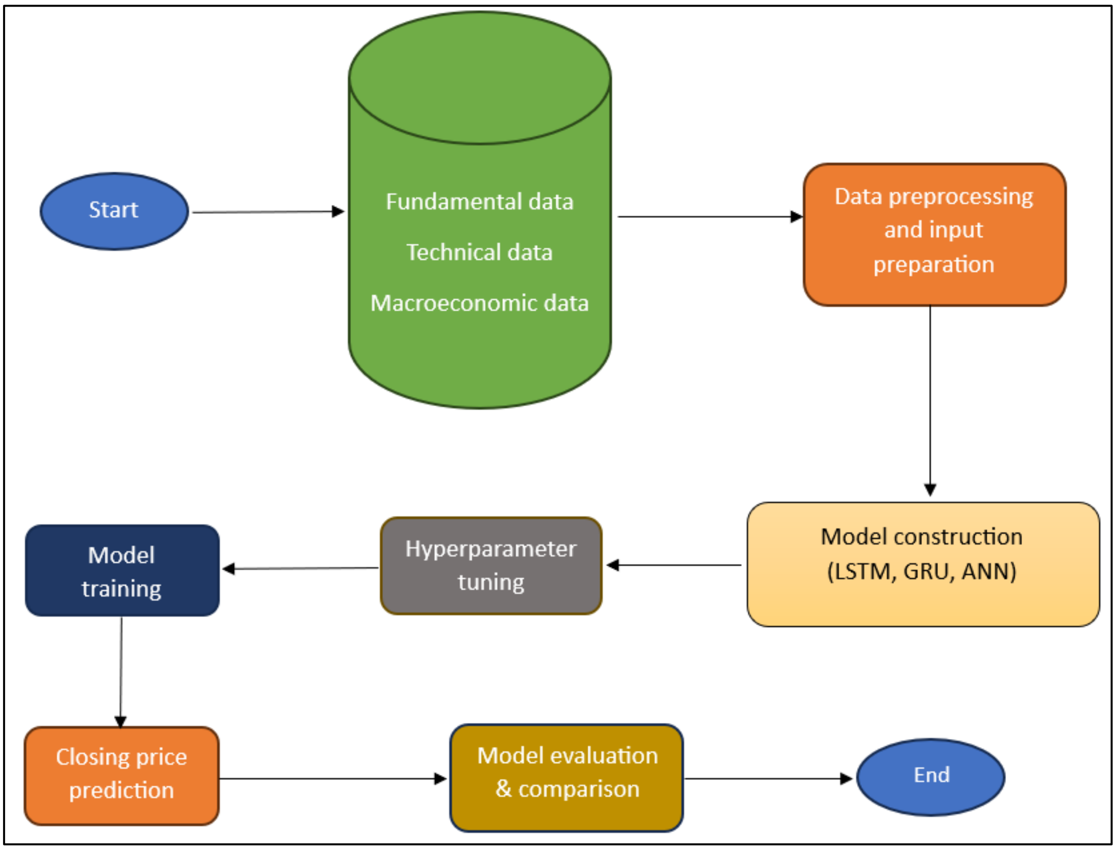

Figure 2 Research design

Source: Author’s own creation (2023)

3.3.1 Data Preprocessing and Input Preparation

The first step in this research after data collection involves aligning the dates in datasets by converting the dates in macroeconomic datasets to the Georgian Calendar (AD). This facilitates the merging of datasets by using date column. This merger is vital for ensuring that all data points pertain to the same time frame, crucial for accurate and meaningful analysis.

Following the merging of datasets, redundant date columns are removed to streamline the data. The next phase involves normalizing the data, which is essential because it standardizes the range of independent variables. Variables like macroeconomic indicators, daily trading data, and turnover have varying ranges, so Min-max normalization scales all data points (except the month column) to a fixed range between 0 and 1. This scaling method is key in reducing the model's sensitivity to outliers and ensures each feature's contribution is based on its pattern rather than scale. The month column, treated as categorical data, undergoes one-hot encoding to convert it into a numerical format understandable by machine learning models. This comprehensive preprocessing approach prepares the data optimally for subsequent analysis and modeling.

Following the data preprocessing steps, the next critical phase in the methodology is the splitting of the dataset into training, validation, and test sets. This division is fundamental for model training and evaluation. The data is split into 60% for training, 20% for validation, and 20% for testing.

3.3.2 Model Construction

In this research, three machine learning models are used: ANN, LSTM, and GRU. Key components in these models are:

Loss Function: It quantifies how well the model performs, by measuring the difference between the model's predictions and the actual data. In this research, Mean Squared Error (MSE) is used as a loss function. It calculates the average squared difference between predicted and actual values. MSE is effective as it heavily penalizes larger errors, which is crucial for accuracy in stock market prediction.

Learning Rate: The learning rate in machine learning controls the rate at which the weights of a machine learning model are updated during training. It's one of the key factors, as it affects the speed and quality of the learning process. A too-high learning rate can cause the model to converge too quickly to a suboptimal solution, while a too-low learning rate can slow down the process or cause the model to get stuck in the training phase. The right learning rate helps the model to learn efficiently and reach the best performance by making precise adjustments to the weights, thereby minimizing the loss function over time.

Optimizer: It's an algorithm to minimize the loss function. The Adam optimizer is used here for its efficiency and adaptability. It adjusts the learning rate dynamically during training, which helps in handling large datasets and complex learning patterns effectively.

The 60-day timestep is used in these models. This allows the models to learn from historical data patterns over a two-month period, which is beneficial for capturing trends and seasonality in the stock market.

For ANN, the input shape is typically a flattened array of features, whereas LSTM and GRU require the data to be reshaped into a format suitable for sequential modeling (samples, time steps, features). This difference in input shape caters to the unique architecture and functioning of these models, with LSTM and GRU designed to process data sequentially and capture time-dependent patterns.

3.3.3 Hyperparameter Tuning

Hyperparameters in machine learning are the settings or configurations that govern the overall behavior of a machine learning model. These are set before the model training process and can significantly impact the performance of the model.

Tuning hyperparameters is crucial for the model to become optimal for a specific dataset or problem. The process involves searching for the combination of hyperparameters that yield the best performance as measured by a predefined metric. In this study, mean squared error, the loss function is used as a metric to determine the best hyperparameter. By evaluating the specific combinations of hyperparameters using mean squared error, the study aims to find the most effective set of hyperparameters for the employed machine learning models.

The tuning is done using random search, a technique used for hyperparameter tuning, where a fixed number of hyperparameter combinations are randomly selected from a specified range of values. This approach contrasts with grid search, which exhaustively tries all possible combinations within the given range.

Random search is particularly effective when dealing with many hyperparameters or when the search space is large. It offers a more efficient and practical way to identify a good combination of hyperparameters because it doesn't require the evaluation of all possible combinations.

The hyperparameters are tuned by training the model using a set of hyperparameters on a train dataset and testing the chosen hyperparameter on the validation dataset.

3.3.4 Model Testing

Once the optimal hyperparameters are determined, the models are trained on a combined dataset of training and validation sets. This combined training approach ensures that the model learns from a more comprehensive dataset, enhancing its ability to generalize.

After the models are trained using the optimal hyperparameters, they are tested on a separate test dataset. This step is crucial to evaluate the model's performance in an unbiased manner using unseen data.

3.3.5 Evaluation Metrics

The model performance is then evaluated using R-squared, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These metrics provide a comprehensive understanding of the model's accuracy and predictive capability. R-squared measures the proportion of variance in the dependent variable that can be predicted from the independent variables, RMSE gives the average magnitude of the error, and MAE offers an average of absolute errors. This thorough evaluation process is essential to ensure the reliability and robustness of the machine learning models in predicting stock market trends.

3.4 Modeling Approach

The modeling approach refers to the systematic methods applied to construct algorithms capable of predicting future trends. This section of research outlines the structure of a model, its functionality, and its relevance.

3.4.1 Feed Forward Artificial Neural Network

Artificial neural networks are like a series of interconnected sets of mathematical equations. They take in variables as inputs, run them through a series of equations, and output one or more results. Three layers make up a neural network's typical structure: an input layer, a hidden layer, and an output layer. Moreover, each of these layers may comprise multiple distinct nodes or components that enhance the overall performance of the network (Moghaddam, et al., 2016).

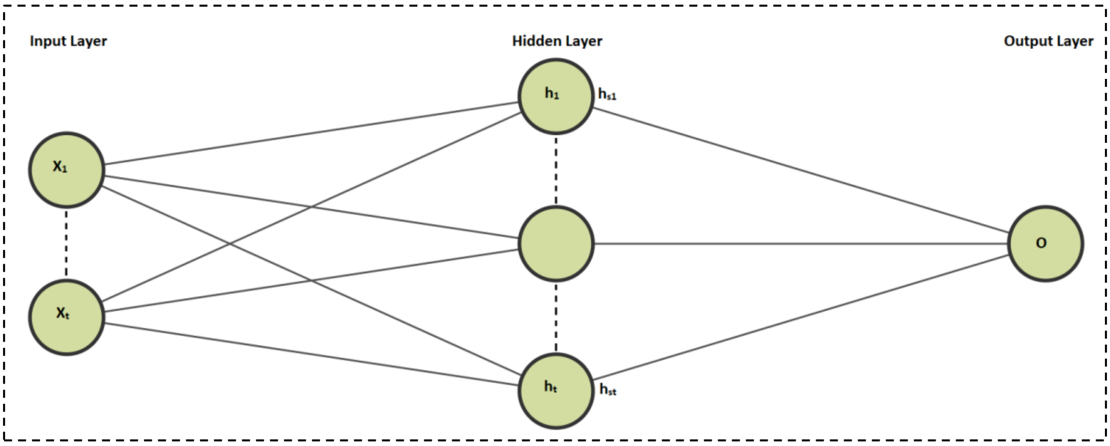

Figure 3 One hidden layer feedforward ANN

Source: Author’s own creation (2023)

The input layer contains nodes corresponding to the amount of input data [x_1, x_2, … , x_t]. Each input node is multiplied by a designated weight and then combined with a bias to get the value for a hidden node, a feature in a hidden layer, which is represented as h_t in fig 4. A rectified linear unit activation is used on each hidden node to map its negative value as zero. In figure 3, h_{st} is the output after applying the ReLU function.

$h_t = b + \sum_{i=1}^{t} x_i w_i$, where w is weight and b is a bias term.

ReLU function = max(0, x) , where x is the input value which is h_t in fig 4.

In the output layer, the result of each hidden node is multiplied by an assigned weight, and then a bias is incorporated to get the value of output node (o).

$$o = b + \sum_{i=1}^{t} h_{si} w_i$$

The mean square error (MSE) is used as a loss function. This averages the difference between actual values and predicted values. Based on this loss function, the weights and biases of the model are adjusted using backpropagation algorithm.

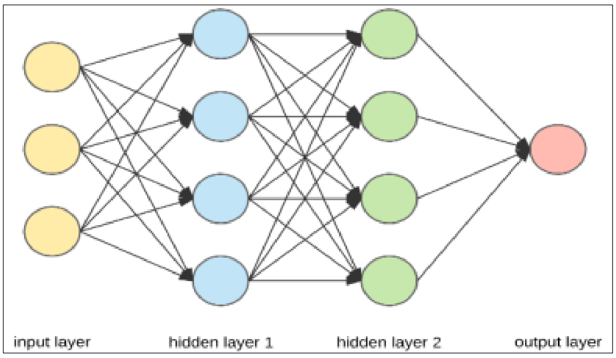

Figure 4 Two hidden layer feedforward ANN

Source: (Jakka & J, 2020)

In this study, a two-hidden layer feedforward ANN is used. Also, for each hidden layer, a dropout is introduced. The dropout rates refer to the probability that a neuron in the neural network will be ignored during training. This is done to prevent overfitting, which occurs when the model learns the training data too well, including noise and fluctuations, leading to poor performance on new, unseen data.

3.4.2 Long-Short Term Memory

Long short-term memory (LSTM), a popular deep learning method in recurrent neural networks (RNNs), is widely used for time series prediction. It uses memory cells to successfully handle the issue of vanishing gradients (Hochreiter, 1998). According to Gers et al. (2000), the architecture consists of an input layer, hidden layer, cell state, and output layer.

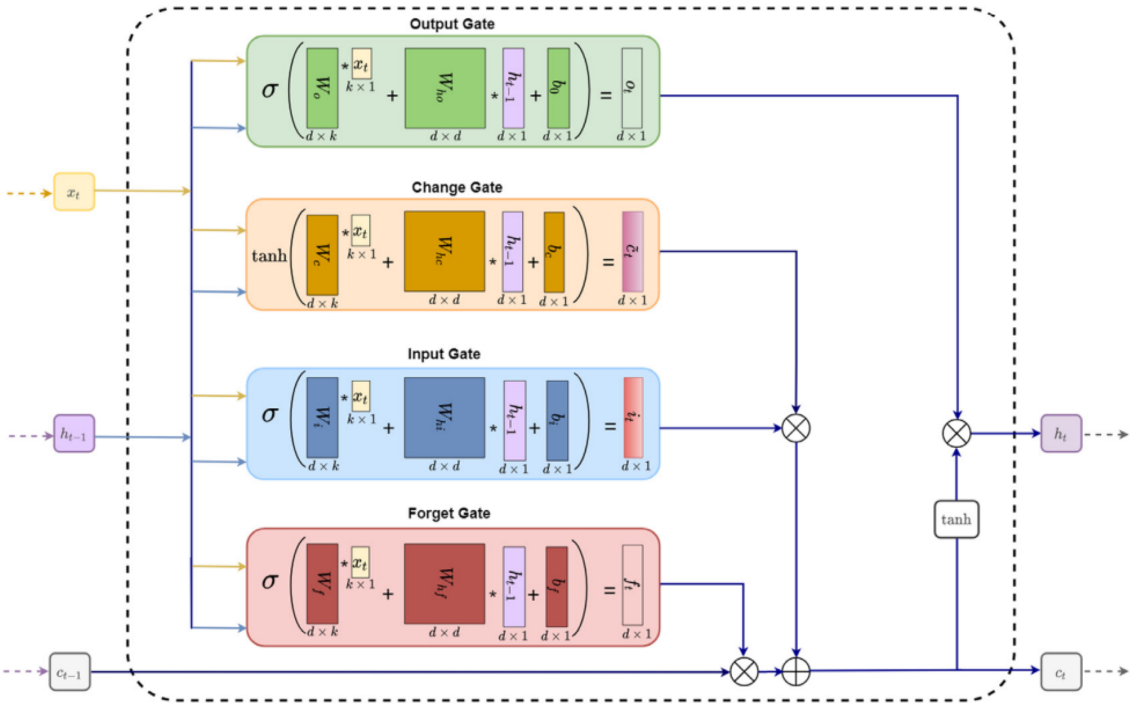

Figure 5 Long short-term memory architecture

Source: (Pokhrel, et al., 2022)

Figure 5 shows the structure of the LSTM at time t, which is designed to process sequential input. The four gates in this design—output, change, input, and forget—all carry out distinct functions at different times.

When considering a data sequence $\{x_1, x_2, \dots, x_n\}$, where $x_t \in R^{k\times1}$ represents input at time t, three gates are used by the memory cell c_t to update information: input gate i_t, forget gate f_t, and change gate $\hat{c}_t$. Furthermore, the output gate o_t and the memory cell c_t are used to update the hidden state h_t. The corresponding gates and layers carry out the following tasks at time t:

$$i_t = \sigma(W_i x_t + W_{hi} h_t - 1 + b_i),$$

$$f_t = \sigma(W_f x_t + W_{hf} h_t - 1 + b_f),$$

$$o_t = \sigma(W_o x_t + W_{ho} h_t - 1 + b_o),$$

$$\hat{c}_t = \tanh(W_c x_t + W_{hc} h_{t-1} + b_c),$$

$c_t = f_t \otimes c_{t-1} + i_t \otimes \hat{c}_t,$

$h_t = o_t \otimes \tanh(c_t)$

Here, σ represents the sigmoid function, and tanh represents the hyperbolic tangent function. The $\otimes$ operator indicates the element-wise product. Variables such as $W \in R^{d\times k}$, $W_h \in R^{d\times d}$, are weight matrices and $b \in R^{d\times 1}$ correspond to bias vectors. Additionally, n, k, and d signify the sequence length, number of features, and hidden size respectively (Qiu, et al., 2020).

In this experiment, ANN with two LSTM layers is used. The number of units on each layer along with dropouts rate are fine-tuned using random search. A dense layer is used at the end to calculate the final output.

3.4.3 Gated Recurrent Unit

Cho et al. (2014) proposed the Gated Recurrent Unit (GRU), a condensed version of the LSTM. GRU combines the short-term (h_t) and long-term (c_t) information of LSTM into a single vector h_t. Three gates are used by GRU: reset, change, and update gates. The update gate in GRU plays the role of both the input and forget gates of LSTM (Géron, 2019).

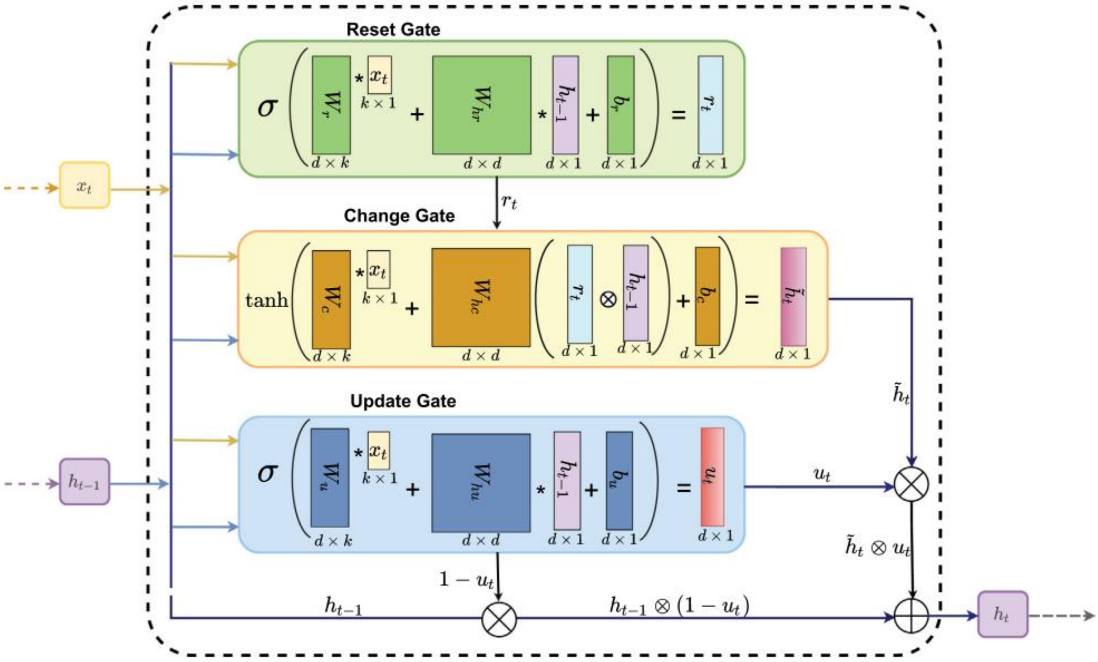

Figure 6 Gated recurrent unit architecture

Source: (Pokhrel, et al., 2022)

Given an input sequence $\{x_1, x_2, \ldots, x_n\}$, where $x_t \in R^{k\times 1}$ represents input at time t, it considers the input x_t and the hidden state h_{t-1} from the previous time step $t-1$ at time t. The outcome is a new hidden state h_t, which advances to the next time step (Zhang, et al., 2022). At each time t, the gates and layers perform the following computations:

$$u_t = \sigma(W_z x_t + W_{hz} h_{t-1} + b_u),$$

$$r_t = \sigma(W_r x_t + W_{hr} h_{t-1} + b_r),$$

$$\tilde{h}_t = \tanh(W_c x_t + W_{hc}\,(r_t \otimes h_{t-1}) + b_c),$$

$$h_t = (1 - u_t) \otimes h_{t-1} + u_t \otimes \tilde{h}$$

Here, σ represents the sigmoid function, and tanh represents the hyperbolic tangent function. The $\otimes$ operator signifies the element-wise product. Variables such as $W \in R^{d\times k}$, $W_h \in R^{d\times d}$, are weight matrices and $b \in R^{d\times 1}$ correspond to bias vectors. Additionally, n, k, and d denote sequence length, number of features, and hidden size respectively.

For this study, a neural network with two GRU layers is used. Like in LSTM, the number of units on each GRU layer and the dropout rate is calculated via hyperparameter tuning.

3.5 Tools and Packages

The following software and libraries are used for data preprocessing and model development:

- Pandas: A Python library used for data manipulation and analysis. In this research, it was used extensively for data cleaning, transformation, and the preparation of datasets for modeling.
- NumPy: A Python library used to perform high-level mathematical functions.
- Scikit-learn: This Python library is used for data normalization, scaling, and dataset splitting.
- Keras / Tensorflow: The open-source software, Keras, and TensorFlow are used to build machine learning models and for hyperparameter tuning.

CHAPTER IV
DATA ANALYSIS AND RESULTS

4.1 Data Preparation

Data preparation is a crucial step in the implementation of machine learning algorithms, as it directly influences the effectiveness and accuracy of the predictive models. The integrity of the data, ensured by a comprehensive and error-free collection process, set the stage for a seamless transition into the preprocessing phase (Bounid, et al., 2022). This section outlines the preprocessing steps, normalization techniques, and feature selection process utilized in the study of predicting Nepal's stock market.

4.1.1 Dataset Description

The dataset used in this study consists of two primary datasets: the daily NEPSE index data and the monthly economic indicators. The NEPSE index dataset includes columns such as Open, High, Low, Close, Change, Change percentage (%), Turnover, and Date (AD). On the other hand, the monthly economic data, sourced from Nepal Rastra Bank's monthly report, comprises Date, Total Deposit/GDP, Total Credit/GDP, Total Credit/Total Deposit, Total Liquid Asset/Total Deposit, Interest on Savings, Interest on Fixed Deposit, and Interest on Credit. Additionally, monthly remittance information from Sharesansar was integrated into the economic dataset. The dates in the economic report were presented in the Bikram Sambat (BS) calendar format.

4.1.2 Date Conversion and Merging

The first step in data preparation involved handling date-related issues. The dates in the monthly economic indicator sheet were initially in the Bikram Sambat (BS) calendar format, which needed to be converted to the Gregorian calendar (AD) to align with the NEPSE index data. This conversion ensured that all data points could be linked correctly based on their dates.

Once the date conversion was completed, the next step was merging the monthly economic data with the daily NEPSE index data. The integration of the economic indicators with the daily stock market data was an essential step to perform comprehensive analysis and prepare data for machine learning algorithms.

4.1.3 Inclusion of Technical Indicators

The dataset was then enriched by the inclusion of several technical indicators. These indicators, pivotal for advanced stock market analysis, comprised the Moving Average Convergence Divergence (MACD), MACD Signal Line, Relative Strength Index (RSI), Money Flow Index (MFI), and Average True Range (ATR).

4.1.4 Date Column Handling

After merging the datasets and calculating technical indicators, it was essential to address any redundant or unnecessary columns to streamline the dataset. In this context, redundant date columns, such as 'Date (AD)' and 'Date (BS),' were removed. The primary focus was on retaining only the month number in the BS calendar to align with Nepal's fiscal calendar. This simplification of date columns reduced redundancy and made the dataset more concise.

4.1.5 Feature Set Finalization

The final dataset was carefully curated to include a comprehensive set of features that would be relevant for analysis and modeling. The columns in the finalized dataset included 'Open,' 'High,' 'Low,' 'Close,' 'Change,' 'Percentage Change (%),' 'Turnover,' 'Total deposit/GDP,' 'Total credit/GDP,' 'Total credit/Total deposit,' 'Total liquid asset/total deposit,' 'Interest on Savings,' 'Interest on fixed deposit,' 'Interest on credit,' 'Remittance,' 'Month,' 'MACD,' 'MACD Signal,' 'RSI,' 'MFI,' and 'ATR.'

4.1.6 Data Normalization

The dataset's preprocessing did not necessitate handling missing values, as the data for the chosen dates was complete. Instead, attention was given to ensuring the quality and uniformity of the data. This involved verifying the accuracy of each entry and confirming that all numerical values conformed to a consistent format. One important step in data preprocessing was data normalization. This step incorporated two pivotal normalization techniques to prepare the data for the predictive models:

One-Hot Encoding: The 'Month' attribute was treated as a categorical variable, representing the month for each data point. Through one-hot encoding, this attribute was converted into a binary matrix, effectively segregating each month as a distinct, independent feature. This transformation is critical as it neutralizes any inherent ordinal bias that numerical representation might impose, ensuring that the model perceives each month as uniquely contributing to the stock market dynamics without any artificial hierarchy.

Min-Max Scaling: For continuous numerical variables, including daily trading figures (Open, High, Low, Close, Change, Turnover) and technical indicators (MACD, RSI, etc.), along with macroeconomic variables, min-max scaling was applied. This technique recalibrates the data to a fixed range from 0 to 1. Such scaling is pivotal in machine learning applications; it prevents variables with larger numerical ranges from disproportionately influencing the model. By normalizing the values, each feature can contribute to the analysis based on its underlying pattern rather than its scale, ensuring equitable treatment across all data points.

4.1.7 Data Organization for Feedforward ANN

To prepare the data for a simple two-layer feedforward ANN model, a specific structure was created. A window of 60 days of features was defined, with the 61st day's closing price as the output variable. This approach allowed the models to learn patterns and relationships in the data by considering a historical window of 60 days. As a result, the data was reorganized into a format where each row represented a set of 60 days' worth of features, and the corresponding output was the closing price on the 61st day.

This restructuring resulted in a dataset with 4653 rows and 1981 columns, with each column representing a specific feature for a specific time step.

4.1.8 Data Splitting

To facilitate model training and evaluation, the dataset was split into three distinct subsets: training, validation, and test sets. For this, the data was divided into the following proportions: 60% for training, 20% for validation, and 20% for testing. This division ensured that the models could be trained on a sufficiently large portion of the data, validated on a separate subset to fine-tune their performance, and ultimately tested on unseen data to assess their generalization capabilities.

4.1.9 Data Reshaping for LSTM and GRU

For models that require sequential input, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), the data needed to be reshaped into a format suitable for sequential modeling. In these cases, the data was reshaped to ensure that it had the shape of (samples, time steps, and features). This reshaping allowed the LSTM and GRU models to consider the temporal dependencies in the data and make predictions based on sequences of features.

4.2 Experiment Results

The experiment results section is critical for evaluating the effectiveness of the proposed model. This section meticulously presents the outcomes of the conducted experiments while also offering a transparent and comprehensive review to the readers.

4.2.1 ANN Model

The Feedforward ANN model is characterized by its layers of interconnected nodes. This interconnectedness requires a specific setting of hyperparameters. Shah et al. (2018) emphasized the importance of hyperparameter optimization in ANNs for stock market predictions. The designed feedforward network consists of two dense, and two dropout layers. The number of neurons in each dense layer is a critical hyperparameter that can affect the network’s ability to model complex relationships in the data (Soon, et al., 2018). Additionally, the dropout rate is another crucial hyperparameter implemented on dropout layers to prevent overfitting, which allows the model to generalize better to unseen data (Gan, et al., 2018). These hyperparameters, along with the learning rate—which dictates the speed at which the model learns—must be carefully determined to enable the feedforward network to achieve high accuracy and generalization capabilities.

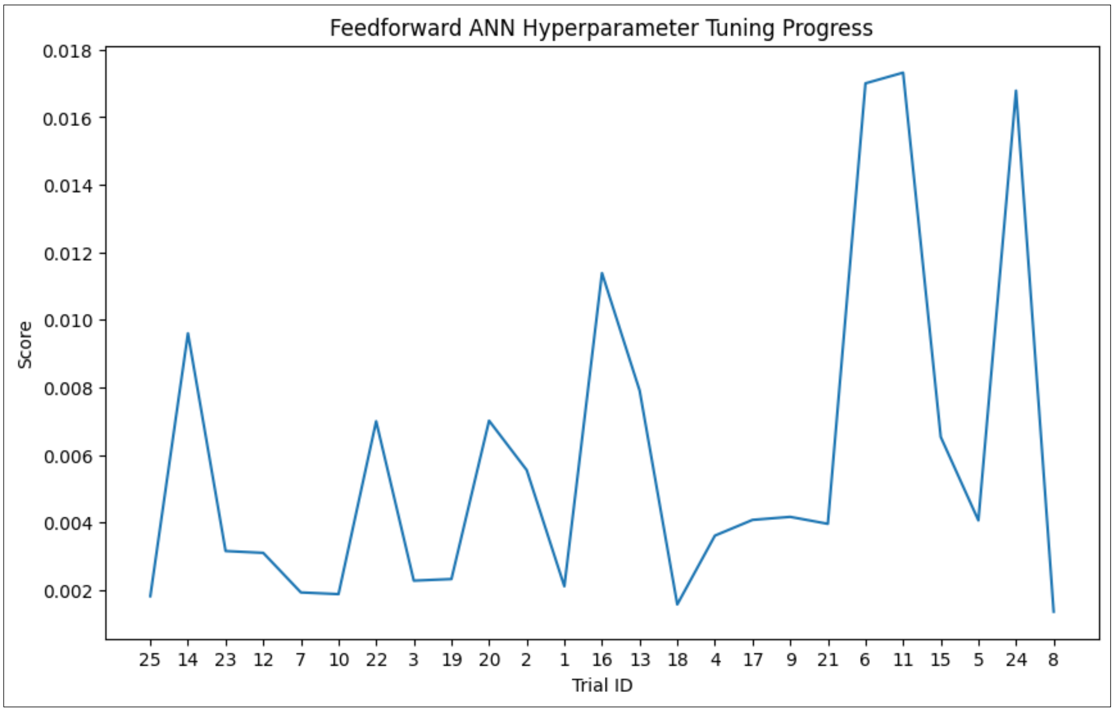

Figure 7 Hyperparameter tuning for feedforward ANN model

Source: Author computation (2023)

The progress of hyperparameter tuning is demonstrated in the graph (fig 7), indicating an iterative search for the optimal settings. The x-axis, labeled "Trial ID," represents different combinations of hyperparameters tested during the tuning process, and the y-axis, labeled "Score," indicates the loss of the model for each trial. The graph indicates multiple trials, with peaks and troughs representing the performance scores of various hyperparameter combinations.

After extensive testing, the ideal settings for the model were determined:

- The first layer of the model was set with 448 points, and the second layer with 480.

- Dropout rates, which prevent the model from overly depending on any single piece of information, were established at 0.0 for the first layer and 0.1 for the second.
- The learning rate was set at 0.001, ensuring effective learning without the risk of errors.

The model was then trained on a combined dataset of train and validation sets. During this process, the model's loss was monitored using its loss function, mean squared error. Initially, the loss decreased rapidly, indicating swift learning. Later, the error amount stabilized, suggesting that the model had reached its learning potential with the given data.

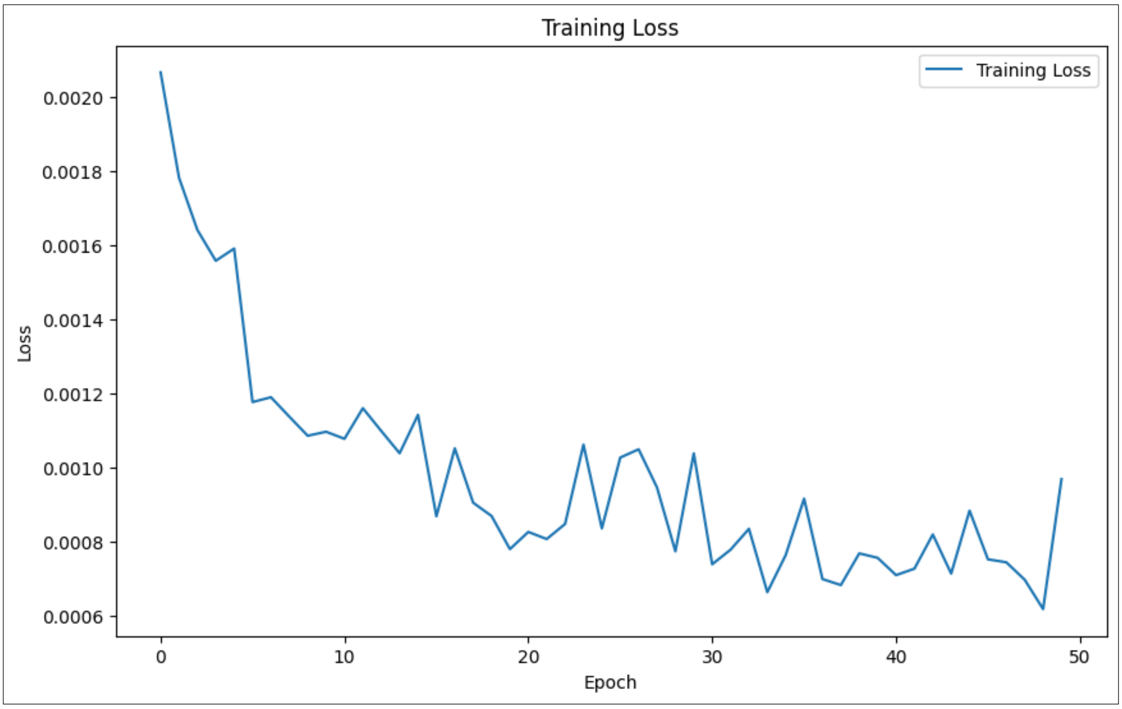

Figure 8 Training loss of feedforward ANN model

Source: Author computation (2023)

When tested, the model demonstrated impressive accuracy:

- The test loss was a mere 0.00065, indicating that the model's predictions were extremely close to the actual stock market figures.

- An R^2 score of 0.99102 was achieved, indicating that the model could explain over 99% of the variations in the stock market.
- The Mean Absolute Error (MAE) stood at 0.01900, suggesting that, on average, the model's predictions were very near to the actual values.
- The Root Mean Squared Error (RMSE) was calculated to be 0.02559, further affirming the model's capability to make predictions closely aligned with real data.

4.2.2 LSTM Model

The Long Short-Term Memory (LSTM) model is a type of recurrent neural network (RNN) designed to process sequences of data, capturing temporal dependencies. Unlike the Feedforward ANN model, LSTMs have feedback connections that make them capable of both retaining information over time and selectively remembering or forgetting details. The designed LSTM network has two LSTM layers and one dropout layer in between them.

Hyperparameter tuning is as critical in LSTMs as it is in ANNs, as it directly impacts the model's ability to learn from and make predictions on time-series data. The configuration involves determining the number of LSTM units in each layer, which controls the capacity of the model to represent the data's complexity. Studies like Samarawickrama and Fernando (2017) highlight the importance of this optimization in the context of financial markets.

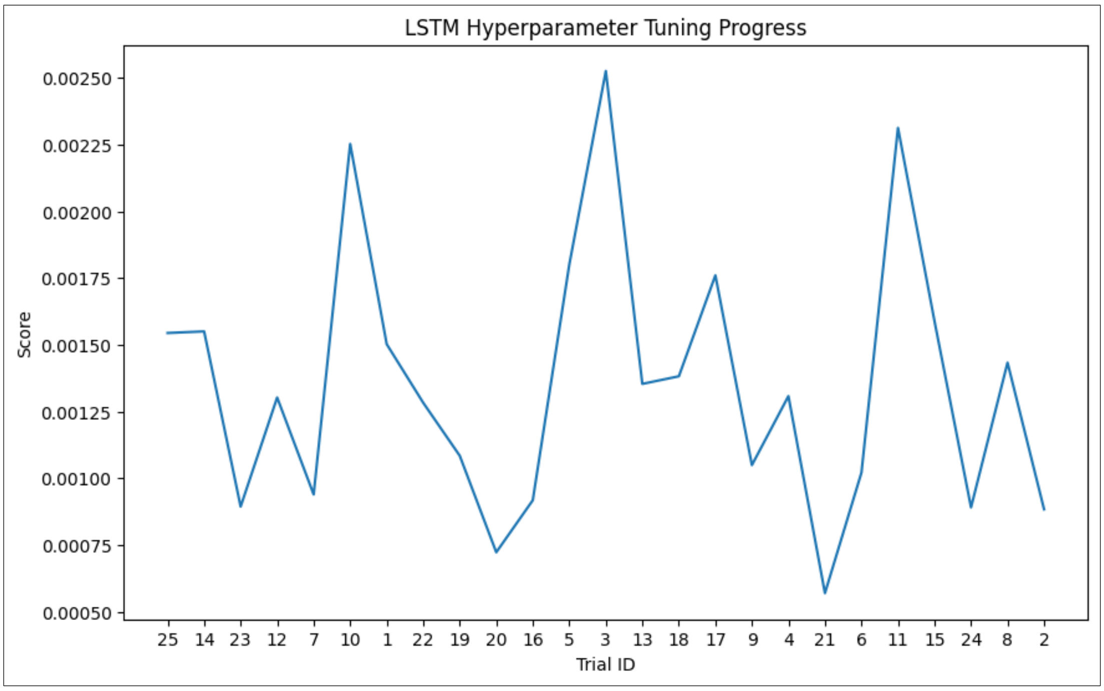

Figure 9 Hyperparameter tuning of LSTM model

Source: Author computation (2023)

The iterative process of hyperparameter tuning for LSTMs is visualized in a graph (fig 9), where each point represents a trial with a specific set of hyperparameters. The "Trial ID" on the x-axis indicates the trial number, and the "Score" on the y-axis reflects the model's prediction error, mean squared error. In the figure, peaks indicate trials where the model's performance was not optimal, and troughs suggest more favorable outcomes.

After an extensive process of hyperparameter tuning, depicted in the graph, the optimal configuration for the LSTM model was determined to be:

- LSTM Layer 1 Units: 160, which defines the capacity of the first layer in processing the sequence data and capturing the temporal dependencies.
- LSTM Layer 2 Units: 160, ensuring that the second layer has the same capacity as the first, which can be crucial for maintaining and refining the temporal information extracted by the first layer.

- Dropout Rate: 0.0, indicating that no units were dropped during the training process, suggesting that the model fully utilizes its learning capacity at each iteration.
- Learning Rate: 0.0099, a value that balances the speed of convergence with the stability of the learning process, allowing the model to adjust its weights efficiently without overshooting the minimum loss.

Following the hyperparameter optimization, the LSTM model was trained on a dataset that combined the training and validation subsets. Throughout this phase, the model's loss was carefully monitored using the same mean squared error metric.

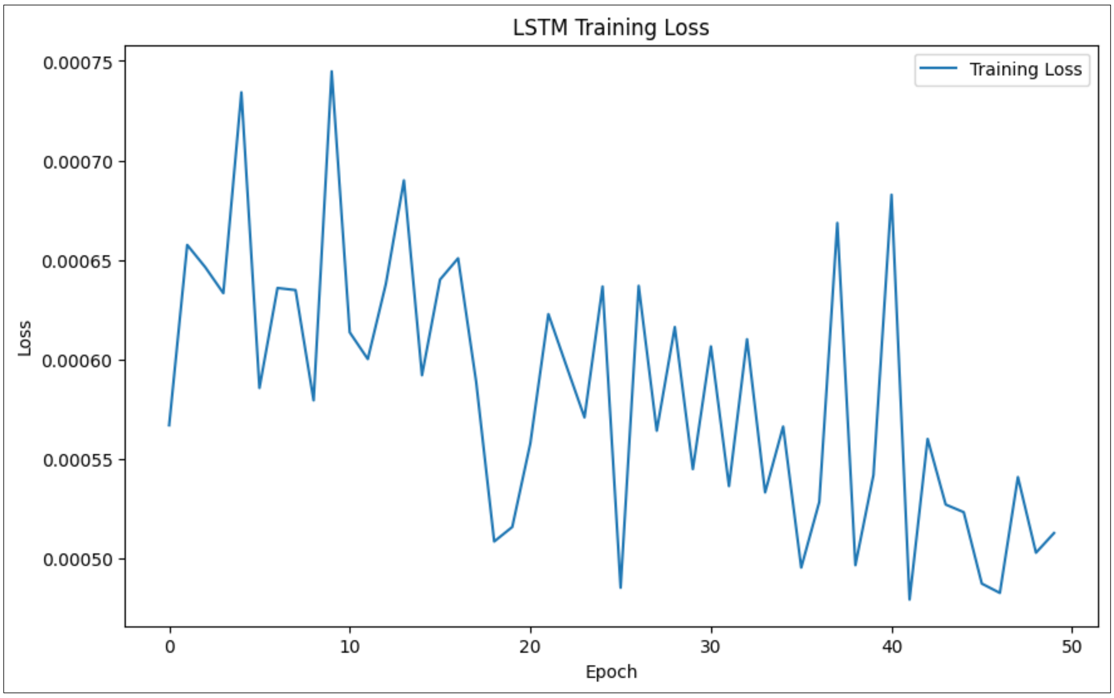

Figure 10 Training loss of LSTM model

Source: Author computation (2023)

From the above graph (fig 10) of training loss, we observe that the loss fluctuates as the number of epoch increases. The loss experiences some variability after the initial learning period, with peaks and troughs that indicate the model's responses to the complexity of the data. Despite the variability, there is a general trend where the loss seems to be stabilizing. It implies that as the model sees the data multiple times, it starts to converge on a solution and makes less dramatic improvements.

When evaluated on a test dataset, the model showed remarkable precision in its predictions:

- The test loss was low at 0.00056, signifying predictions that closely match the actual stock market figures.
- An R^2 score of 0.99229 demonstrates the model's ability to explain over 99% of the variance in the stock market.
- The Mean Absolute Error (MAE) was recorded at 0.01096, indicating precise average predictions.
- The Mean Squared Error (MSE) was also low at 0.00056, echoing the model's accuracy.
- The Root Mean Squared Error (RMSE) was calculated to be 0.02371, confirming the model's effectiveness in prediction.

4.2.3 GRU Model

Gated Recurrent Unit (GRU) models, akin to Long Short-Term Memory (LSTM) networks, are a variant of recurrent neural networks that excel in processing sequences of data. GRUs simplify the LSTM design by combining the forget and input gates into a single "update gate" and by merging the cell state and hidden state. Just as with Long Short-Term Memory (LSTM) models, hyperparameter tuning is paramount for Gated Recurrent Unit (GRU) models, particularly when applied to the domain of time-series forecasting. They are designed to capture temporal dependencies effectively, often requiring fewer parameters than LSTMs, which can make them more efficient in certain scenarios.

The process of hyperparameter tuning in GRUs involves fine-tuning various settings that dictate the model's performance. One crucial hyperparameter is the number of GRU units in each layer, which determines the model's capacity to capture and represent the complexity of the dataset. The appropriate number of units is essential to enable the GRU to model the intricate patterns within time-series data efficiently.

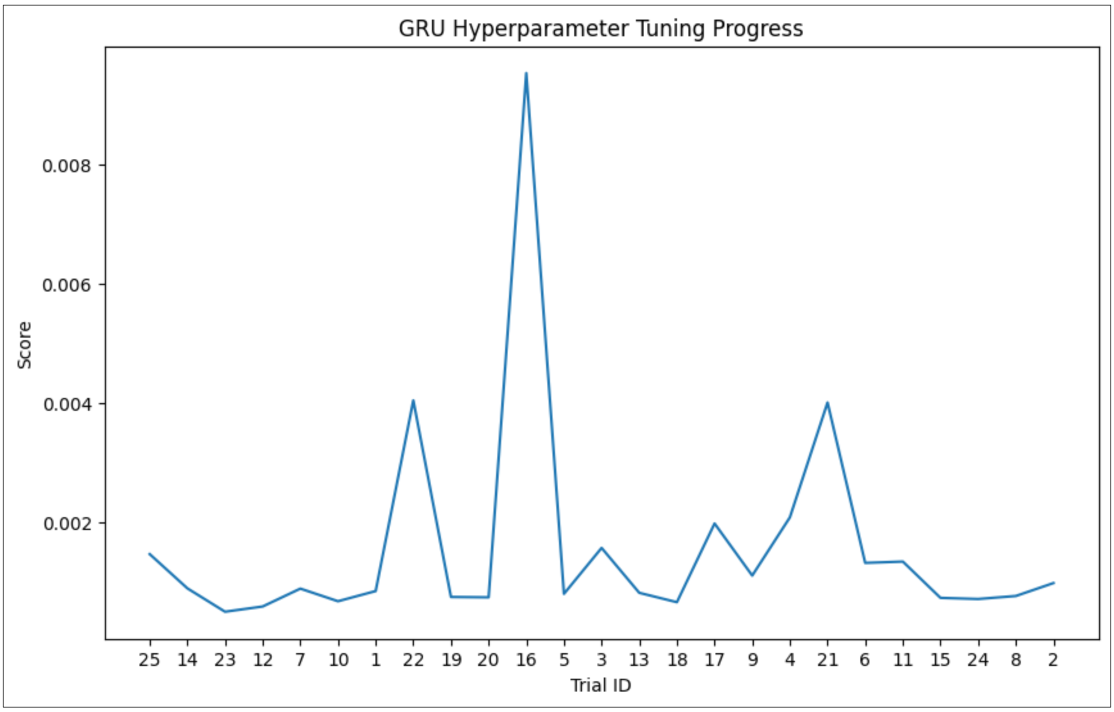

Figure 11 Hyperparameter tuning for GRU model

Source: Author computation (2023)

The graph (fig 11) illustrates the process of hyperparameter tuning for a GRU (Gated Recurrent Unit) model, where each point indicates a specific combination of hyperparameters tested. The peaks are the hyperparameter combinations that resulted in a higher score, which typically means the model predictions were less accurate for that set of hyperparameters. Similarly, troughs highlight the trials where the model achieved a lower score, representing the most successful hyperparameter combinations.

The result of rigorous hyperparameter testing for the GRU model was as follows:

- GRU Layer 1 Units: 96, outlines the number of memory units for the initial GRU layer, balancing the model's complexity and computational efficiency.
- GRU Layer 2 Units: 96, ensures that the subsequent GRU layer matches the first in terms of capacity, potentially aiding in refining the temporal information processed by the model.

- Dropout Rate: 0.0 means no units are omitted during the training phase, thus allowing the model to leverage the full potential of the data provided.
- Learning Rate: Set at 0.001, a rate that is often used as a starting point for many models and can contribute to stable convergence during the training process.

After fine-tuning the hyperparameters, the model training loss was closely observed, using the mean squared error metric to gauge how well the model was learning and making predictions.

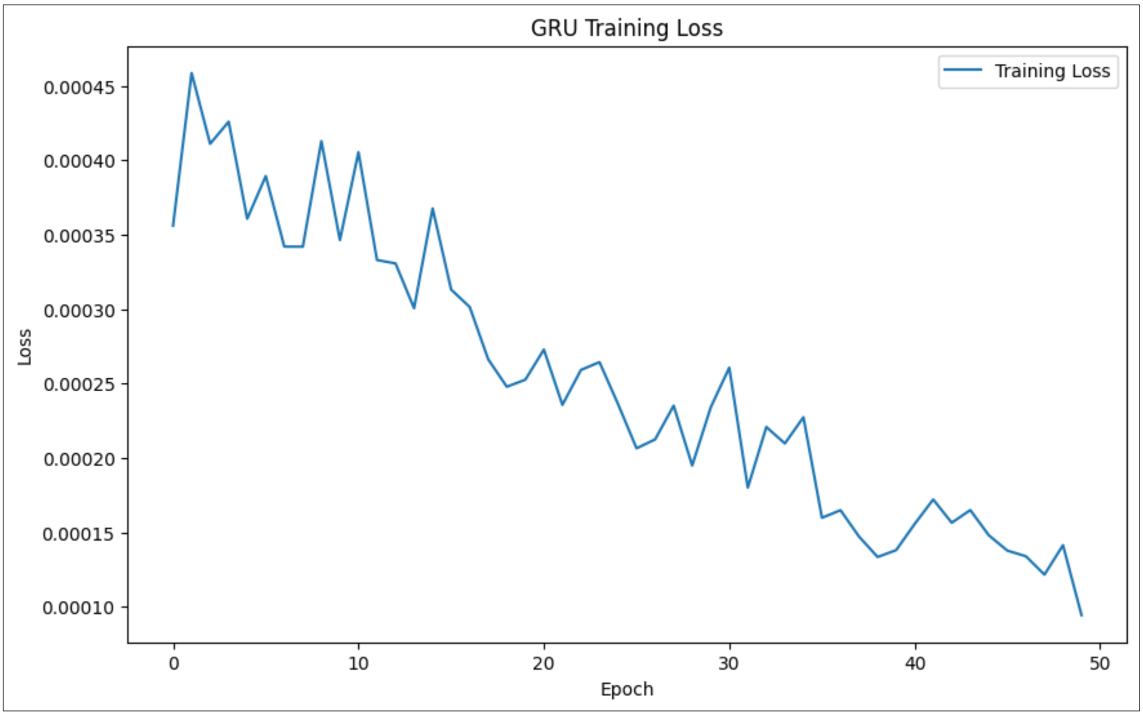

Figure 12 Training loss of GRU model

Source: Author computation (2023)

The graph (fig 12) displays the training loss for a Gated Recurrent Unit (GRU) model over numerous epochs. As the epochs progress, the graph shows the loss starting high and then generally trending downwards.

Here's what we can infer from the graph:

- Variability in Loss: There's a noticeable up-and-down pattern in the loss across epochs. This could be the model adjusting to the data, learning certain features and patterns as it iterates.
- Downward Trend: Despite the ups and downs, there is a clear overall downward trend in the loss. This indicates that the GRU model is learning from the data, and with each epoch, it's getting better at predicting the target variable.
- Stabilization of Loss: As the epochs increase, the loss decreases and begins to level out, suggesting that the model is reaching a point of stability. This often means the model is starting to find the best version of itself for the data it has been given.
- Final Epochs: By the last epochs, the loss is much lower than at the start, although it still shows some minor fluctuations.

Upon testing, the GRU model's performance on the test dataset revealed high accuracy in its forecasting ability:

- The test loss was remarkably low at 0.00021, suggesting that the model's predictions were highly consistent with the actual figures from the stock market.
- An R^2 score of 0.99716 indicates that the model could explain approximately 99.72% of the variance within the stock market data, indicating a very high level of predictive power.
- The MAE stood at 0.00985, showing that, on average, the model's predictions were extremely close to the actual values.
- The MSE was also quite low at 0.00021, mirroring the test loss and emphasizing the precision of the model's predictions.
- The RMSE was calculated at 0.01438, which, given its closeness to zero, affirms the model's accuracy in forecasting the data.

4.3 Evaluation and Comparison

Table 2 Evaluation of machine learning models

Metrics	Machine Learning Models		
	Feedforward ANN	LSTM	GRU
Test loss	0.00065	0.00056	0.00021
R-squared score	0.9910	0.99229	0.99716
Mean Absolute Error	0.0190	0.01096	0.009848
Root Mean squared Error	0.02559	0.0237	0.01438

Source: Author's computation (2023)

The performance of machine learning models is typically evaluated on several metrics that offer insight into their predictive capabilities. This section assesses the ANN, LSTM, and GRU models across four metrics: test loss, R-squared score, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

Test loss: Test loss quantifies the error between the predicted values and the actual values during the evaluation of the model on the test dataset. Lower values indicate a model with better predictive accuracy. In comparison, the GRU model outperforms with the lowest test loss of 0.00021, suggesting a highly accurate model for the data it was tested on. This is followed by the LSTM model with a test loss of 0.00056 and the Feedforward ANN with 0.00065. The smaller test loss in recurrent models like LSTM and GRU indicates their superior ability to capture temporal dependencies in the data (Goodfellow, Bengio, & Courville, 2016).

R-squared Score: The R-squared score measures the proportion of variance in the dependent variable that is predictable from the independent variables, with a range from 0 to 1. The closer the score is to 1, the better the model's predictions match the actual data. The LSTM model exhibits a remarkable R-squared score of 0.99229, followed closely by the Feedforward ANN at 0.9910, and then the GRU at 0.99716. These high scores indicate that all models have a strong predictive power, with LSTM slightly leading, implying its effectiveness in the context of the problem being solved (Zhang et al., 2018).

Mean Absolute Error (MAE): MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It provides a straightforward average of error magnitudes, offering a clear measure of prediction accuracy without emphasizing outlier effects. When expressed as a percentage, MAE reflects the average error relative to the standardized range of the dataset, which in this context has been normalized between 0 and 1. This percentage is particularly informative because it conveys the magnitude of prediction errors in easily understandable terms, even for those who may not have a deep background in statistical analysis.

The GRU model achieves the lowest MAE at 0.009848, indicating its predictions deviate from the actual values by an average of just 0.9848% in the context of the standardized data. This suggests a high degree of accuracy, with the model's predictions closely aligning with the true values on average. The relatively small MAE percentage emphasizes the GRU model's precision and reliability in predictive tasks.

In comparison, the LSTM and Feedforward ANN models show slightly higher MAE percentages of 1.096% and 1.9%, respectively. Although these values represent a strong predictive performance, the higher percentages suggest these models have a greater average deviation from the actual values compared to the GRU model. While still effective, the LSTM and Feedforward ANN may not match the precision offered by the GRU, according to the MAE metric.

Root Mean Squared Error (RMSE): The Root Mean Squared Error (RMSE) is a widely used measure to assess the accuracy of a model's predictions. It does so by quantifying the square root of the average squared differences between the predicted and actual values. However, interpreting RMSE values directly can be challenging, particularly for those not deeply versed in statistical metrics. This is where, like in MAE, the percentage representation of RMSE becomes invaluable. Representing RMSE as a percentage is particularly insightful as it provides a standardized measure of error across models, making comparisons more intuitive and understandable.

The GRU model showcases the lowest RMSE of 0.01438, which translates to a remarkable 1.438% when assessed in percentage terms against the standardized range of data. This low percentage implies that, on average, the GRU model's predictions are within 1.438% of the actual values, affirming the model's precise predictive capability within a normalized scale. The small RMSE value highlights the GRU's effectiveness in not only fitting the data but also in its robustness against outlier influences, which can significantly skew predictions.

In contrast, the LSTM and Feedforward ANN models present higher RMSE values of 0.0237 and 0.02559, corresponding to 2.37% and 2.559% in percentage terms, respectively. While these percentages are still indicative of a strong fit—especially given the standardized scale—they suggest that these models, particularly the Feedforward ANN, may be slightly less accurate in their predictions compared to the GRU model.

4.4 Findings

The aggregation of performance measures paints a detailed portrait of each model's strengths and weaknesses when applied to the standardized NEPSE index data.

The GRU model emerges as a frontrunner, boasting the lowest test loss and RMSE, coupled with a high R-squared score. This suggests not only its adeptness at minimizing prediction errors but also its capacity to explain a significant portion of the variance observed in the data. The low RMSE, 1.438%, corroborates its precision and its robustness in handling outlier data, which can often mislead models. Such a small error percentage is indicative of the GRU's high reliability, especially in applications where even minor prediction errors can have substantial repercussions.

On the other hand, the LSTM model, while slightly trailing behind the GRU in terms of RMSE and MAE, exhibits a marginally better R-squared score. This nuanced difference indicates that while the LSTM is exceptionally capable of capturing the variance in the dataset, it may not be as effective as the GRU in consistently maintaining low prediction errors across the board. Nevertheless, its performance is still impressive and points to its usefulness in complex time-series predictions where understanding long-term patterns is crucial.

The Feedforward ANN, despite its simplistic architecture relative to the other two models, demonstrates commendable predictive capabilities. It holds its ground with respectable scores across all metrics, suggesting that traditional neural network structures can still be valuable in forecasting tasks. Although its error percentages are higher, indicating less precision, it could serve well in scenarios where interpretability and model simplicity are prioritized.

The aggregated analysis of these machine learning models suggests a hierarchy in their performance, with the GRU model standing out for its accuracy and consistency. The LSTM and Feedforward ANN, while slightly less precise, offer their unique advantages in modeling complex patterns and providing simpler, more interpretable predictions, respectively. This comprehensive evaluation is instrumental for practitioners to discern which model aligns best with their specific predictive needs, especially in the nuanced and often unpredictable domain of financial forecasting.

CHAPTER V

DISCUSSION, CONCLUSION, AND IMPLICATIONS

5.1 Discussion

In this research, the application of Artificial Neural Networks (ANN), Gated Recurrent Unit (GRU), and Long-Short Term Memory (LSTM) algorithms for forecasting the Nepal Stock Exchange (NEPSE) index is explored. The outcomes are significant in understanding the efficacy of these machine learning techniques in a less-explored market like Nepal. These findings contribute to the broader field of AI in financial forecasting.

Our findings resonate with existing literature, which indicates the growing effectiveness of machine learning models in predicting stock market trends. Studies reviewed suggest a strong potential for feedforward ANN, GRU, and LSTM in various global markets because of their capacity for handling nonlinear and complex market data. However, our research diverges in focusing on the Nepalese market, a context less represented in the existing literature. This market-specific approach provides new insights into how these algorithms perform under different economic and market conditions.

Methodologically, our approach mirrors several reviewed studies by employing data normalization and time-series analysis. The robustness of our models was tested against historical data, ensuring a comprehensive understanding of market dynamics. However, we acknowledge certain limitations, such as the reliance on historical data which may not fully capture future market uncertainties. Moreover, the unique economic factors influencing the NEPSE index necessitated adaptations in our algorithmic implementation, distinguishing our approach from others that primarily focus on more established markets.

5.1.1 Output Discussion

The analysis of the model outputs reveals a nuanced understanding of the predictive capabilities and efficiency of the implemented artificial intelligence models in forecasting the NEPSE index.

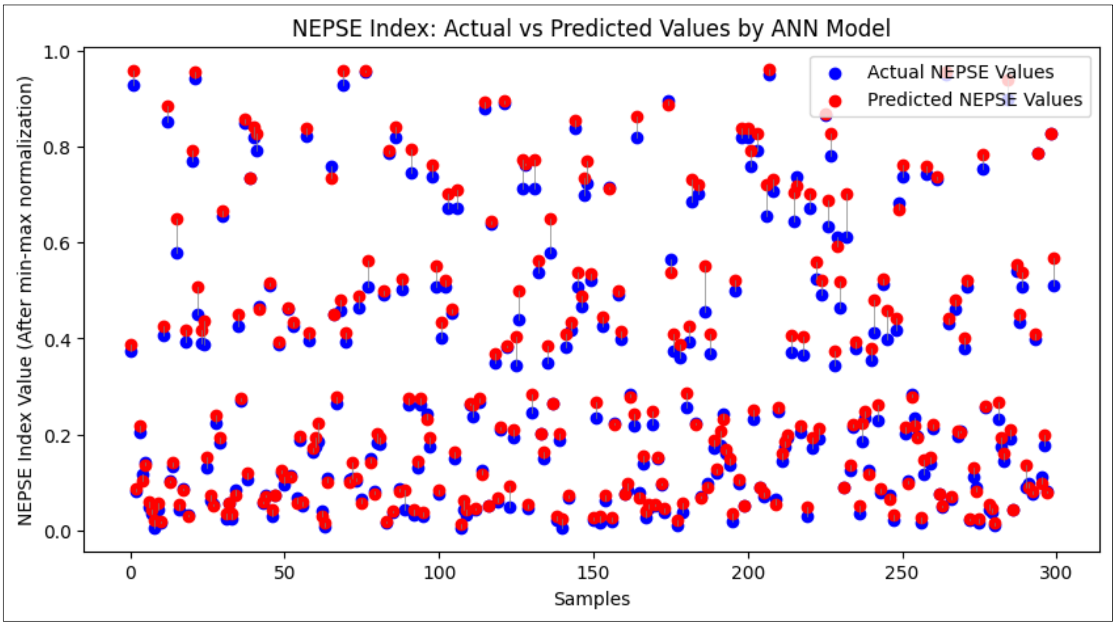

Figure 13 Actual vs predicted values of ANN Model

Source: Author computation (2023)

In figure 13, the proximity of the red dots to the blue dots indicates how close the predictions are to the actual values. A perfect prediction would have every red dot directly on top of a blue dot. In the scatter plot, the line joining an actual NEPSE Index value (blue dot) to its corresponding predicted value (red dot) would illustrate the error for that sample, with the length of the line representing the magnitude of the prediction error.

The feedforward ANN model can predict the NEPSE Index to a certain degree; however, there is room for improvement. To enhance the prediction capability, the model may need refinements, or the data may require more thorough preprocessing.

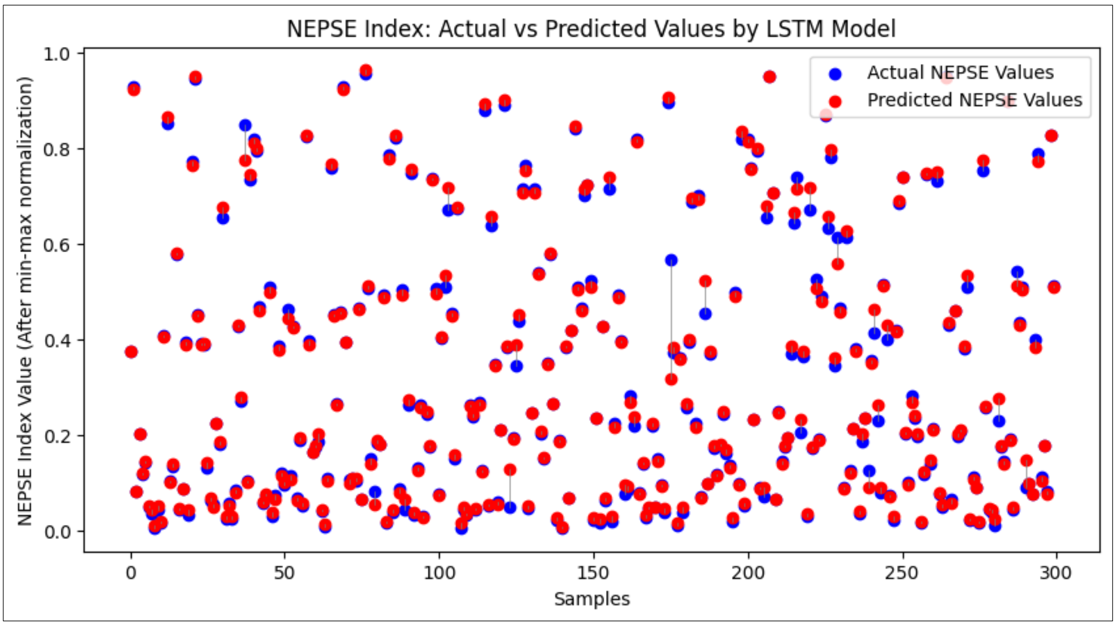

Figure 14 Actual vs predicted values of LSTM model

Source: Author computation (2023)

The scatter plot (fig 14) suggests that the LSTM model captures the general trend of the NEPSE Index but with notable prediction errors in some samples. The variability in the distance between the predicted and actual values indicates that the model's performance could be improved if trained for longer. Moreover, this model seems to have a degree of predictive ability regarding the NEPSE Index, as indicated by the clustering of predicted values around the actual values.

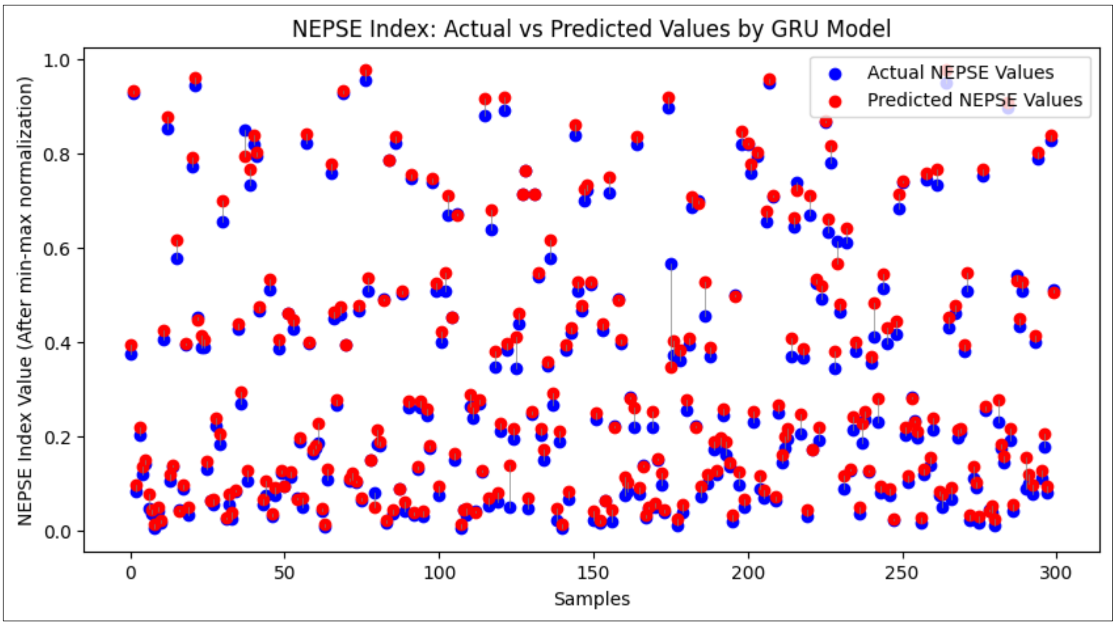

Figure 15 Actual vs predicted values of GRU model

Source: Author computation (2023)

Fig 15 displays a scatter plot that compares the NEPSE Index's actual values to those predicted by a GRU model, after min-max normalization. The plot shows varying degrees of closeness between the predicted (red) and actual (blue) values. Where the dots are closer, the model's predictions are more accurate. The accuracy of the model appears to vary across the dataset, with some predictions being quite close to the actual values and others showing more significant deviations. This variability and spread of the points could be due to the inherent noise in stock market data, possible overfitting or underfitting of the model, or the need for more complex features that capture the underlying trends more effectively.

5.1.2 Hypothesis Discussion

Hypothesis 1 (ANN outperforming LSTM and GRU): This hypothesis is rejected. Our ANN model showed substantial predictive capabilities with an MAE of 0.01900 and an RMSE of 0.02559. However, it did not outperform the GRU and LSTM models in terms of accuracy.

Hypothesis 2 (LSTM outperforming ANN and GRU): This hypothesis is partially accepted. The LSTM model's RMSE of 0.02371 and MAE of 0.01096 indicate its proficiency, especially in handling time-series data. It showed higher precision than ANN but was slightly outperformed by the GRU model.

Hypothesis 3 (GRU outperforming LSTM and ANN): This hypothesis is accepted. The GRU model demonstrated high accuracy and efficiency with an RMSE of 0.01438 and an MAE of 0.00985, standing out for its robust performance.

Table 3 Hypothesis results

S. No.	**Hypothesis**	**Decision**
1	Artificial neural networks have better accuracy than long short-term memory and gated recurrent units in predicting Nepal’s stock market.	Rejected
2	Long short-term memory has better accuracy than artificial neural networks and gated recurrent units in predicting Nepal’s stock market.	Partially Accepted
3	Gated recurrent units have better accuracy than long short-term memory and artificial neural networks in predicting Nepal’s stock market.	Accepted

Source: Author’s own creation (2023)

5.1.3 Comparison with other works

The study’s outcomes reveal distinctive strengths and limitations of each model. Comparing these findings with existing literature, the research underscores the growing importance of machine learning models in forecasting financial markets. The study's results align with previous works, highlighting the increasing reliability and precision of these algorithms.

Artificial Neural Network: The feedforward ANN model demonstrated an MAE of 0.01900 and an RMSE of 0.02559, showcasing substantial predictive capabilities. It maintained a balance between complexity and interpretability, suggesting its utility in scenarios where simplicity is prioritized. This model's performance becomes particularly notable when compared to the study by Selvamuthu, Kumar, and Mishra (Selvamuthu, et al., 2019), who applied ANNs to the Indian stock market and reported higher error rates. This suggests that our ANN model might have benefitted from more refined data preprocessing techniques or a more optimized network structure.

Long Short-Term Memory: The LSTM model achieved an RMSE of 0.02371 and an MAE of 0.01096, indicating its proficiency in capturing long-term temporal patterns. This effectiveness is highlighted when compared with the study by Fischer and Krauss (Fischer & Krauss, 2018), which, despite demonstrating the effectiveness of LSTM in stock market predictions, reported slightly higher error metrics. Moreover, Sakshi & Vijayalakshmi's (2020) study, which achieved an RMSE of 0.012 with LSTM, underscores the potential for even higher accuracy in LSTM models. These comparisons suggest that our LSTM model, while effective, might be further optimized for enhanced performance, particularly in the context of the NEPSE index.

Gated Recurrent Unit: The GRU model stood out for its high accuracy and low error rates. This study found it to be extremely effective, with an RMSE of 0.01438 and an MAE of 0.00985. Its performance is especially significant when compared to the work by Cho et al. (2014) and Liu et al. (2022). Cho et al. highlighted the general applicability of GRUs to time-series prediction, while Liu et al. used a complex model (NMC-BERT-LSTM-DQN-X) for forecasting China's stock market trends and reported an MAE of 0.104. The lower error rates of our GRU model underscore its efficiency and robustness, likely due to its simplified architecture and tailored adaptation to the specific dynamics of the NEPSE index.

5.2 Conclusion

In our research focused on the Nepal Stock Exchange, we implemented Artificial Neural Networks (ANN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) algorithms for forecasting the NEPSE index. The study revealed that the GRU model outshined others with its superior forecasting performance. Meanwhile, the LSTM model proved highly effective, particularly in processing and interpreting time-series data. The ANN model, though exhibiting notable predictive strength, did not perform as well as the other two. These outcomes collectively enhance the understanding of machine learning's applicability in stock market forecasting, especially in a market like NEPSE.

The hypothesis testing in the study revealed distinct performances of the machine learning models used. In the evaluation of the study's hypotheses, Hypothesis 1, which posited that Artificial Neural Networks (ANN) would outperform both LSTM and GRU, was not supported by the findings, indicating ANN's comparative limitations. Hypothesis 2, suggesting the superiority of Long Short-Term Memory (LSTM) over ANN and GRU, received partial support, acknowledging LSTM's effectiveness in certain scenarios but not its overall dominance. Finally, Hypothesis 3, proposing that the Gated Recurrent Unit (GRU) would excel beyond the capabilities of ANN and LSTM, was confirmed, highlighting GRU's superior performance in the context of the Nepal Stock Exchange.

This research makes a significant contribution to the field of AI in financial forecasting, particularly within the unique context of Nepal's market. It offers critical insights and benchmarks the efficacy of advanced machine learning algorithms like ANN, LSTM, and GRU, showcasing their capabilities in a distinctive economic environment like the Nepalese stock market. This study not only enhances the understanding of AI applications in emerging markets but also sets a precedent for future research in similar economic settings.

The study's findings both align with and offer new perspectives compared to existing literature. But, the limitations, particularly the reliance on historical data underscores the need for future research. Future directions include exploring various other models and integrating diverse data sources, aiming to enhance the forecasting accuracy and adaptability of these algorithms.

5.3 Implications

5.3.1 Practical Implications

This research on AI applications in financial forecasting, particularly within the Nepalese stock market, holds significant potential for various real-world scenarios. Its insights can be leveraged in diverse fields, ranging from financial analysis to economic policymaking. The finding also offers a blueprint for how emerging markets can harness AI for more informed and accurate decision-making processes in financial sectors.

The practical implications for using AI, especially ANN, LSTM, and GRU models, in stock market forecasting are profound. These models can provide more accurate predictions, helping to navigate the complexities and volatilities inherent in financial markets. Their ability to process vast amounts of data and identify patterns offers a substantial advantage over traditional forecasting methods.

For investors and financial analysts, these AI models present an opportunity to refine investment strategies and enhance portfolio management. The advanced predictive accuracy of these models aids in better risk assessment and identification of lucrative opportunities, playing a pivotal role in informed decision-making. This improved foresight is crucial for navigating the complexities and maximizing returns in the dynamic landscape of stock market.

Similarly, financial intermediaries and portfolio managers stand to gain substantially from these AI models. Their use in comprehensive market analysis and investment planning can lead to more effective portfolio diversification and risk management strategies. The enhanced prediction accuracy of machine learning algorithms enables these professionals to anticipate market shifts more accurately. This strategic application of AI tools aids in safeguarding investments against market volatility and ensuring better financial outcomes.

Policymakers and market regulators can also benefit from the insights provided by AI models in understanding and managing market dynamics. The application of ANN, LSTM, and GRU models in forecasting market trends offers a more nuanced view of market behavior, enabling the development of robust regulatory frameworks. These models' predictive accuracy facilitates the anticipation of market fluctuations, aiding in the formulation of policies that stabilize markets and enhance investor confidence. This is particularly relevant in emerging economies like Nepal, where market volatility is comparatively higher. Moreover, the insights can guide risk management strategies and help in making investor protection policies. The results can also assist in monitoring and responding to market anomalies. By leveraging AI's predictive capabilities, regulators can better safeguard the integrity of financial markets, promote sustainable growth, and build investors’ trust.

Overall, the study paves the way for varied stakeholders, from investors to policymakers, to harness the power of machine learning algorithms for more informed and strategic decision-making. Its implications extend beyond mere financial gains, contributing to a more stable, transparent, and efficient market environment. This research not only accomplishes the academic requirement but also provides practical solutions for real-world financial challenges, marking a significant step forward in the integration of technology and finance.

5.3.2 Implications of Future Research

Machine learning in financial forecasting, particularly within emerging markets, presents extensive research avenues for professionals and academic students. Future investigations could significantly expand upon this study by delving into the adaptability and performance of AI models under various market conditions. This exploration is crucial for understanding how these models can be tailored to different economic environments and market volatilities. It not only enriches academic knowledge but also has the potential for financial innovations, providing fertile ground for theoretical advancements and practical solutions in the field of finance.

A key area for future research involves refining these algorithms to incorporate real-time data sources, such as news feeds and social media sentiment. The integration of real-time information can drastically enhance the predictive accuracy of models like ANN, LSTM, and GRU. It allows these algorithms to account for immediate market influences, such as economic news, geopolitical events, and public sentiment shifts. This would enable a more dynamic and responsive approach to market analysis, leading to forecasts that are not only data-driven but also contextually aware and timely. This integration could bridge the gap between historical data analysis and current market realities, offering a more holistic view of market trends and movements.

Further research should also be conducted to test the performance of these machine learning models in various financial contexts, such as commodity markets, forex trading, or specific stock indices. Each of these markets has its unique characteristics and variables that influence trends and movements. Testing and tailoring these models to specific financial environments allows for a deeper understanding of their applicability and effectiveness. It helps in identifying the strengths and limitations of each model in different market scenarios, leading to more specialized and accurate forecasting tools. Such targeted research is essential for developing AI models that can adapt to and accurately predict the nuances of diverse financial markets.

It would also be beneficial to compare the performance of ANN, LSTM, and GRU models with other machine learning algorithms like Support Vector Machines (SVM) and transformers. Such comparative studies could reveal the strengths and limitations of different approaches, guiding the development of more advanced and efficient forecasting tools. SVMs, known for their effectiveness in classification tasks, could offer insights into market trend categorization, while transformers, renowned for handling sequential data, might provide advanced time-series analysis. These comparisons would help identify which models are best suited for specific forecasting scenarios. Understanding the strengths of each algorithm could lead to the development of more sophisticated and efficient forecasting tools, potentially enhancing performance in diverse financial market predictions.

The exploration of machine learning in financial forecasting, particularly in emerging markets like Nepal, has opened vast avenues for future research. This study has laid the groundwork for further investigation into the adaptability and performance of various machine learning models under varying market conditions.

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APPENDICES

Appendix I: Data Preprocessing

```python
import pandas as pd
import nepali_datetime

# Load the datasets
calendar_bs_path = 'calendar_bs.csv'
monthly_data_path = 'monthly data.xlsx'

# Read the datasets
calendar_bs = pd.read_csv(calendar_bs_path)
monthly_data_bs = pd.read_excel(monthly_data_path)

# Split the 'Date' column into 'Year' and 'Month' in the monthly data
monthly_data_bs[['Year', 'Month']] = monthly_data_bs['Date'].str.split('/', expand=True).astype(int)

# Define a function to get the Gregorian start and end dates for a BS month
def get_ad_dates(year, month, calendar):
    # Mapping BS month number to calendar_bs column names
    month_names = {
        1: "Baisakh", 2: "Jestha", 3: "Ashar", 4: "Shrawan", 5: "Bhadra",
        6: "Asoj", 7: "Kartik", 8: "Mangsir", 9: "Poush", 10: "Magh",
        11: "Falgun", 12: "Chait"
    }

    # Get the number of days in the BS month from the calendar
    days_in_month = calendar[calendar['Year'] == year][month_names[month]].iloc[0]

    # Convert the start and end of the BS month to Gregorian dates
    start_bs = nepali_datetime.date(year, month, 1)
    start_ad = start_bs.to_datetime_date()
    end_bs = nepali_datetime.date(year, month, days_in_month)
    end_ad = end_bs.to_datetime_date()

    return start_ad, end_ad

# Apply the function to each row in the monthly data
monthly_data_bs['Start_Date_AD'], monthly_data_bs['End_Date_AD'] = zip(*monthly_data_bs.apply(lambda row: get_ad_dates(r
```

Fig: Date conversion

```python
import numpy as np
import pandas as pd
from datetime import datetime
```

```python
# Paths to the data files
file_path_monthly_data = 'monthly data.csv'
file_path_nepse_index = 'NEPSEindex.csv'
```

```python
# Loading the datasets again
monthly_data = pd.read_csv(file_path_monthly_data)
nepse_index = pd.read_csv(file_path_nepse_index)
```

```python
# Converting the Start_Date_AD and End_Date_AD columns in monthly data to datetime objects
monthly_data['Start_Date_AD'] = pd.to_datetime(monthly_data['Start_Date_AD'])
monthly_data['End_Date_AD'] = pd.to_datetime(monthly_data['End_Date_AD'])
```

```python
# Converting the Date column in NEPSE index data to datetime objects
nepse_index['Date'] = pd.to_datetime(nepse_index['Date (AD)'])
```

```python
# Initializing a DataFrame to store the merged data
merged_data = pd.DataFrame()
```

```python
# Iterating over each row in the monthly data to merge with NEPSE index data
for index, row in monthly_data.iterrows():
    # Filtering NEPSE index data to include only the dates within the Start and End dates
    nepse_filtered = nepse_index[(nepse_index['Date'] >= row['Start_Date_AD']) & (nepse_index['Date'] <= row['End_Date_A

    # Adding the monthly data columns to the filtered NEPSE data
    for col in monthly_data.columns:
        nepse_filtered[col] = row[col]

    # Appending the result to the merged_data DataFrame
    merged_data = pd.concat([merged_data, nepse_filtered], ignore_index=True)
```

Fig: Dataset merging

```
# Ensure necessary columns ('Close', 'High', 'Low', 'Volume') are present
if set(['Close', 'High', 'Low', 'Turnover']).issubset(merged_data.columns):
    # MACD Calculation
    ema12 = merged_data['Close'].ewm(span=12, adjust=False).mean()
    ema26 = merged_data['Close'].ewm(span=26, adjust=False).mean()
    macd = ema12 - ema26
    signal = macd.ewm(span=9, adjust=False).mean()
    merged_data['MACD'] = macd
    merged_data['MACD_Signal'] = signal

    # RSI Calculation
    delta = merged_data['Close'].diff()
    gain = (delta.where(delta > 0, 0)).rolling(window=14).mean()
    loss = (-delta.where(delta < 0, 0)).rolling(window=14).mean()
    rs = gain / loss
    merged_data['RSI'] = 100 - (100 / (1 + rs))

    # MFI Calculation
    typical_price = (merged_data['High'] + merged_data['Low'] + merged_data['Close']) / 3
    money_flow = typical_price * merged_data['Turnover']
    positive_flow = money_flow.where(typical_price > typical_price.shift(1), 0)
    negative_flow = money_flow.where(typical_price < typical_price.shift(1), 0)
    mfi = 100 - 100 / (1 + positive_flow.rolling(window=14).sum() / negative_flow.rolling(window=14).sum())
    merged_data['MFI'] = mfi

    # ATR Calculation
    high_low = merged_data['High'] - merged_data['Low']
    high_close = np.abs(merged_data['High'] - merged_data['Close'].shift())
    low_close = np.abs(merged_data['Low'] - merged_data['Close'].shift())
    ranges = pd.concat([high_low, high_close, low_close], axis=1)
    true_range = ranges.max(axis=1)
    merged_data['ATR'] = true_range.rolling(window=14).mean()

    # Return the first few rows of the DataFrame with the new indicators
    merged_data.head()
```

Fig: Adding technical indicator

```
# Load the merged data
merged_data = pd.read_csv('merged data.csv')

min_val = merged_data['Close'].min()
max_val = merged_data['Close'].max()

# Normalizing the numeric columns using Min-Max Scaling
for column in merged_data_cleaned.select_dtypes(include=['float64', 'int64']).columns:
    if column != 'Month':
        min_val = merged_data_cleaned[column].min()
        max_val = merged_data_cleaned[column].max()
        merged_data_cleaned[column] = (merged_data_cleaned[column] - min_val) /
        (max_val - min_val) if max_val != min_val else merged_data_cleaned[column]

# Create 12 new columns for each month (1 for Baisakh, 2 for Jestha, etc.)
month_names = ['Baisakh', 'Jestha', 'Ashar', 'Shrawan', 'Bhadra', 'Asoj', 'Kartik',
               'Mangsir', 'Poush', 'Magh', 'Falgun', 'Chaitra']
for month in month_names:
    merged_data_cleaned[month] = (merged_data_cleaned['Month'] == (month_names.index(month) + 1)).astype(int)
merged_data_cleaned
```

Fig: Normalizing data

```
# Create 60-day windows with the 61st day's Close as output
for i in range(len(df) - 60):
    input_data = df.iloc[i:i+60].values.flatten()  # Include 'Close' in input
    output_data = df.iloc[i+60]['Close']           # 61st day's closing price
    organized_row = list(input_data) + [output_data]
    organized_data.append(organized_row)

# Generate column names for each feature across 60 days
column_names = [f"{feature}_Day{day}" for day in range(1, 61) for feature in df.columns] + ['Output']

# Convert to a DataFrame
organized_df = pd.DataFrame(organized_data, columns=column_names)

# Save the organized data
organized_df.to_csv('organized_final_data.csv', index=False)
```

Fig: Adding timestamp

```python
import pandas as pd
from sklearn.model_selection import train_test_split

# Load the organized data
df = pd.read_csv('organized_final_data.csv')

# Split the data into features (X) and target (y)
X = df.drop('Output', axis=1)
y = df['Output']

# First, split the data into a training set and a temporary set (combining validation and test)
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.4, random_state=42)

# Next, split the temporary set into validation and test sets
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)

# Save the train, validation, and test sets
train_set = pd.concat([X_train, y_train], axis=1)
val_set = pd.concat([X_val, y_val], axis=1)
test_set = pd.concat([X_test, y_test], axis=1)
```

Fig: Data splitting

Appendix II: Machine Learning Models

```python
# ANN model structure
def build_model(hp):
    model = Sequential()
    model.add(Dense(units=hp.Int('units_1', min_value=32, max_value=512, step=32),
                    activation='relu', input_shape=(1980,)))
    model.add(Dropout(rate=hp.Float('dropout_1', min_value=0, max_value=0.5, step=0.1)))
    model.add(Dense(units=hp.Int('units_2', min_value=32, max_value=512, step=32),
                    activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_2', min_value=0, max_value=0.5, step=0.1)))
    model.add(Dense(1))  # Output layer
    model.compile(optimizer='adam', loss='mean_squared_error')
    return model
```

```python
# Hyperparameter tuner
tuner = RandomSearch(
    build_model,
    objective='val_loss',
    max_trials=25,  # Number of trials
    executions_per_trial=5,  # Number of models to train per trial
    directory='my_dir',
    project_name='ann_tuning'
)

# Hyperparameter search
tuner.search(X_train, y_train, epochs=10, validation_data=(X_val, y_val))
```

Fig ANN Model

```python
# LSTM model structure
def build_lstm_model(hp):
    model = Sequential()
    model.add(LSTM(
        units=hp.Int('units', min_value=32, max_value=512, step=32),
        input_shape=(num_days, features_per_day),
        return_sequences=True))
    model.add(Dropout(hp.Float('dropout', min_value=0, max_value=0.5, step=0.1)))
    model.add(LSTM(units=hp.Int('units', min_value=32, max_value=512, step=32)))
    model.add(Dense(1))
    model.compile(
        optimizer=Adam(hp.Choice('learning_rate', values=[1e-2, 1e-3, 1e-4])),
        loss='mean_squared_error')
    return model
```

```python
tuner = RandomSearch(
    build_lstm_model,
    objective='val_loss',
    max_trials=5,
    executions_per_trial=2,
    directory='lstm_tuning',
    project_name='stock_prediction')

tuner.search(X_train_reshaped, y_train, epochs=10, validation_data=(X_val_reshaped, y_val))
```

Fig LSTM Model

```python
# GRU model structure
def build_gru_model(hp):
    model = Sequential()
    model.add(GRU(
        units=hp.Int('units', min_value=32, max_value=512, step=32),
        input_shape=(num_days, features_per_day),
        return_sequences=True))
    model.add(Dropout(hp.Float('dropout', min_value=0, max_value=0.5, step=0.1)))
    model.add(GRU(units=hp.Int('units', min_value=32, max_value=512, step=32)))
    model.add(Dense(1))
    model.compile(
        optimizer=Adam(hp.Choice('learning_rate', values=[1e-2, 1e-3, 1e-4])),
        loss='mean_squared_error')
    return model
```

```python
# hyperparameter tuner
tuner = RandomSearch(
    build_gru_model,
    objective='val_loss',
    max_trials=5,
    executions_per_trial=2,
    directory='gru_tuning',
    project_name='stock_prediction')

# hyperparameter search
tuner.search(X_train_reshaped, y_train, epochs=10, validation_data=(X_val_reshaped, y_val))
```

Fig GRU model

Appendix III: Proposal with Ethical Considerations Form

UNIVERSITY PARTNER

Academic Year	Module	Assessment Number	Assessment Type
S23	7MG001- The Masters Research Project	A1	Report

Research Proposal

on

Predicting Nepal's Stock Market Using Machine Learning Algorithms

University Student ID: 2223095
Student Name: Komal Niraula
Lecturer: Dr. Sudan Kumar Oli
Supervisor: Dr. Sudan Kumar Oli
Second Marker: Mr. Aadersh Joshi

Submitted On: September 15th, 2023

Word Count: 3198

<u>7MG001: Research Proposal</u>

Student Name: Komal Niraula

Student ID: 2223095

Provisional Topic Title: Predicting Nepal's Stock Market Using Machine Learning Algorithms

Introduction

1.1.Research context

Stocks are the most widely used financial instrument ever created for accumulating wealth (Poterba, 2000). The advancement in technology has made it possible for anyone to open a trading account and own the stocks (Tamrakar & Sahu, 2018). However, the market's unpredictability has led to substantial losses for many investors (Kolte, et al., 2023). Because of this, stock market predictions have become an important topic and have attracted researchers' attention for decades. The basic principle of stock market prediction is that historical information available to the public can be used to predict possible stock returns in the future (Al-Radaideh, et al., 2013). This information includes a variety of components, including economic indicators (such as interest rates and currency rates), sector-specific information (such as rates of industrial output growth and consumer prices), and information particular to individual companies (such as income statements and dividend yields) (Kolarik & Rudorfer, 1997).

The stock market behaviours have been captured using a variety of modelling techniques, with the two predictive spheres of technical analysis and fundamental analysis receiving most of the attention (Chowdhury, 2021). Technical analysis, which aims to forecast future price movements, is based on the idea that market activity reveals crucial new information and insights into psychological elements that affect stock values. The fundamental analysis focuses on monetary policies, government initiatives, and economic benchmarks like GDP, exports, and imports for market prediction (Nazir, et al., 2010).

This study focuses on applying artificial intelligence to forecast the stock prices of some of the companies at Nepal Stock Market. This method falls within the category of technical analysis of stock market. The underlying presumption in this situation is that forecasts can be generated using only stock price data and do not adhere to a random walk in which subsequent changes have zero association (Andrew W. Lo, 1988). The prices of stocks are predicted using Artificial Neural Networks (ANN), Gated Recurrent Unit (GRU), and Long-Short Term (LSTM) algorithms.

1.2 Statement of the problem

Stock market fluctuations can have substantial influence over both the economies and individuals. A decline in share price has the capacity to severely disrupt an economy's functioning. A prime example is the stock market crash of 1929, which served as the key reason for the great depression in 1930s (Romer, 1990). Conversely, when stock prices are high, companies are more inclined to initiate Initial Public Offerings (IPOs) to raise capital. Rise in mergers and acquisitions are also witnessed during this period. This heightened investment activity contributes to notable economic growth (Regmi, 2012).

Technological advancement has made it possible for anyone to open a trading account and own stocks. However, the unpredictable nature of the stock market has led to substantial financial losses for numerous individuals (Asgharian, et al., 2023). So, the question arises, what if investors possess the ability to accurately predict the fluctuation of a stock price?

In such a scenario, they would naturally invest all their resources in those stocks that are predicted to increase to gain maximum profit. However, predicting the fluctuation with 100% accuracy is not possible. What is feasible is making educated estimates and informed predictions based on historical and present data (Al-Radaideh, et al., 2013). For this, several mathematical models have been developed and tested. The recent development in artificial intelligence has surely increased the capacity to predict nonlinear approximations. These advancements have garnered interest from governments, industries, and academic circles, particularly within the realm of machine learning-an essential facet of artificial intelligence.

The problem addressed in this research revolves around the challenge of accurately predicting Nepal's stock market behaviour using machine learning algorithm. The central issue lies in developing effective prediction models that can utilize historical data to forecast future trends and stock prices accurately. The complexity of market dynamics, coupled with factors like economic indicators and company specific information, necessitates the exploration of advanced machine learning techniques to overcome the inherent unpredictability of the stock market in Nepal. This research aims to tackle the problem by applying and identifying the most robust machine learning algorithms and their accuracy in predicting the Nepal's stock market.

1.3 Significance

This study will examine stock data of Nepal Stock Exchange with a specific focus on applying linear regression machine learning models for predicting the stock prices. Furthermore, a comparative analysis will be conducted to evaluate the performance of the models. As a result, investors, researchers, and financial market enthusiast are likely to derive substantial value from the findings of this study.

1.4 Limitations

While this research has been thoughtfully designed and conducted with thorough exploration of the subject matter, there still are certain limitations that must be acknowledged. Actual stock prices are influenced by a myriad of external factors including trader sentiment, company filings and even extraordinary events like the Covid-19 pandemic. Not having the opportunity for direct interactions with regulators and stockbrokers has limited the depth of understanding on such factors. Lastly, it's important to recognize that this research is time-restricted and self-funded, relying heavily on secondary data.

Aims/objectives of the research followed by research questions:

The main objective of the study is:

- To predict Nepal's stock market using machine learning algorithms and compare the accuracy of those algorithms.

The following chapters will be used to achieve the aim of the study:

- Chapter 1: Introduction will provide the research background, problem statement, significance, and limitations of the research.
- Chapter 2: Literature review will explain the theoretical concepts and research works on the use of various machine learning algorithms for stock price predictions.
- Chapter 3: Methodology explains the data and used machine learning models.
- Chapter 4: Implementation and evaluation provides the accuracy of used machine learning algorithms.
- Chapter 5: Conclusion and recommendations will highlight the outcomes, determine the best model and provide recommendations for future research.

The hypothesis of the research are:

- H1: Artificial neural networks have better accuracy than long short term memory and gated recurrent network in predicting Nepal's stock market.
- H2: Long short term memory have better accuracy than artificial neural networks and gated recurrent network in predicting Nepal's stock market.
- H3: Gated recurrent network have better accuracy than long short term memory and artificial neural networks in predicting Nepal's stock market.

Brief Literature Review:

3.1 Introduction

This section comprises a comprehensive review of the existing literature, encompassing both theoretical and empirical perspectives.

3.2 Theoretical reviews

3.2.1 Stock Exchange

The term "stock market" refers to a platform of marketplaces and exchangers with frequent buying and selling activities involving shares that are publicly issued (Hiransha, 2018). There are two unique phrases used in the context of the stock market: "stock exchange" and "stock market," both of which refer to the official trading of assets. According to Ben Moews et al. (2019), a stock exchange is defined as a place where traders can buy and sell shares of one or more companies. There can be numerous stock exchange marketplaces on a national and international scale.

The only stock exchange in Nepal is called the Nepal Stock Exchange (NEPSE), where investors and traders can trade shares of different listed firms (Chalise, 2020). It plays a crucial role in the nation’s financial ecosystem by offering a transparent and well-organized capital market supporting Nepal's economic growth and creating investment opportunities (Baral, 2019).

3.2.2 Machine learning

A computer cannot gain intelligence on its own. The knowledge must be given either in a form that computer understands, or computer must be capable of learning on its own. Additionally, an intelligent computer system must be able to continuously improve its knowledge through real-world applications (T. Young, 2018). The process of training computers to gain human skills like learning, judging, and decision-making to emulate intelligent behaviour is known as machine learning (L. D. Xu, 2021). The core idea behind ML is the use of an algorithm whose performance is improved by the process of learning from data (Li Liu, 2020). It has shown impressive results in the field of speech recognition, machine translation, text generation, computer vision and the creation of intelligent robots.

ML algorithms has also been successfully applied in financial markets. Some of its applications are risk management, market forecasting and credit scoring. Through the embedding of AI, finance has entered a new era of innovation (Si Shi, 2022). Some of the companies in Silicon Valley are trying to apply ML algorithms to reduce the bar for people to adopt financial products (Caiming Zhang, 2021).

3.2.3 Machine Learning Algorithms

Artificial Neural Networks are the most used machine learning algorithms to predict stock market movements because of their accuracy in time series data (Dharmaraja Selvamuthu, 2019). Financial forecasting can be tagged as data-intensive, noisy, non-stationary, unstructured, and hidden relations (Parth Solanki, 2022). Other algorithms: gated recurrent unit and long short-term memory is known for being able to learn order dependence on sequence prediction problems (Do-Eun Choe, 2021). So, in this paper, we will be using ANN, GRU, and LSTM for stock market predictions.

3.3 Empirical reviews

As financial markets continue to evolve, the integration of technology, particularly machine learning, has garnered significant attention for its potential to enhance predictive capabilities. This review focuses on synthesizing and analyzing a collection of previous studies that have explored the application of machine learning algorithms to forecast stock market movements.

Moghaddam et al., (2016) explored the potential of Artificial Neural Networks (ANN) in forecasting the NASDAQ index. They constructed and validated two distinct networks for predicting the NASDAQ index. Their study incorporated short-term and historical stock prices, as well as daily data. The approach adopted by the researchers involved utilizing input parameters spanning the previous four to nine working days. Interestingly, the output of the model was found to be independent of the number of days used as inputs for the prediction process. This study underscores the potential of ANN as a predictive tool for stock market dynamics, particularly showcasing its prowess in handling intricate relationships within data. However, ANN can also have significant disadvantages like vanishing gradient problem and over fitting (Jihoon Moon, 2019).

The use of Gated Recurrent Unit (GRU) can overcome the problem of overfitting and vanishing gradient (Mohammad Obaidur Rahman, 2019). A 2019 study by Saud and Shakya examined the performance of various optimization techniques, including momentum, RMSProp, and Adam, in relation to the accuracy of stock price predictions made using Gated Recurrent Units (GRUs). The two stocks they concentrated on were traded on NEPSE. The study's findings showed that the GRU model using the Adam optimization technique had better accuracy and maintained consistent prediction performance (Arjun Singh Saud, 2019).

Long short term memory (LSTM) is regarded to be better than other algorithms in sequential task like predicting stock market (Yaping Hao, 2020). Zou and Qu (Zhichao Zou, 2020) conducted a study utilizing the daily prices and volumes of the top 10 S & P 500 stocks. The statistical data was collected between 2004 and 2013. The dataset was divided into three portions: 70% for training, 15% for development, and 15% for testing purposes. After evaluating four distinct models, it was discovered that the Long Short-Term Memory (LSTM) model performed better than the others. This advantage was ascribed to LSTM's better capacity to forecast financial time series since it can identify long-term dependencies in the time series data.

Shahi et al. (Tej Bahadur Shahi, 2020) conducted a comparative study with the objective of predicting stock prices through the gated recurrent unit (GRU) and long short-term memory (LSTM) models. They integrated financial news sentiments alongside stock features as input for stock market prediction. The authors theorized that adding sentiment data from financial news to the predictive process would improve the performance of deep learning models in stock market prediction.

Methodology:

4.1. Data

This research considers both the conventional data like fundamental, technical, and macroeconomic information along with sentiment analysis of news for stock market prediction. The data is collected from fiscal year 2073/74 to fiscal year 2079/80.

List of data for the model:

Fundamental (Daily): Open price, High price, Low price, Close price, Volume

Macroeconomic (Monthly): Remittance, Inflation rate, Government revenue, Government expenditure, Total credit/Total deposit (%), Total liquid asset/Total deposit(%), Weighted average interest rate – Savings (%), Weighted average interest rate – Fixed (%), Weighted average interest rate on credits (%)

Technical indicator (Daily): Moving average convergence divergence (12, 26, 9 period), Relative strength index (14 period), Money flow indicator (14 period), Average true range (14 period)

Company news (Based on latest news): Sentiment Score

4.2 Companies

Companies are selected based on following criteria:

- Companies should have been traded in the Nepal stock exchange since Shrawan, 2073.
- Maximum 3 companies from each sector based on market capital.

4.3 Research design

The study methodically utilizes chosen features from fundamental, macroeconomic, technical, and financial news data to construct the model. First, all the fundamental data, macroeconomic data and company specific news is collected. Based on the fundamental data, the technical indicators are calculated. Sentiment score for each company is also calculated via sentiment analysis. All the prepared features are then normalized using min-max normalization.

An input sequence for the LSTM, GRU and ANN is formed using specific time steps.

Regularization techniques are used to fine-tune hyperparameters such as neuron count, filter count, filter size, epochs, learning rate, batch size, and time step to improve model performance and avoid overfitting concerns. The final model is trained on the input data with timestamp of 60 days to forecast the closing price of the selected companies after hyperparameters have been optimized. The model's quality is evaluated using three metrics: RMSE, MAPE, and R scores.

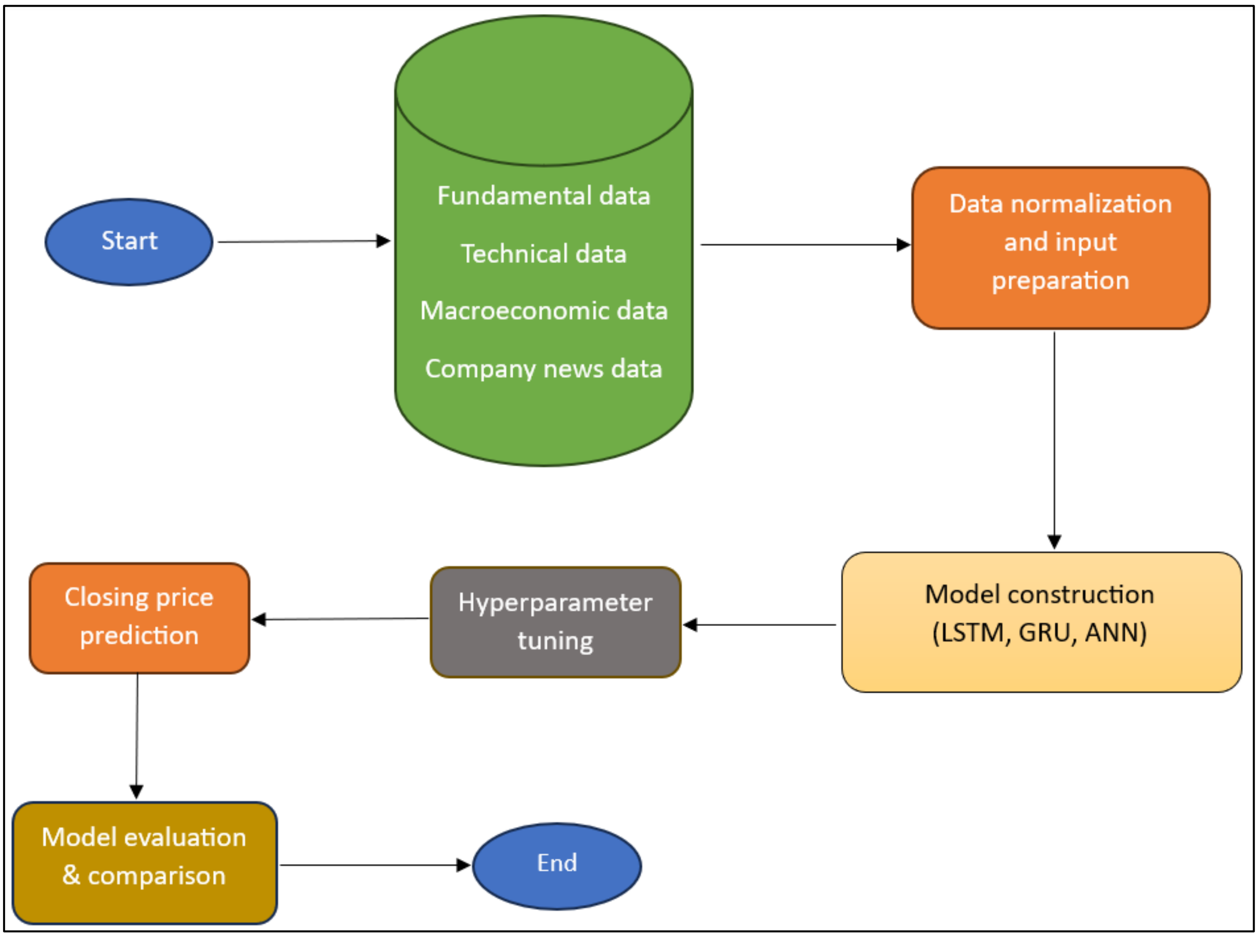

Fig 1: Research design

4.4. Modelling approach

4.4.1 Long-short term memory

The long short-term memory (LSTM), a popular deep learning method in recurrent neural networks (RNNs), is widely used for time series prediction. It uses memory cells to successfully handle the issue of vanishing gradients (Hochreiter, 1998). According to Gers et al. (2000), the architecture consists of an input layer, hidden layer, cell state, and output layer.

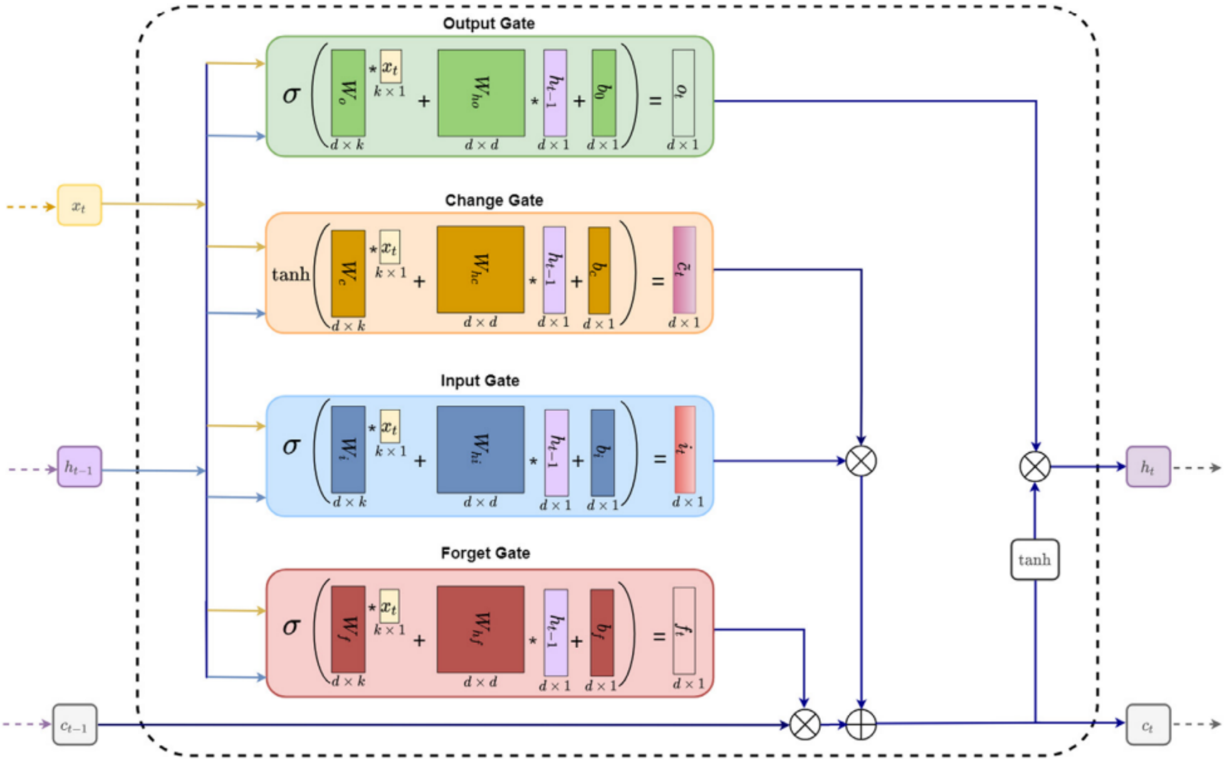

Fig 2: Long short-term architecture (Pokhrel, et al., 2022)

Figure 2 shows the structure of the LSTM at time t, which is designed to process sequential input. The four gates in this design—output, change, input, and forget—all carry out distinct functions at different times.

When considering a data sequence $\{x_1, x_2, \dots, x_n\}$, where $x_t \in R^{k\times1}$ represents input at time t, three gates are used by the memory cell c_t to update information: input gate i_t, forget gate f_t, and change gate $\hat{c}_t$. Furthermore, the output gate o_t and the memory cell c_t are used to update the hidden state ht. The corresponding gates and layers carry out the following tasks at each time t:

$i_t = \sigma(W_i x_t + W_{hi} h_t - 1 + b_i),$

$f_t = \sigma(W_f x_t + W_{hf} h_t - 1 + b_f),$

$o_t = \sigma(W_o x_t + W_{ho} h_t - 1 + b_o),$

$\hat{c}_t = \tanh(W_c x_t + W_{hc} h_{t-1} + b_c),$

$c_t = f_t \otimes c_{t-1} + i_t \otimes \hat{c}_t,$

$h_t = o_t \otimes \tanh(c_t)$

Here, σ represents the sigmoid function, and tanh represents the hyperbolic tangent function. The $\otimes$ operator indicates the element-wise product. Variables such as $W \in R^{d \times k}$, $W_h \in R^{d \times d}$, are weight matrices and $b \in R^{d \times 1}$ correspond to bias vectors. Additionally, n, k, and d signify the sequence length, number of features, and hidden size respectively (Qiu, et al., 2020).

4.4.2 Gated Recurrent Unit

The Gated Recurrent Unit (GRU), proposed by Cho et al. (2014) is a condensed version of the LSTM. GRU combines the short-term (h_t) and long-term (c_t) information of LSTM into a single vector h_t. Three gates are used by GRU: reset, change, and update gates. The update gate in GRU plays the role of both the input and forget gates of LSTM (Géron, 2019).

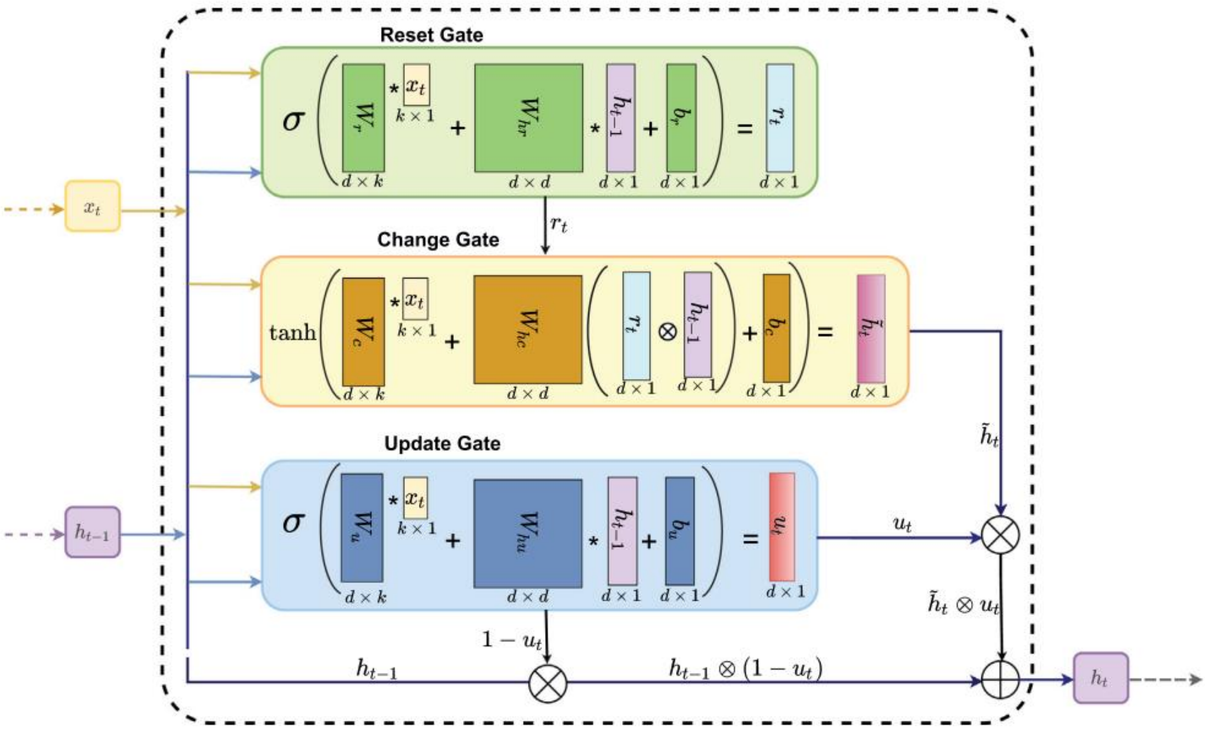

Fig 3: Gated Recurrent Unit (Pokhrel, et al., 2022)

Given an input sequence $\{x_1, x_2, \ldots, x_n\}$, where $x_t \in R^{k \times 1}$ represents input at time t, it considers the input x_t and the hidden state h_{t-1} from the previous time step $t-1$ at time t. The outcome is a new hidden state h_t, which advances to the next time step (Zhang, et al., 2022). At each time t, the gates and layers perform the following computations:

$$u_t = \sigma(W_z x_t + W_{hz} h_{t-1} + b_u),$$
$$r_t = \sigma(W_r x_t + W_{hr} h_{t-1} + b_r),$$
$$\tilde{h}_t = \tanh(W_c x_t + W_{hc}\,(r_t \otimes h_{t-1}) + b_c),$$
$$h_t = (1 - u_t) \otimes h_{t-1} + u_t \otimes \tilde{h}$$

Here, σ represents the sigmoid function, and tanh represents the hyperbolic tangent function. The $\otimes$ operator signifies the element-wise product. Variables such as $W \in R^{d\times k}$, $W_h \in R^{d\times d}$, are weight matrices and $b \in R^{d\times 1}$ correspond to bias vectors. Additionally, n, k, and d denote sequence length, number of features, and hidden size respectively.

4.4.3 Artificial neural network

Artificial neural networks are like a series of interconnected sets of mathematical equations. They take in variables as inputs, run them through a series of equations, and output one or more results. Three layers make up a neural network's typical structure: an input layer, a hidden layer, and an output layer. Moreover, each of these layers may comprise multiple distinct nodes or components that enhance the overall performance of the network (Moghaddam, et al., 2016).

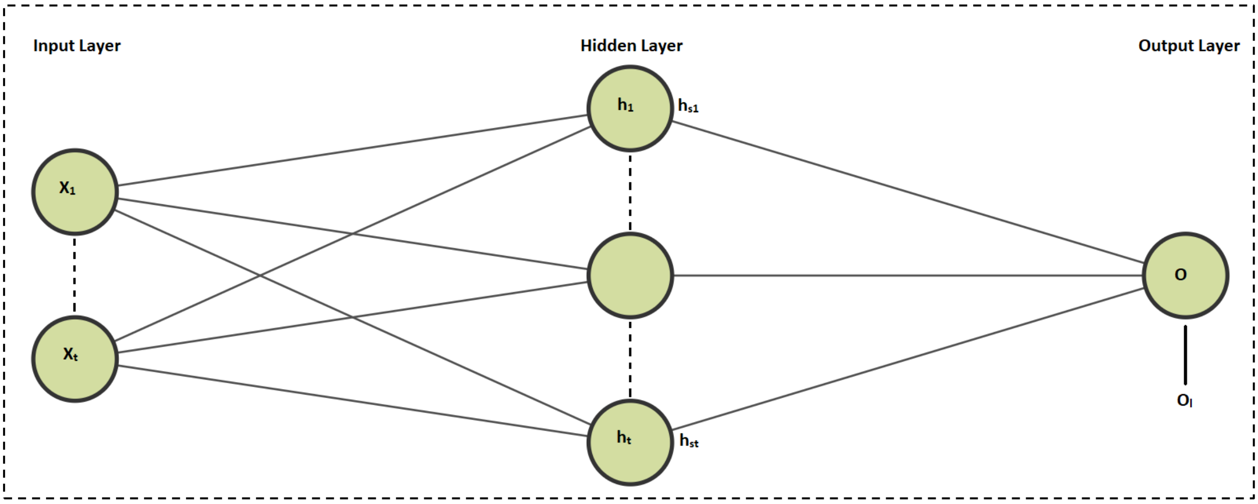

Fig 4: Artificial Neural Network

The input layer contains nodes corresponding to the amount of input data [x_1, x_2, … , x_t]. Each input node is multiplied by a designated weight and then combined with a bias to get the value for a hidden node, which is represented as h_t in fig 4. A sigmoid activation is used on each hidden node to map its value between 0 and 1. In the given figure, h_{st} is the output after applying the sigmoid function.

$h_t = b + \sum_{i=1}^{t} x_i \, w_i$, where w is weight and b is a bias term.

Sigmoid function = $\frac{e^x}{e^x+1}$, where x is the input value which h_t in fig 4.

In the output layer, the result of each hidden node is multiplied by an assigned weight, and then a bias is incorporated to get the value of output node (o). An identity function is used as an activation function in the output layer to get the final output (o_l), which is the predicted value.

$o = b + \sum_{i=1}^{t} h_{si} \, w_i$

Identity function = f(o) = o, where o is the value of output node

The mean square error (MSE) is used as a loss function. This averages the difference between actual values and predicted values. Based on this loss function, the weights and biases of the model are adjusted using backpropagation algorithm. The gradient descent, a backpropagation algorithm usually suffers from the problem of slow convergence and inefficiency. So, to tackle this problem, momentum is added to the gradient descent.

MSE = $\frac{1}{N} \sum_{i=1}^{N}(y_t - \hat{y_t})$, where N is the number of inputs, y_t is the actual value and $\hat{y}_t$ is the predicted value.

Resources you need/Access to primary and secondary data:

As the research is based on the secondary data of stock market, macroeconomic indicators and financial news, access to internet and specific website like Share Sansar and Nepal Rastra Bank is required.

To train the machine learning model, large compute power is needed. So, the google collab pro version will be used. The pro version of google collab provides faster GPU and higher compute per month at $9.99.

Project Schedule

Steps	Description	Due date
1	**Preparation Stage**	
	Week -1-2: Area of interest identified	**March 3, 2023**
	Weeks 3-4: Topic selected/form submitted	**July 25, 2023**
	Weeks 4-5: Topic refined to develop dissertation proposal	**August 21, 2023**
	Weeks 5-8: Proposal written and submitted	**September 15, 2023**
2	**Chapters 1-3 completed**	
	Chapter 1 Draft Introduction completed	**September 22, 2023**
	Chapter 2 Draft Literature Review completed	**October 10, 2023**
	Chapter 3 Draft Research Methodology completed	**October 31, 2023**
3	**Collection of data and information**	
	Data analysis and Interpretation of data	**November 14, 2023**
	Chap 4 Draft Results, Analysis and Discussion completed	**December 8, 2023**
	Chapter 5 Draft Conclusions, Implications & recommendations	**December 29, 2023**
4	**Final Writing up**	
	Structure, presentation and proof reading	**January 10, 2023**
5	**Final Stage**	
	Final proof reading, printing and binding	**January 20, 2023**
6	**Submission of Project (WOLF and hard copy submission)**	

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4. Subject to which the study will contribute: Machine learning and Stock market

5. Name of supervisor: Dr. Sudan Kumar Oli

7. Module Code and Title: 7MG001 – The Masters Research Project

8. Project Title: Predicting Nepal's Stock Market Using Machine Learning Algorithms

9. I confirm that I have: (Tick to confirm)

a. Discussed my research with my supervisor. ✓

b. Read the Guide to Ethics and consulted the Ethics Guidance Web pages ✓

9. **Which category does your project fall?**

Tick as applicable:

Category 0 • **Research that does not involve human subjects or raise any ethical concerns.**	✓
Category A • **Research that involves human subjects that are considered not to cause any physical or psychological harm.**	
Category B **(Note: Undergraduate and Taught Masters students are not normally permitted to** **undertake Category B research).** • **Research that may be considered likely to cause physical or psychological harm.** • **Research that may be contentious and/or risks bringing the University into disrepute.** • **Research that requires accessing confidential data.** • **Research that involves individuals considered to be vulnerable.**	

10. Does your study involve any of the following?

(Please tick ALL that apply.)

Making video/DVD	
Making audio recording	
Observation of human subjects	

Participant observation	
Telephone and/or Email contact with individuals or organisations	
Interviews (structured/ semi-structured/un-structured)	
Questionnaires (including on-line questionnaires)	
Access to confidential information	
Contact with minors (anyone under the age of 18)	
Contact with other vulnerable people (e.g. victims of crime, the recently bereaved)	
Research about a controversial issue	

Other: please specify (e.g. will your finished project be accessible to the public outside the university?)

<u>The finished project will be published online after being graded from the university.</u>

11. Brief outline of project.

The study applies machine learning models to predict stock prices of various companies listed in Nepal Stock Exchange. This study identifies accuracy of those models.

12. Methodology.

The study trains machine learning models (LSTM, GRU, and ANN) based on fundamental, macroeconomic, technical, and financial news data. These data are collected from secondary sources: Share Sansar and Nepal Rastra Bank. All collected data are first normalized using min-max normalization. The models are trained on a 60-day timestamp to forecast the closing prices of selected companies, and their performance is evaluated using RMSE, MAPE, and R scores.

13. Ethical Issues

Algorithmic bias: The model might be biased if the published data is itself biased.

Transparency and accountability: The writer might be biased on selecting companies for stock price prediction.

For this, specific criteria is established to select the companies from each sector. Also, the transparency will be maintained to show that the results are accurately presented.

14. Is ethical approval required by an external agency/parents?

Please provide further details.

No

15. Is a DBS check required?

No

This may be required if the research involves vulnerable groups and/or anyone under the age of 18.

If yes, please attach your disclosure letter.

Student Signature	
Date:	September 15, 2023
Name of Supervisor	Dr. Sudan Kumar Oli
Approval Signature of Supervisor	
Date:	September 15, 2023