

AI-Driven Stock Price Prediction: A Case Study on Agricultural Development Bank Limited (ADBL) using LSTM, GRU and TCN with and without News-Headling Sentiment

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Abstract

Stock price prediction in emerging markets such as Nepal presents significant challenges due to high market volatility, limited liquidity, and the strong influence of investor sentiment. This study presents a comparative analysis of three deep learning architectures Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Temporal Convolutional Networks (TCN) for stock price prediction using historical OHLCV data from the Nepalese capital market. To assess the contribution of market sentiment, financial news headlines are incorporated and transformed into sentiment scores using the FinBERT model. Model performance is evaluated under two experimental settings, with and without sentiment features, using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). The empirical results demonstrate that the GRU model consistently outperforms LSTM and TCN, exhibiting superior predictive accuracy and robustness. Furthermore, sentiment integration enhances the performance of the GRU model, while its impact varies across other architectures. These findings underscore the effectiveness of sentiment-aware deep learning models for stock price forecasting and provide valuable insights for AI-driven decision-making in emerging financial markets such as Nepal.

Keywords: Stock Price Prediction, Nepal Stock Exchange (NEPSE), LSTM, GRU, TCN, sentiment analysis, FinBERT, deep learning, financial forecasting, ADBL.

Introduction

Stock price prediction is the estimation of a stock or financial instrument's future value based on its historical time-series data, technical indicators,

sentiment information, or with the help of machine learning and deep learning techniques (Zhao, Chen, Zhang, Wang, & Li, 2025). Prediction remains a very challenging task

because the nature of financial markets is volatile, dynamic, and nonlinear. Accurate forecasting can be helpful in decision-making for investors, businesses, and policymakers. This challenge has compelled researchers to seek advanced computational techniques that can provide better forecast accuracy.

Neural networks, inspired by the structure and function of the human brain, represent powerful tools capable of handling nonlinear and sequential data. The models that show very good performance in capturing long-term dependencies in financial time series include, but are not restricted to, the Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (BiLSTM) (Hochreiter & Schmidhuber, 1997; Cho, van Merriënboer, Gulcehre, Bahdanau, Bougares, Schwenk, & Bengio, 2014). Other than the recurrent models, many other architectures have been adopted for stock forecasting. Very recently, Temporal Convolutional Networks (TCN) have been introduced as an alternative to model sequences with causal and dilated convolutions, which capture temporal dependencies efficiently in time-series data (Bai, Kolter, & Koltun, 2018). All these architectures form the backbone of modern stock price forecasting methods.

In recent years, news and social media sentiment have emerged as influential external factors affecting stock price movements, particularly in emerging capital markets such as Nepal. Investor reactions to economic news, policy announcements, and corporate disclosures often lead to short-term price fluctuations that are not fully captured by historical price data alone (Ghimire, 2025; Giri, Dam, Kamar, & Tulachan, 2025). Integrating news sentiment features with

traditional time-series data offers an opportunity to enhance predictive performance by incorporating market psychology into forecasting models. However, the effectiveness of sentiment integration varies across deep learning architectures and remains underexplored in the context of Nepalese capital markets (Saud & Shakya, 2019; Shahi, Shrestha, & Neupane, 2020). Therefore, this study aims to comparatively analyze the performance of LSTM, GRU, and TCN models using stock price data both with and without news sentiment information, providing empirical evidence on how sentiment influences prediction accuracy. The findings are expected to contribute to the growing application of AI-driven techniques in Nepal's capital markets and support more informed investment decision-making.

Literature Review

Despite the growing importance of Nepal Stock Exchange (NEPSE) as the primary platform for capital market activities in Nepal, investors continue to face significant challenges in accurately predicting stock price movements. The NEPSE market is highly volatile, influenced by limited liquidity, frequent policy changes, information asymmetry, and strong investor sentiment driven by news and rumors. Traditional forecasting methods and basic technical analysis often fail to capture the nonlinear and dynamic behavior of stock prices, leading to unreliable predictions and increased investment risk. Although artificial intelligence and deep learning models have shown promising results in global financial markets, their application in the Nepalese context remains limited, particularly in integrating news sentiment with historical price data. This gap creates a need for robust, AI-

driven forecasting approaches that can effectively model both market trends and investor sentiment to improve prediction accuracy and support informed decision-making in NEPSE.

Recent research on stock price prediction in the context of the Nepal Stock Exchange (NEPSE) highlights growing interest in machine learning and deep learning methods to address the complex, nonlinear nature of financial time-series data. Traditional machine learning approaches such as Back Propagation Neural Networks (BPNN) have been compared with recurrent architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), with findings suggesting that deep models generally outperform conventional methods in capturing temporal patterns in stock behavior on NEPSE data (Ghimire, 2025). Studies conducted on NEPSE and specific Nepalese stocks have shown that LSTM networks provide improved forecasting accuracy, particularly when used to assist investment decision-making by modeling historical trends (Giri, Dam, Kamar, & Tulachan, 2025). Comparative investigations extending to models such as Bidirectional LSTM (BiLSTM) and Support Vector Regression (SVR) report that sequence-based networks like BiLSTM can capture intricate temporal dependencies more effectively than traditional regression models (Gurung, Neupane, & Shrestha, 2024). Moreover, broader deep learning comparisons in Nepalese markets have begun exploring advanced architectures and external features, including research that integrates macroeconomic variables and sentiment analysis to enhance predictive performance (Saud & Shakya, 2019). Despite these advances, most existing work in the Nepalese context has primarily relied on

historical price data, with relatively limited empirical focus on the impact of news sentiment integration in deep forecasting models. This indicates a notable gap in the literature where sentiment-augmented models like LSTM, GRU, and Temporal Convolutional Networks (TCN) applied to NEPSE with and without sentiment remain underexplored, motivating the current study.

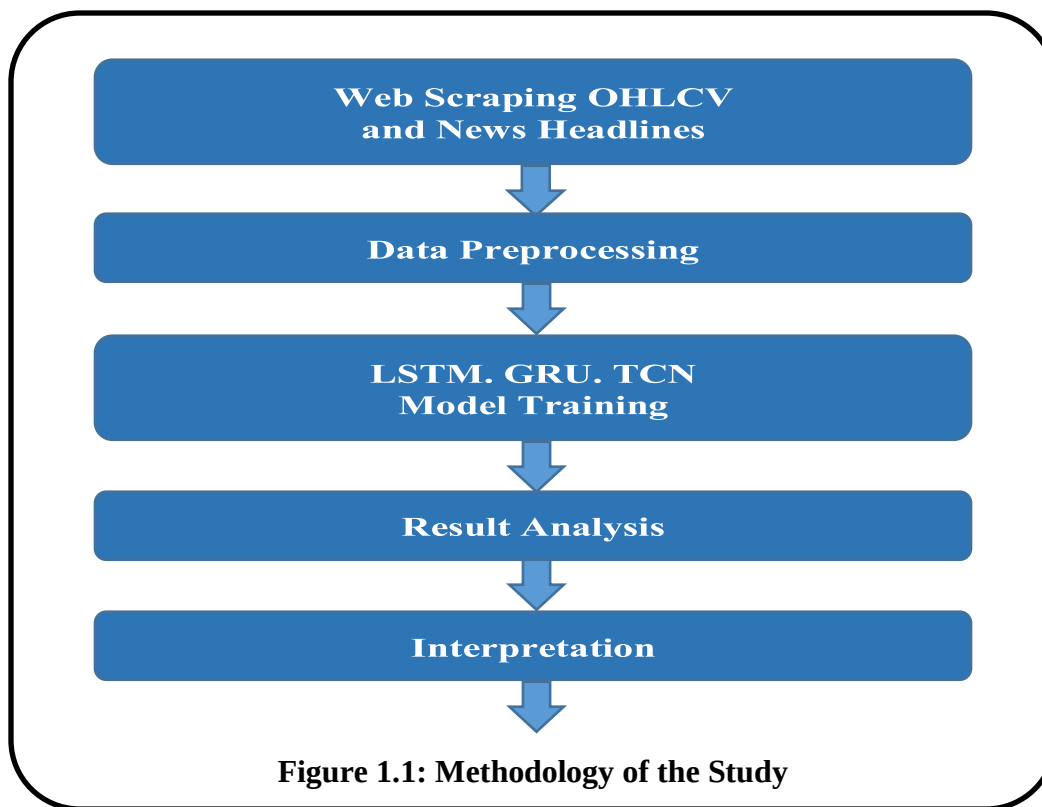
So, To evaluate and compare the effectiveness of LSTM, GRU, and TCN deep learning models in predicting NEPSE stock prices using historical market data **with and without news sentiment integration**, in order to identify the most suitable AI-based approach for Nepalese capital markets this research has been carried out.

Research Methods

This study employed a time series forecasting approach to predict stock prices, comparing the performance of LSTM, GRU, and Temporal Convolutional Network (TCN) models. The methodology began with data loading, integrating historical stock price data with external news sentiment data. Both datasets underwent preprocessing, including converting date formats and normalizing numerical features using Min-Max scaling. The sentiment data was specifically processed by aggregating daily average sentiment scores. Feature sequences were then created from the preprocessed data, with a sequence length of 30, and subsequently split into 80% training and 20% testing sets. Each of the three models (LSTM, GRU, TCN) was trained and evaluated under two conditions: first, using only stock price features, and second, incorporating the aggregated sentiment features. All models were compiled using the Adam optimizer and Mean Squared Error loss function, trained for 50

epochs, and evaluated using a comprehensive suite of metrics including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R²).

Finally, their performance, both with and without sentiment data, was compared and visualized through bar charts and loss plots.



Results and Analysis

The performance measures for LSTM, GRU and TCN without adding finbert sentiment data is shown in below table 1.

Table 1
Model Performance without Sentiment

Model	MSE	RMSE	MAE	R ²
LSTM	0.000039	0.006251	0.004451	0.998482
GRU	0.000037	0.006085	0.004882	0.998562
TCN	0.001144	0.033819	0.027726	0.955583

The performance measures for LSTM, GRU and TCN after adding finbert sentiment data is shown in below table 2.

Table 2
Model Performance with Sentiment

Model	MSE	RMSE	MAE	R ²
LSTM	0.000071	0.008455	0.006004	0.997262
GRU	0.000030	0.005484	0.003968	0.998848
TCN	0.002978	0.054575	0.043303	0.885917

The schematic diagram for the representation of the performance with and without attaching sentiment score is shown in below figure 1.2.;

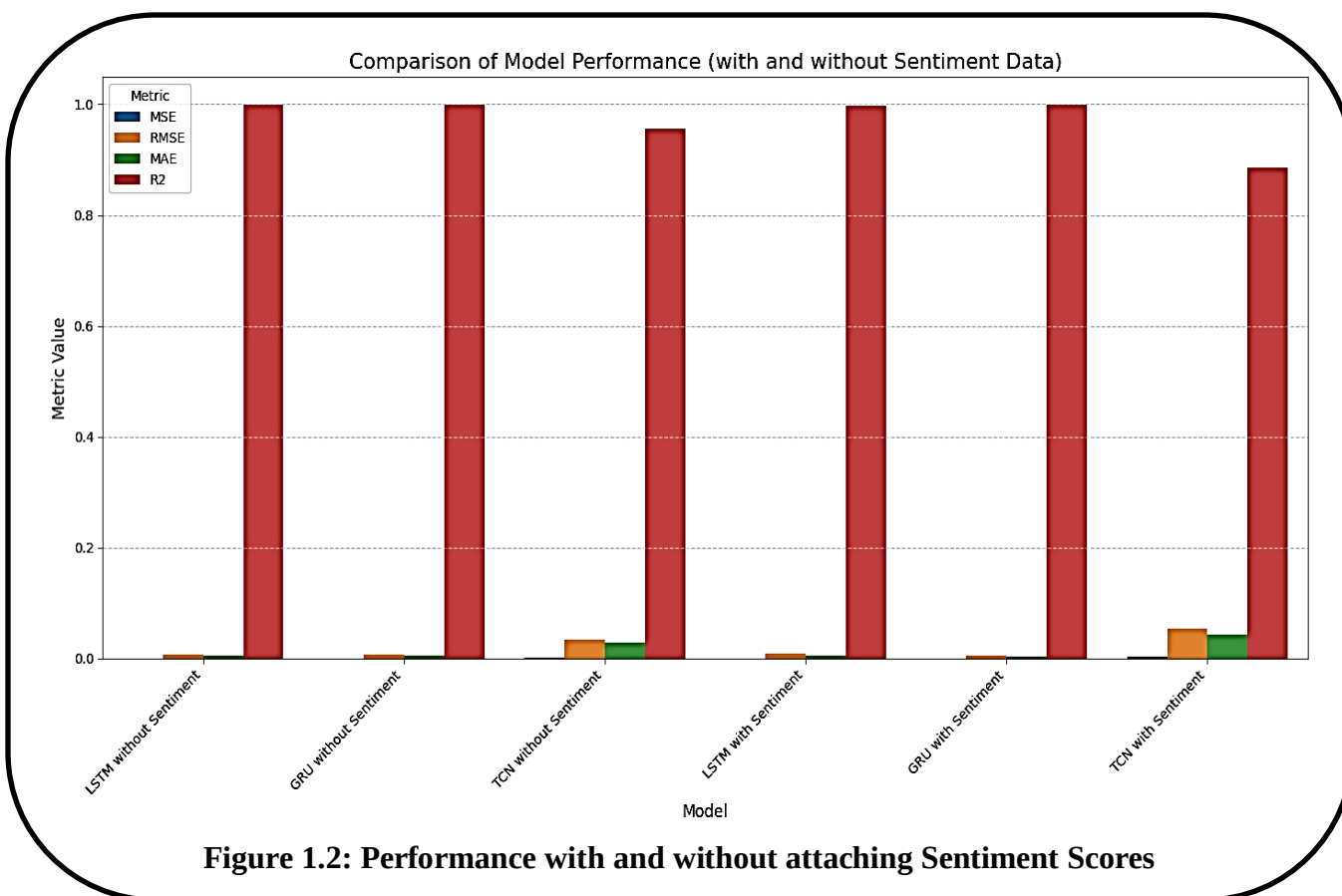


Figure 1.2: Performance with and without attaching Sentiment Scores

Discussions

This study evaluates the predictive performance of LSTM, GRU, and TCN models on the ADBL stock dataset under two experimental settings: **without sentiment features and with sentiment features**. Model performance is assessed using MSE, RMSE, MAE, and R^2 metrics to ensure a comprehensive evaluation.

Performance without Sentiment Information

Without incorporating sentiment data, both LSTM and GRU models demonstrate strong

predictive capability. The GRU model slightly outperforms LSTM, achieving the lowest MSE (0.000037) and RMSE (0.006085), along with the highest R^2 value (0.998562), indicating excellent goodness of fit. The LSTM model also performs comparably well, with an R^2 of 0.998482 and low error values, confirming its effectiveness in capturing temporal dependencies in stock price movements. In contrast, the TCN model shows comparatively weaker performance, with higher MSE (0.001144), RMSE (0.033819), and MAE (0.027726), and a reduced R^2 of 0.955583,

suggesting limited effectiveness in modeling the ADBL time-series data without auxiliary information.

Performance with Sentiment Information

When sentiment features are integrated, notable changes in model performance are observed. The GRU model exhibits the **best overall performance**, achieving the lowest MSE (0.000030), RMSE (0.005484), and MAE (0.003968), along with the highest R^2 value (0.998848). This improvement indicates that GRU effectively leverages sentiment signals to enhance prediction accuracy. Conversely, the LSTM model shows a slight degradation in performance after incorporating sentiment data, as reflected by increased error metrics and a marginally reduced R^2 of 0.997262. This suggests that LSTM may be less robust to additional noisy or weakly correlated sentiment features in the ADBL dataset. The TCN model experiences a significant decline in performance, with increased MSE (0.002978), RMSE (0.054575), and a substantial drop in R^2 to 0.885917, indicating poor generalization when sentiment information is introduced.

Conclusion and Implications

This study concludes that deep learning-based time-series models are effective for predicting ADBL stock prices; however, the impact of sentiment information is highly dependent on model architecture. Among the evaluated models, GRU consistently demonstrates superior performance, particularly when sentiment features are incorporated, achieving the lowest error metrics and highest explanatory power, which highlights its robustness in integrating both numerical OHLCV data and textual sentiment

signals. In contrast, LSTM shows marginal performance degradation with sentiment inclusion, suggesting limited sensitivity or potential overfitting to sentiment noise, while TCN exhibits a significant decline in predictive accuracy, indicating poor adaptability to sentiment-augmented inputs for the ADBL dataset. Overall, the findings suggest that sentiment-aware stock price prediction can enhance forecasting accuracy when appropriately modeled, with GRU emerging as the most reliable and effective architecture for sentiment-integrated financial forecasting in emerging market datasets such as ADBL.

Limitations and Future Research

Despite the promising results, this study has several limitations that warrant consideration. The analysis is limited to a single stock (ADBL), which restricts the generalizability of the findings across different sectors and firms within the Nepal Stock Exchange (NEPSE). Moreover, the models rely primarily on historical OHLCV data and aggregated news headline sentiment, without incorporating macroeconomic indicators, firm-specific fundamentals, or technical indicators that may significantly influence stock price dynamics. The sentiment analysis is conducted using FinBERT, which may not fully capture Nepal-specific financial context, local language nuances, or intraday sentiment variations due to daily aggregation. Additionally, fixed hyperparameters and a single train-test split are employed, potentially affecting model robustness and raising concerns of overfitting, particularly in sentiment-integrated settings. Future research should extend the analysis to multiple stocks and sectors, integrate broader financial and macroeconomic variables, adopt domain-adapted or multilingual

sentiment models, and explore advanced architectures such as Transformer-based or hybrid models with robust validation strategies to enhance predictive reliability and real-world applicability in emerging markets like Nepal.

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