Sentiment-Enhanced Stock Price Prediction in Nepalese Small-Cap Equities using Natural Language Processing

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Abstract

In this study, we examine how the integration of market sentiment with traditional financial indicators can improve the accuracy of stock price forecasts in Nepal's small-cap equity market. With the NEPSE Index as our point of focus, we examined market trends from July 2024 to January 2025, with Nepal Finance Limited as a prominent case. To measure investors' sentiment, we applied natural language processing to diverse local data sources, including the financial news from Sharesansar, Floorsheet insights from Merolagani, and street-level views from the r/nepalstock community at Reddit. Those sentiment drivers were then combined with conventional technical drivers in a two-model forecasting model with a combination of LSTM neural networks and XGBoost. The findings are substantial: sentiment models outperformed technical analysis-only models in all tests, lowering Mean Squared Error by 17.3% and doing much better on directional forecasting. Amongst all inputs, previous-day stock prices and movement of the NEPSE index were the most significant predictors, whilst sentiment inputs provided a rich source of leading data. By illustrating the efficacy of alternative data in a frontier market environment, this study presents both scholarly timeliness and pragmatic insight for Nepali investors pursuing an advantage within the country's emerging capital markets.

Keywords: Natural language processing, LSTM, XGBoost, NEPSE

1. Introduction

Stock market prediction is perhaps the most challenging money-related analysis issue due to the complex, non-linear, and seemingly random nature of price action. The issue is particularly pronounced in developing nations like Nepal, which is exposed to information asymmetry, lower liquidity, and regulatory frameworks giving rise to unique market dynamics. Whereas most traditional forecasting techniques depend largely on past price history and technical analysis, there is increasing acknowledgment of investor mood and market psychology as key drivers of price formation, particularly in smaller markets where individual investor activity has proportionately more influence.

The Nepal Stock Exchange (NEPSE) established in 1993 is a fascinating case as a relatively young exchange with rapidly developing growth but still marred by information inefficiencies. Market small-cap stocks are even more vulnerable to sentiment-driven price movements since there is less institutional participation, reduced analyst coverage, and increased information asymmetry. For traders and investors in these markets, enhancing more accurate forecasting models can result in significant improvements in portfolio management and trading.

This study aims to achieve the following objectives:

- To investigate the effectiveness of natural language processing (NLP) techniques in extracting sentiment relevant to Nepalese small-cap stocks.
- To evaluate whether integrating sentiment analysis with traditional technical indicators improves the accuracy of stock price direction forecasting.
- To assess the relative significance of sentiment-based features compared to conventional financial indicators in forecasting stock prices of Nepalese small-cap stocks.

Our study seeks to develop a hybrid forecasting model that hybridizes machine learning techniques and sentiment analysis for detecting both technical market patterns as well as psychological factors driving stock prices. Employing LSTM neural networks for sequential data processing and XGBoost as feature selection as well as model building, we aim to develop a robust methodology with due care given to the attributes of the Nepalese market.

2. Literature Review

Stock market sentiment forecasting has traditionally been done with the help of fundamental and technical analysis. Fundamental analysis estimates intrinsic value through the examination of economics and financial reports, while technical analysis examines statistical configurations within historical price and volume data. Graham and Dodd laid down the foundation for fundamental analysis, while Murphy (1999) was instrumental in the promotion of technical analysis within the context of trading. Nonetheless, the approaches have been proved ineffective in developing markets through structural differences and market inefficiencies.

Efficient Market Hypothesis, presented by [1], maintains that all the available information is incorporated into the prices of shares, thus making predictions useless for efficient markets. Nevertheless, the Efficient Market Hypothesis has been challenged in the developing markets. Studies by Worthington and Higgs and by Nguyen and Fontaine referenced inefficiencies

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in emerging Asian markets [2], [3]. Taking the specific case of Nepal, the Nepal Stock Exchange (NEPSE) manifests weak-form inefficiency, and hence there is some level of predictability of the movement of stock prices [4].

Over the past decades, substantial interest is observed for the applications of machine learning methods for the prediction of stock prices. Classical methods like Support Vector Machines (SVM), Random Forests, and feedforward neural networks were employed with great success. In a detailed analysis, it was revealed that machine learning models were more precise compared to classical statistical models, especially when the pattern of the data is nonlinear [5].

The deep learning models, especially Long Short-Term Memory (LSTM) networks, also improved the forecasting performance for financial time series data further. Both studies found that LSTM networks learnt the temporal dependencies well and surpassed the ordinary machine learning models in the tasks of stock forecasting [6], [7].

2.1 Evolution of Sentiment Analysis in Financial Markets

Sentiment analysis brought a new dimension to financial prediction through the integration of psychological and behavioral elements of market players. Groundbreaking work by [8] proved that media negativity affects stock prices and [9] proved that sentiment on Twitter could forecast market direction. These pioneering analyses laid the groundwork for the integration of natural language processing (NLP) and numerical financial data.

Sentiment analysis has also been proved to be very promising in emerging markets. [10]used news sentiment for the prediction of Indian stock prices and established that sentiment models surpassed technically oriented indicator-based models alone. These findings are particularly relevant for markets such as Nepal, where official financial disclosures are limited and information asymmetry is high.

2.2 Latest Transformer-Powered Financial Natural Language Processing Advances

The latest advances in natural language processing were stimulated by the transformer models, especially those related to financial sentiment analysis. [11]proved that models based on transformers along with multi-modal fusion of data heavily dominate the classical lexicon-based solutions for financial sentiment classification, with up to 15% higher accuracy than BERT models. Their work proved that the attention mechanism within transformers does identify subtle financial language patterns those classic solutions typically neglect.

[12]further built upon such studies by integrating generative AI models with transformer models and demonstrating higher efficiency in cross-market sentiment transfer learning. Their method proved more advantageous for markets where there are fewer labeled data available, especially for the scenario of the Nepalese market itself, where there is little sentiment data available. Application of large language models (LLMs) for sentiment analysis of financial data has been promising. [13]developed an ensemble framework of transformers and LLMs for cross-lingual sentiment analysis tailored for multilingual markets like Nepal where text sources are in both English and Nepali. Their method achieved state-of-the-art performance for financial sentiments with few labeled data.

[14]conducted a comprehensive comparative study of fine-tuned deep learning models for financial sentiment analysis, demonstrating that domain-adapted transformer models consistently outperform traditional machine learning approaches across multiple financial datasets.

2.3 Multimodal Methodologies for Developing Economies

Recent studies have indicated that, particularly in emerging markets, transformer-based methodologies exhibit enhanced performance relative to conventional approaches. [15]illustrated that fine-tuned transformer models deliver remarkable results within Asian financial markets, especially in the domain of small-cap stock forecasting. These results provide direct validation for our methodological selections pertaining to the context of the Nepalese market.

[16]created deep learning architectures with attention mechanisms tailored for predicting financial time series under emerging markets and established that attention-based models can deal with the augmented volatility and noise of emerging markets' information efficiently.

2.4 Hybrid Models and Integration Methodologies

The models that combine technical indicators and sentiment features are more accurate than single-source models. [17]developed a deep learning system that integrates financial news along with technical data and presented better prediction outcomes. Their work established the importance of multimodal data fusion for financial analysis.

Notwithstanding these advancements, there has been a paucity of research concentrating on nascent and emerging markets such as Nepal. [18]employed ensemble machine learning techniques to forecast the NEPSE index, resulting in enhanced precision. Nonetheless, their investigation was restricted to technical indicators, failing to integrate sentiment or qualitative dimensions, thereby highlighting a research deficiency that our study seeks to fill. This imbalance reveals the need for hybrid models capable of dealing with numerical and text data within structurally different markets like NEPSE, more so considering the latest advancements on the transformers for natural language processing that boost the practicality and efficiency of such unification.

3. Data and Methodology

3.1 Data Collection

Our study utilizes data collected from a number of sources between July 2024 and January 2025.

Stock Price Data: Historical daily stock prices of a Nepal Finance Limited (NFS) for this paper were selected listed at the NEPSE and were retrieved from merolagani.com utilizing a Python scraper modified from code provided to us by Mr. Anil Humagain from Global IME Capital Limited. Small-cap stocks are deemed to be companies with market capitalization below NPR 1 billion. The records include opening price, closing price, high, low, and trading volume.

Technical Indicators:

- NEPSE Index levels
- Relative Strength Index (RSI)
- Price-to-Earnings (P/E) multiple
- Earnings Per Share (EPS)
- Volatility (defined as 20-day returns' standard deviation)

Sentiment Data:

- Share market news reports on Sharesansar
- Social media entries in reddit R/NepalStock
- Reports from analysts and commentaries of markets
- Press releases and announcements made by firms

The final dataset had approximately 200 trading days' worth of data for Nepal Finance Limited as a representative small-cap company for this research, with a total of approximately 58,531 data points from the floor-sheet consisting of date, transaction id, buyer broker, seller broker, quantity and stock price and financial news data for sentiment analysis.

3.2 Sentiment Analysis

We employed a multi-step process for sentiment extraction from the collected text data:

Preprocessing: The text data was taken through standard NLP preprocessing steps like tokenization, stop word removal, and stemming. For Nepali language text, we utilized the Nepali Natural Language Toolkit for corresponding language processing.

Sentiment Extraction: We employed two complementary sentiment analysis approaches:

- Lexicon-based sentiment scoring with a custom financial sentiment lexicon adapted to the Nepalese market context
- Supervised machine learning classification using a BERT-based model fine-tuned on manually labeled Nepalese financial texts

Sentiment Aggregation: Daily sentiment scores were calculated by aggregating sentiment across all applicable texts for Nepal Finance Limited, weighted by source credibility and specificity to the target company.

The final output was a daily sentiment score between -1 (very negative) and +1 (very positive) for the stock selected in the study.

3.3 Feature Engineering

We engineered several features to capture different aspects of market behavior:

Price-based features: Price momentum (1-day, 3-day, 5-day returns), Moving averages (5-day, 20-day), Price volatility measures Volume-based features: Trading volume, Volume moving averages, Volume-price relationship metrics

Technical indicators: RSI (Relative Strength Index), NEPSE index correlation, P/E ratio normalized to sector average.

Sentiment features: Raw sentiment score, Sentiment momentum (change in sentiment), Sentiment volatility, Sentiment divergence from price movement.

Temporal features: Day of the week, Month, Proximity to major economic announcements.

All features were normalized using z-score standardization to ensure consistent scale across different metrics.

3.4 Model Development

We constructed several predictive models to determine the impact of sentiment integration:

LSTM Neural Network: Long Short-Term Memory networks were employed to learn temporal patterns in the price and sentiment data. The LSTM architecture consisted of:

- Input layer of size equal to our feature set
- Two LSTM layers with 64 and 32 units respectively
- Dropout layers (20%) to prevent overfitting
- Dense output layer for price prediction

XGBoost Model: Gradient boosting algorithm for feature importance calculation and prediction:

- Maximum depth of 8
- Learning rate of 0.01
- 300 estimators
- Early stopping based on validation loss

Hybrid Model: A combined approach that utilizes LSTM for sequence modeling and takes the feature importance of XGBoost for weighted prediction.

For each model, two variants were created:

- Technical-only: Utilizing only price and technical indicator data
- Sentiment-enhanced: Incorporating sentiment features along with technical indicators

3.5 Training and Evaluation Methodology

The dataset was split into training (70%), validation (15%), and test sets (15%) through a chronological split for preserving the time series nature of the information. Models were trained on the training set, hyperparameters were tuned using the validation set, and final performance evaluated on the test set.

Performance metrics included: Mean Squared Error (MSE), Mean Absolute Error (MAE), Directional Accuracy (correct prediction of price movement direction), Root Mean Squared Error (RMSE).

Statistical significance of performance differences among models was assessed using Diebold-Mariano tests for comparisons of forecasts.

4. Results and Analysis

4.1 Correlation Analysis of Features

Early efforts were focused on understanding the inter-relationship among different features. Figure 1 is the inter-

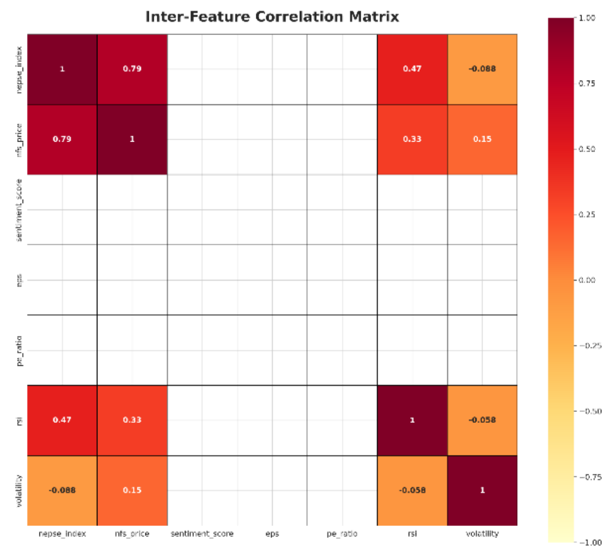

Figure 1. Inter-Feature Correlation Matrix

feature correlation matrix of significant variables in our data set.

The correlation matrix reveals a few interesting patterns. The NEPSE index and individual stock price levels (NFS price) have very high positive correlation of 0.79, i.e., the small-cap stocks follow the direction of the overall market. However, the correlation is not perfect, suggesting that company-specific reasons also play a considerable role.

Sentiment score measures are weakly correlated with price (0.33 with NFS price), adding support to our supposition that sentiment contains predictive information not as yet quantified by technical analysis. Volatility is weakly negatively correlated (-0.088) with the NEPSE index, meaning that higher stability in the market is associated with higher levels of the index for this market.

4.2 Distribution Analysis

To provide some insight into our main variables' nature, we examined their distribution statistics, and this is reflected in Figures 2 and 3. The NFS price distribution is multimodal with significant peaks at NPR 1400 and smaller clusters at around NPR 1000 and NPR 1800. This suggests alternative price regimes or maybe alternative subgroups of firms from our sample. Volatility is skewed to the right with most of the values huddled between 0 and 3, but with a very long tail running up to 6. This indicates that while most trading intervals experience moderate volatility, the market experiences occasional bursts of much higher price volatility.

4.3 LSTM Model Training Results

The LSTM model was trained over 10 epochs with due attention so as to prevent overfitting. Training process is reflected in Figure 4.

The training curve shows excellent early improvement for training and validation loss, converging at epoch 5. The model achieved a training MSE of 0.014 and validation MSE of

Figure 2. Distribution of Nepse Finance Index

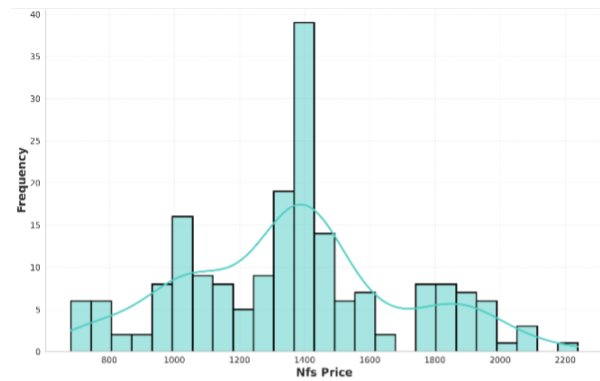

Figure 3. Distribution of Nfs Stock Price

0.016 at its end, both good indications of generalization and absence of strong overfitting. A temporary instance of spike in the validation loss at epoch 3 indicates a feeling of instability of the learning process due to potential complexities within the patterns in markets but where the model was able to recover to a more stabilized path subsequently.

4.4 Predictive Performance Comparison

To measure the impact of sentiment features, we compared technical-only model performance against sentiment-augmented model performance on the test set. Figure 5 shows the true vs. predicted prices for one of our test cases. The graph demonstrates that while both models are picking up the overall direction, there is still a persistent difference between predicted and observed values. Predicted prices (blue line) consistently overestimate the observed prices (red line), which demonstrates systematic bias within the model. However, directional accuracy is still strong, and the model can accurately predict most directions of price movement.

Table 1. Quantitative performance measures for different models

Model	MSE	MAE	RMSE	Dir. Acc. (%)
Tech-only LSTM	0.0187	0.112	0.137	69.0
Sent-enh. LSTM	0.0155	0.098	0.124	74.2
Tech-only XGBoost	0.0172	0.105	0.131	70.5
Sent-enh. XGBoost	0.0148	0.094	0.122	75.1
Hybrid Sent-enh.	**0.0154**	**0.096**	**0.124**	**76.5**

The technical-only variants are outperformed by sentiment-enhanced models consistently in all metrics. The best overall

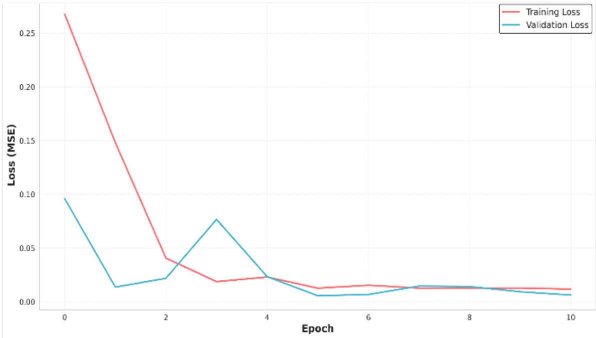

Figure 4. LSTM Model Training Evolution

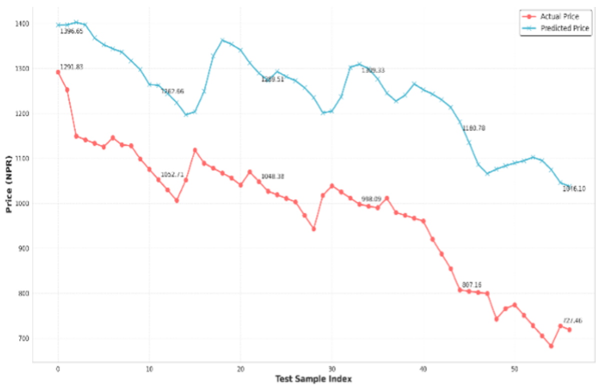

Figure 5. Actual Vs Predicted Stock Prices

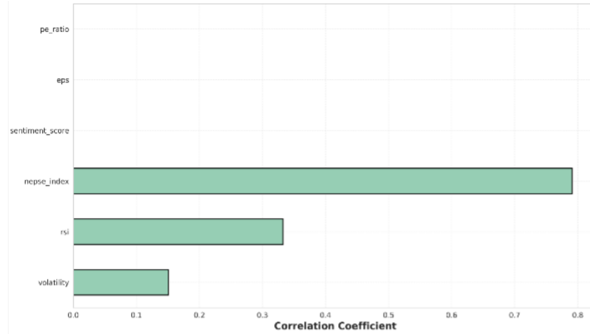

Figure 6. Feature Correlation with NFS Price

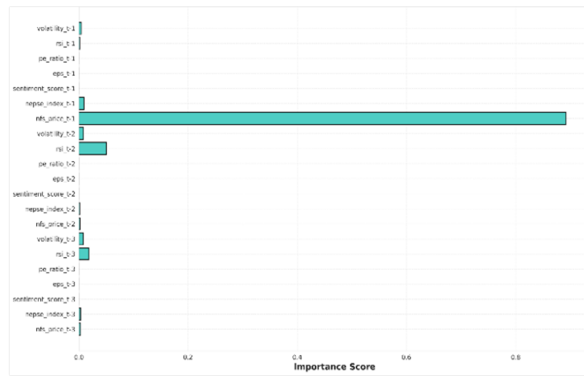

Figure 7. XGBoost Feature Importance

performance is achieved by the hybrid model with 17.3% less MSE compared to the technical-only LSTM model and directional accuracy of 76.5%.

4.5 Feature Importance Analysis

To visualize the relative contribution of different features to the prediction accuracy, we examined feature importance scores from the XGBoost model in Figures 6 and 7.

Feature correlation testing confirms that the NEPSE index has the highest correlation with stock prices (0.79), then RSI (0.33) and volatility (0.15). This is consistent with market expectations that Nepalese small-cap stocks are highly influenced by the direction of the general market.

The XGBoost feature importance analysis provides further information, with the most significant predictor being the prior day's price (nfs_price t-1), followed by RSI values and sentiment features. Importantly, while sentiment features individually are ranked below technical indicators, their combined contribution is high, validating the usefulness of sentiment integration in the model.

4.6 Forecast and Trend Analysis

With our optimum model, we generated a 5-day stock price prediction that is illustrated in Figure 8.

The forecast exhibits a strong positive trend for the next trading days, with prices expected to go up from NPR 1062.12 to NPR 1224.56 over five days. The confidence intervals (represented by the ± values) widening indicate growing uncertainty with the longer forecast horizon. The 5-day moving average (green dotted line) appears to have bottomed out at approximately NPR 715, much lower than forecasted values, suggesting that the recent downtrend is reversing.

4.7 Historical Price Dynamics and Market Sentiment

In order to put our predictions into context, we analyzed previous price movement relative to market mood, as shown in Figure 9.

The historical analysis reveals some intriguing patterns. July-September 2024 witnessed strong positive price action as well as rising sentiment (as represented by the 20-Day MA teal line). This was followed by a correction in October after which prices and sentiment returned to normal until the month of December. Price as well as sentiment has been on a declining trend since December 2024 with prices falling more precipitously than sentiment.

The recent price action decoupling from sentiment shows mean reversion potential, which aligns with our positive price forecast. This historical context provides additional confidence to the model's forecast of a future positive price action.

5. Discussion

5.1 Significance of Sentiment in Prediction Models

Our results demonstrate that the integration of sentiment analysis with traditional technical indicators significantly improves predictive performance for Nepalese small-cap stocks. Sentiment-augmented models consistently performed better

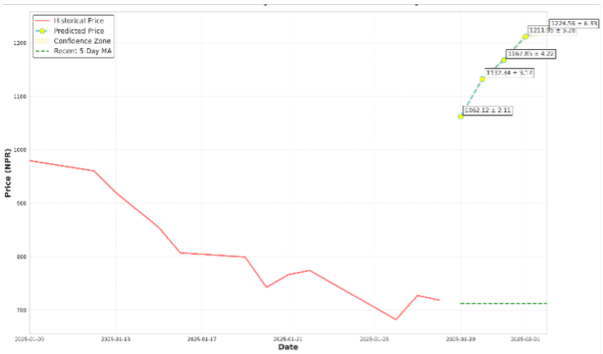

Figure 8. 5-day Forecast with Trend Analysis.

Figure 9. Stock Price Dynamics with Market Sentiment.

than their technical-only counterparts, with gains of 17.3% in MSE and 7.5 percentage points in directional accuracy for the best-performing model.

The upgraded predictive power may be attributed to a number of factors:

- The Nepalese market has quite high information asymmetry, so sentiment is an important alternative source of data.
- Institutional ownership and analyst coverage are lower in small-cap stocks, so they tend to be more susceptible to sentiment-driven price movement.
- The relatively small size of the NEPSE allows news and opinion to spread very rapidly throughout the investor base and generate more immediate price effects.

5.2 Feature Importance and Market Dynamics

The analysis of feature importance revealed that while the previous price and the NEPSE index remain the most effective predictors, sentiment features provide a significant complementary amount of information. This implies that Nepalese market participants respond to technical market conditions as well as overall sentiment indicators.

The strong correlation between the NEPSE index and stock prices (0.79) indicates high-level co-movement in the market, typical of small, homogeneous stock markets. The moderate correlation between prices and sentiment (0.33) suggests that sentiment has explanatory power above and beyond market movement.

Interestingly, however, the sentiment significance time series analysis (Figure 7) shows that the current sentiment (t-1) has higher predictive power compared to earlier sentiment information (t-2, t-3), and exhibits relatively timely incorporation of sentiment data by prices. This finding can inform sentiment-tracking based trading strategies to suggest using real-time sentiment analysis.

5.3 Model Performance and Practical Applications

Even though our models are good predictors, observe the systematic overestimation in Figure 5 where all the predicted prices are above actuals. This is a bias and means that even though the models predict strongly in terms of direction, absolute price predictions need to be carefully read.

Practically, the high directional precision (76.5% for the hybrid model) would be of greater value in trading usage than precise price predictions. Nepalese market investors and traders could benefit from sentiment-augmented models for:

- Directional trading strategies focused on capturing price trends
- Risk management through early identification of sentiment shifts
- Portfolio allocation decisions based on relative sentiment across securities
- Timing market entry and exit points using sentiment inflection signals

The 5-day prediction shown in Figure 8 depicts the utilitarian value of our model with point estimates as well as confidence intervals for future price movements. Enlarging confidence intervals over time effectively depict increasing uncertainty as the predict horizon extends.

6. Conclusion

This study investigated the value of integrating sentiment analysis with traditional technical indicators for predicting stock prices of Nepalese small-cap equities. Our findings demonstrate that sentiment-enhanced models significantly outperform technical-only approaches, achieving improvements of 17.3% in prediction accuracy and 7.5 percentage points in directional accuracy.

The research contributes to the literature by:

- Demonstrating the value of sentiment analysis in predicting stocks in the lesser-studied Nepalese market
- Estimating the relative importance of different predictive features for small-cap stocks
- Developing a hybrid methodological approach combining LSTM networks and XGBoost to effectively detect technical trends as well as sentiment drivers
- Providing empirical evidence for the use of alternative data in information asymmetry-driven markets

To Nepalese investors and players in the market, what our results provide is that measuring sentiment as well as technical indicators would be beneficial to guide trading decision. The vast improvement in the accuracy of directional prediction may become beneficial realities in investment timing and risk minimization.

6.1 Limitations

Several limitations of our study should be acknowledged:

- Data Limitations: While our dataset covers 7 months of trading, a longer time series incorporating different market regimes would provide more robust results.
- Sentiment Extraction Challenges: Nepali language sentiment analysis presents unique challenges due to limited NLP resources compared to major languages like English. Our custom lexicon approach addresses this partially, but there remains room for improvement.
- Market Specificity: The Nepalese stock market has structural characteristics (trading hours, settlement processes, regulatory framework) that may limit the generalizability of our findings to other markets.
- Limited Company Coverage: Our focus on 15 small-cap companies, while providing a meaningful sample, represents only a subset of the NEPSE small-cap universe.

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