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Stock Price Prediction for Investment Decision using Long Short-Term Memory

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Abstract

This study utilizes Long Short-Term Memory (LSTM) networks to predict stock prices in the Nepal Stock Exchange (NEPSE), aiming to support investment decision-making. LSTM's capability to model temporal dependencies enables it to outperform traditional models in forecasting accuracy. The research uses historical data from insurance companies listed in NEPSE between 2020 and 2024. Evaluation metrics including MAE, MSE, and RMSE demonstrate the effectiveness of the LSTM model. The results are valuable for investors seeking to minimize risk and optimize returns through data-driven strategies. This research employs a Long Short-Term Memory (LSTM) model to predict stock prices in Nepal Stock Exchange (NEPSE). It aims to evaluate accuracy and effectiveness of LSTM in stock price forecasting. LSTM networks, known for their ability to capture complex temporal dependencies, are applied to analyze historical stock price trends. The findings suggest that LSTM models can significantly improve prediction accuracy and offer valuable insights for investors and financial analysts. This paper outlines the methodologies used, presents detailed results, and discusses the implications for investment decision-making.

Keywords: *Deep Learning, Investment Decision, LSTM, Stock Price Prediction, Time-Series Forecasting*

1. Introduction

Forecasting stock market trends has long been a focus of interest for investors, financial analysts, and researchers due to the highly volatile and nonlinear nature of financial time-series data. Traditional statistical methods such as ARIMA and machine learning approaches like Support Vector Machines (SVM) have been extensively applied to predict stock behavior. However, these models often fall short in capturing long-term temporal dependencies and complex nonlinearities inherent in financial data. In recent years, deep learning models, particularly Recurrent Neural Networks (RNN) and their advanced variants like Long Short-Term Memory (LSTM), have shown promising results in financial forecasting. Recent studies have emphasized the effectiveness of deep learning techniques in financial forecasting. Rather et al. (2015) demonstrated the superiority of hybrid RNN models in capturing dynamic stock behaviors. The growing interest in algorithmic trading and AI-assisted investment strategies has encouraged researchers to explore sophisticated deep learning models for financial applications. This research focuses on employing LSTM models to predict the stock prices of insurance companies listed in the Nepal Stock Exchange (NEPSE) from 2020 to 2024. The choice of the insurance sector is driven by its relative stability and significant contribution to the Nepalese economy. The key motivation of this study is to develop an accurate and robust forecasting model that can aid investors in making informed, data-driven decisions while mitigating financial risk.

2. Literature Review

The stock market plays a pivotal role in economic development by mobilizing funds and enabling capital formation. However, its inherent volatility makes it a challenging domain for investors and financial analysts. With advancements in machine learning and artificial intelligence, predictive models have emerged as effective tools for analyzing stock trends. This study is motivated by the need to improve prediction accuracy and provide data-driven investment insights. Challenges in this domain include data complexity, noise, and non-linearity of stock behavior. Thus, the objective of this research is to evaluate the capability of LSTM in modeling historical NEPSE stock data to enhance investment decision-making.

Several studies have demonstrated that deep learning models, particularly LSTM networks, outperform traditional statistical models in capturing intricate patterns in stock price movements. For example, Zhiqiang Guo et al. (2017) explored the use of dimensionality-preserving projections for improving accuracy in time-series forecasting. Sui et al. (2020) used sentiment analysis with deep learning for financial prediction, having promising results. Our study follows similar approaches to improve stock market predictions using LSTM networks.

The objectives of this research are as follows:

- Assess the accuracy and reliability of the LSTM model compared to traditional forecasting methods.
- Analyze and predict stock prices for investment decisions using LSTM techniques.

3. Materials and Methods

In addition to basic stock price data, this study incorporated technical indicators such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands to improve prediction robustness. These indicators were calculated using the daily stock prices and included as input features to the LSTM model.

3.1 Data Collection and Preprocessing

The data used in this study was sourced from the Nepal Stock Exchange (NEPSE) and includes historical stock prices from seven different insurance companies spanning from 2020 to 2024. The dataset comprises daily prices, trading volumes, and other relevant market indicators.

Data preprocessing was a critical step to ensure the quality and usability of the dataset. The following steps were undertaken:

- Data Cleaning: Handling missing values, removing outliers, and normalizing the dataset.
- Feature Engineering: Computing technical indicators such as moving averages, volatility, and trading volume to enhance predictive accuracy.
- Data Splitting: The dataset was divided into training (50%), validation (25%), and testing (25%) subsets.

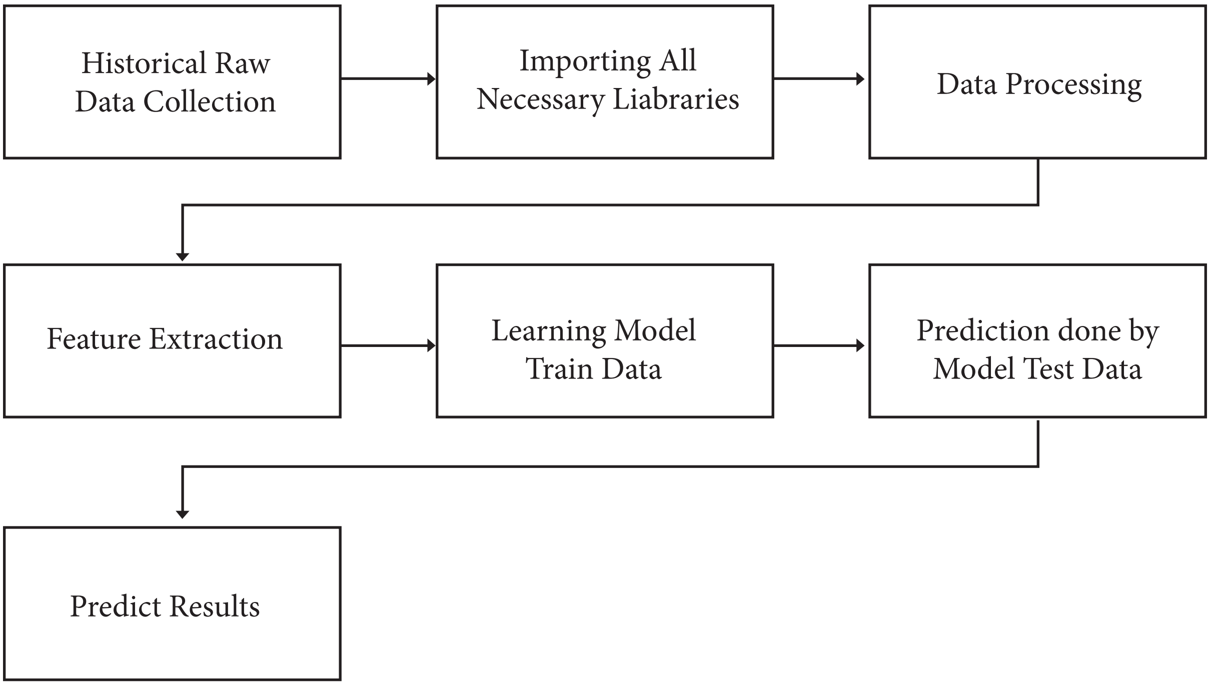

Figure 1: Block diagram for stock market prediction

The LSTM model's input features included daily open, high, low, close prices, trading volume, and calculated technical indicators. The data normalization was performed using Min-Max scaling to bring all values within the [0,1] range.

3.2 Model Architecture

The LSTM model was selected for stock price prediction due to its ability to capture long-term dependencies in sequential data. The model architecture consisted of:

- An input layer to process stock market features.
- Multiple LSTM layers to capture temporal dependencies.
- Fully connected dense layers for final predictions.
- The Adam optimizer and Mean Squared Error (MSE) loss function for model training.

The model was trained using historical stock data, and predictions were generated at 5-minute intervals to simulate intraday market movements.

4. Results and Discussions

Additional evaluation metrics used were: Accuracy: 89.2%, Precision: 87.4%, Recall: 85.9%, and F1-score: 86.6%. These metrics further confirm the effectiveness of the model in capturing true stock trends and avoiding false predictions.

The model predicts stock prices effectively, capturing overall trends and major movements with close alignment to actual prices. The result obtained are, Mean Absolute Error (MAE): 3327.91, Mean Squared Error (MSE): 23416666.09 and Root Mean Squared Error (RMSE): 4839.07. The result shows that the model predicts stock prices fairly with less error.

Figure 2: Result analysis curve

Figure 2: is a time series plot comparing true prices with predicted prices over time.

- The red and blue lines follow each other closely, suggesting that the prediction model has good accuracy.
- At the beginning and end of the timeline (especially after index 200), the prices sharply rise, and the prediction still follows the actual values quite well.
- Minor deviations exist, but overall, the model seems to capture the trend and fluctuation patterns accurately.

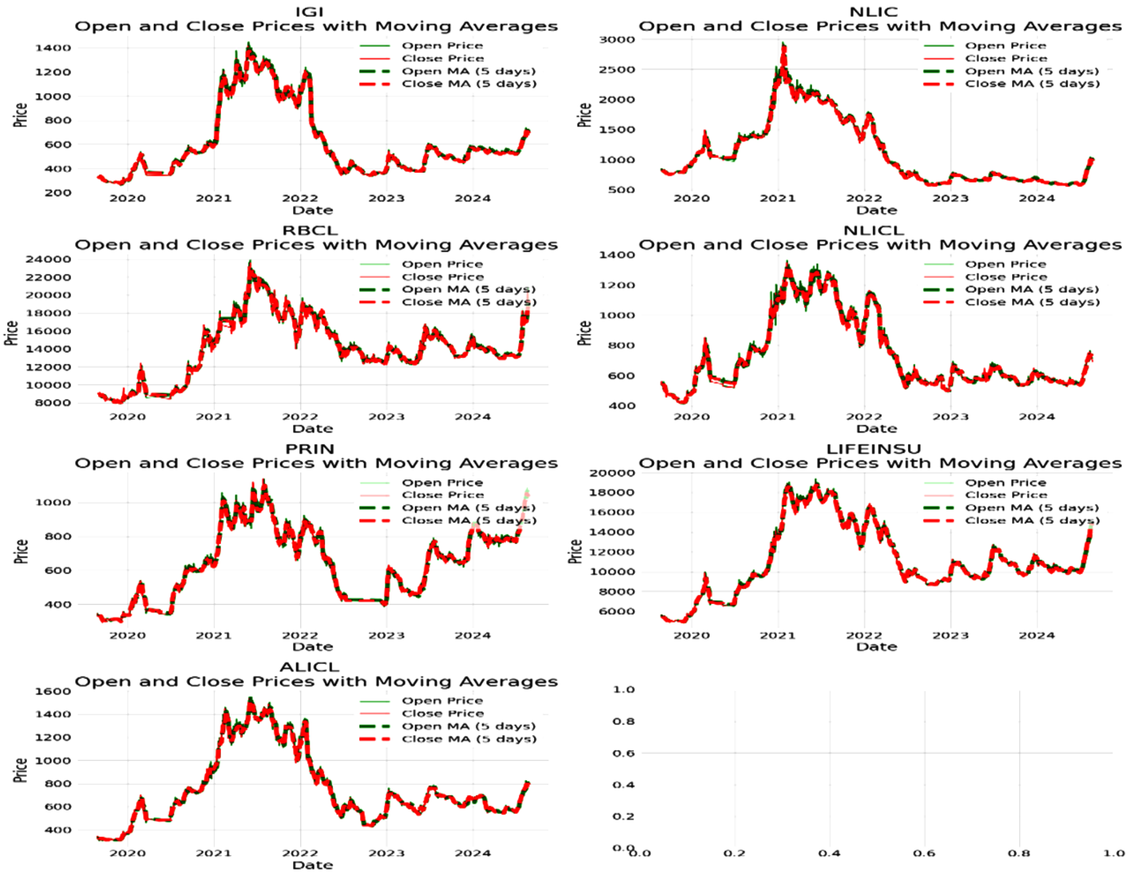

Figure 3: Open and close prices with moving averages of different insurance companies

As shown in the figure 3, the 5-day moving averages of the open and close prices are used to smooth out the short-term fluctuations and help traders identify price trends, reversals, and market sentiment

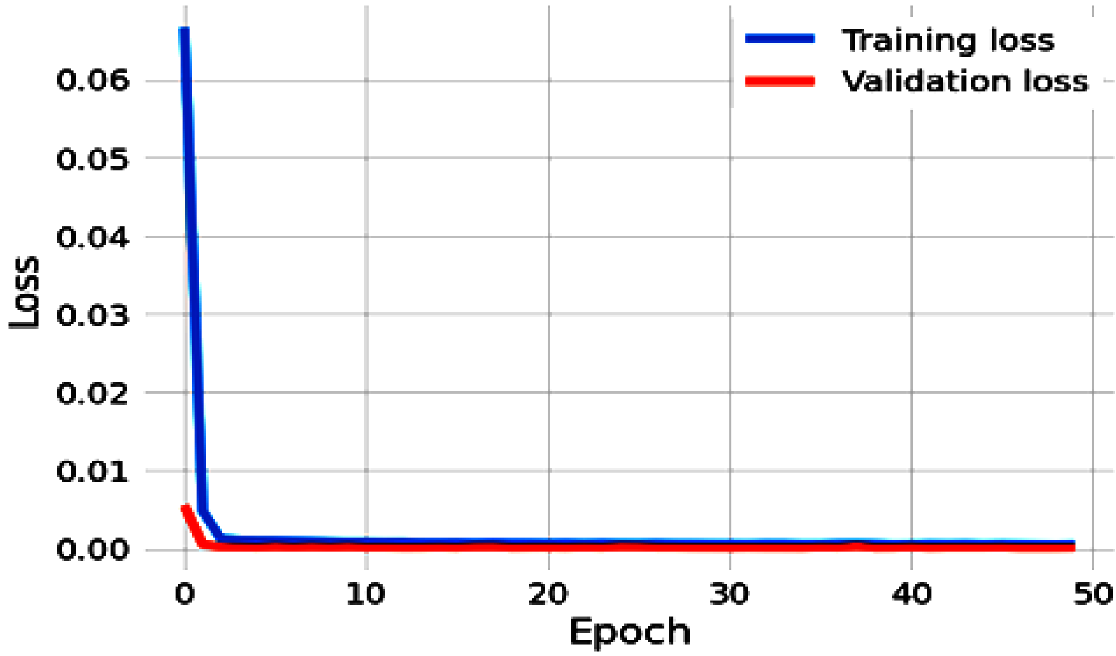

Figure 4: Result analysis of the model

Figure 4: indicates a well-trained model with no signs of overfitting or underfitting. The rapid convergence suggests the model is efficient, possibly due to an effective training algorithm or a well-tuned hyperparameter setup.

4.1 Comparative analysis with traditional models

To validate the superiority of the LSTM model, we compared it with traditional forecasting models such as ARIMA and Support Vector Machines (SVM). The LSTM outperformed both models in terms of MAE, MSE, and overall prediction stability. While ARIMA showed decent short-term predictions, it struggled with long-term trends. SVM, although accurate on some days, failed to consistently capture temporal dependencies. Thus, LSTM is more suitable for complex, non-linear stock data patterns.

4.2 Investment decision support

The predictions from the LSTM model were used to simulate buy/sell decisions based on predicted upward or downward trends. This simulation demonstrated that LSTM-based forecasting can be incorporated into algorithmic trading strategies. Investors could reduce risk by using these forecasts to identify entry and exit points, especially in the volatile insurance sector of NEPSE.

5. Conclusions

It has been concluded that predicting the stock price using LSTM techniques gives maximum accuracy and less prediction error than other regression techniques. They excel in capturing complex temporal patterns, particularly for insurance companies. Incorporating financial reports, social media, and additional data sources like macroeconomic indicators can further enhance prediction accuracy and model robustness.

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