Application of Deep Learning Algorithms and Genetic Programming for Forecasting Stock Prices in Nepal: A Comparative Study

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Abstract

As developers and software engineers enter the stock market with new strategies, such as machine learning models, the potential for stock price prediction has increased. However, other potential alternatives, such as GP, have been explored less in this area. This paper aims to validate the accuracy of existing Deep learning algorithms and compare their effectiveness with Gene Programming in forecasting stock prices in Nepal. Here are the stock data from 2014 to 2024, along with the DL and GP, to predict the stock prices of 29 stocks from 15 sectors within NEPSE. The performance metrics are evaluated in terms of accuracy and resistance to volatility. The results show that GP consistently outperforms the DL algorithms across all performance metrics, further validated by the Mann-Whitney U test. The findings also suggest the potential for integrating advanced forecasting methods, such as GP and GRU (or LSTM), into financial decision-making to enhance investment strategies.

Keywords: *data strategies and data-driven innovations, deep learning (dl), gene programming (gp), nepal stock market, price prediction*

Introduction

Deep Learning Algorithms are a subset of machine learning based on neural networks with multiple layers. It is inspired by the structure and function of the human brain, specifically its neurons and synapses. It learns by adjusting weights through backpropagation and gradient descent. It requires large datasets and lots of computation to train. It is a deterministic training approach: fixed architecture and learning rules. It works primarily with trained, labeled data. Mostly found in applications using image recognition, Natural language processing, Time-series forecasting, and anomaly detection. Examples of applications include CNN (Convolutional Neural Networks), RNN (Recurrent Neural Networks), LSTM, GRU, and Transformer models, such as GPT.

Genetic Programming (GP) algorithm is a type of evolutionary algorithm inspired by biological evolution**.** It has evolved under computer programs or models over generations. It utilizes concepts of natural selection, including selection, crossover (also known as recombination), and mutation. It has a tree structure, and no features of gradient descent or backpropagation. It is non-deterministic and stochastic. It is flexible in use. Its applications seem in Symbolic regression and program synthesis.

Predicting the stock market was previously captivating to investors and stock traders. They typically relied upon traditional tools and techniques, such as fundamental and technical analyses. (Wellington Garikai, 2015), which are still in use. However, developers and software engineers have recently entered this space with various strategies and approaches, including machine learning (ML) and deep learning (DL). Compared to traditional and manual methods, these approaches enable the autonomous, accurate, and reliable analysis of stock trends. Various deep learning (DL) algorithms, such as LSTM and GRU, demonstrate the potential to uncover patterns in stock price trends over time. (Khanal & Shakya, 2016).

Genetic Programming (GP) challenges Deep Learning (DL) in stock prediction, leveraging evolutionary adaptability over neural network-based determinism for superior performance in volatile markets

As evidenced by the rise of AI and ML-focused companies, Nepal is also gradually paving the way for the adoption of modern forecasting methods. Previous studies focused on traditional statistical models like ARIMA and GARCH. (Gaire, 2019) to analyze the Nepal Stock Exchange (NEPSE) index.

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Evolutionary Genetic Programming (GP) challenges conventional Deep Learning methods in Nepal's volatile stock market, offering higher accuracy, interpretability, and resilience to external shocks compared to neural networks

Nepal has a volatile stock market, and algorithms must capture the dynamic nature of stock price movements, which are influenced by numerous external factors, including political events and economic shifts. (Khanal & Shakya, 2016). While investors remain uncertain about incorporating deep learning techniques into their day-to-day stock decisions, extensive research has been conducted in this sector regarding its implementation and accuracy.

Besides DL algorithms, GP also shows excellent potential in predicting stock prices on a global scale. While little to no research has been done in the Nepal Stock market regarding its utilization, this evolutionary algorithm can model relationships within data, offering unique advantages like automatic feature selection and interpretability compared to the DL algorithms. While GP is primarily used for gene expression profiling and has been widely employed to characterize cellular states in response to various disease conditions and genetic perturbations, it also shows potential for use in the prediction space. It can capture a relationship in the raw data and stock prediction with more than 99% accuracy. (Yifei Chen, 2016) Accuracy is helpful for a volatile market like Nepal.

Alghieth (Alghieth, 2016) Explored a GEP-FAMR approach in comparison to Neural and Fuzzy methods, addressing challenges like overfitting, algorithmic blackboxing, and data snooping. This study revealed GEP's exceptional accuracy in short-term forecasting, with a performance rate of 95.99%, compared to 88.23% for Genetic Programming (GP) in medium-term predictions. The results underscored GEP's capability to produce simple, algebraic expressions, making it an efficient alternative for financial forecasting.

Another Researcher implements this advanced algorithm into the Stock market, showing the potential to predict and find the relationship between the input factors and the prediction close to 100% (Bin, WeiZhang, & Wang, 2019). Although it has been researched on a global scale, its implementation in the Nepal Stock market is not yet explored.

This research aims to validate the accuracy of four popular deep learning (DL) algorithms (RNN, LSTM, GRU, and CNN) and compare their effectiveness with that of the GP in forecasting stock prices in Nepal.

Literature review

Deep learning algorithms in Nepal Stock market

Gaire (2019) provided foundational insights by analyzing various concepts of time series analysis, such as the autoregressive model, moving average, and seasonal effects in the NEPSE stock index. The study identified SARIMA as the best model for forecasting daily NEPSE index values. At the same time, EARCH was best suited for capturing market volatility caused by both positive and negative shocks. It strongly indicated that the NEPSE index trends depended on the prior index values and some random factors. Investors and policymakers could utilize this for market-related decisions. (Gaire, 2019).

Deep learning models, such as LSTM and GRU, have expanded on these insights by employing a hybrid approach. Shahi et al. (2020) incorporated the financial news sentiments into these models. This study revealed that LSTM with News sentiments achieved superior performance, with an MAE of 17.7 and an R^2 of 0.979, compared to GRU with News Sentiment, with an MAE of 24.5 and an R^2 of 0.967 (Shahi, Ashish, Neupane, & Guo, 2020).

Saud and Shakya (2020) conducted a case study on the Nepal Stock Exchange (NEPSE) banking sector, which provided further insights into the predictive capabilities of LSTM and GRU models. The research found that GRU outperformed LSTM with slightly lower average MAPEs. GRU had an MAPE of 4.74 for NIB and 4.71 for NABIL compared to 5.58 for NIB and 5.06 for NABIL for LSTM. GRU's predicting accuracy was attributed to its fewer parameters, faster training, and ability to perform better even with moderate data sizes. Additionally, optimal look-back periods were identified for both models, where LSTM was less than 5 and 5–10 for GRU, indicating that higher look-back periods are less effective in improving prediction accuracy. (Saud & Shakya, 2020).

Lal et al. (2022) proposed another hybrid model for predicting stock prices, combining CNN and BRGU in sequence over short-term (next day), mid-term (15 days), and long-term (30 days) horizons. The BRGU-BCNN model outperformed other algorithms (such as LSTM, GRU, BLSTM, and BGRU) in prediction accuracy with the lowest MAPE. (Lal & Timalsina, 2022). The model first used CNN to extract features using stock close prices as input, while BGRU learned and predicted based on these features.

In a comparative study between three ML algorithms (BPNN, LSTM and GRU) by Gurung et al. (2024) to predict the future stock price trends, the study found that LSTM had the best forecast accuracy. LSTM's advanced memory capabilities allow it to achieve remarkable accuracy, reportedly averaging 98%, and to maintain consistent performance across diverse feature sets. GRU, a streamlined alternative to LSTM, offers efficiency and performs well in specific contexts but shows inconsistency with different datasets (Gurung, Prabin, & Sujan, 2024).

Genetic programming: a promising alternative

Genetic programming (GP) has emerged as a compelling alternative to traditional stock price forecasting methods. Several studies have demonstrated its effectiveness in capturing complex market dynamics across various global stock markets and enhancing forecasting accuracy; however, it has not been implemented in the Nepali market to date. Although GP has been successfully applied elsewhere, its use in the context of the Nepal Stock Exchange (NEPSE) is unexplored, which is an exciting area for research and development.

Tsai et al. (2017) conducted a significant study using the application of GP for stock movement forecasting on the Taiwan Stock Exchange (Tsai & Hong, 2017). The researchers developed an artificial intelligence system, named GPLAB, to predict stock price movements across various time frames using GP for this purpose. The findings demonstrated that GP could predict stock price trends more accurately and effectively than traditional statistical methods. The findings of this study suggest that GP is a reliable tool for financial prediction.

Another study by Abraham et al. (2022) combined genetic algorithms (GA) and Random Forests for improved stock trend forecasting. (Abraham, et al., 2022). This research primarily focused on GA but highlighted the importance of feature selection, a crucial aspect of the GP methodology. It demonstrates that optimizing input variables has a significant impact on the prediction outcome. The integrated GP can provide better forecasting models than when combined with other machine learning techniques.

Kaboudan (1998) used GP and compared stock returns to traditional forecasting methods. (Kaboudan, 1998). This study demonstrates that GP can deliver competitive performance in forecasting stock returns and maintains this competitive performance across various market conditions and data features, revealing itself to be resilient to the volatile behavior of the financial market.

Also, Garcia-Almanza and Tsang (2021) combined GP with chance discovery techniques for stock price forecasting. (Garcia-Almanza & Tsang, 2006). They found that combining these approaches could enhance the potential to uncover hidden patterns and relationships in financial data, thereby improving prediction accuracy. The synergy of other analytical methods and GP shows the versatility of GP in the financial market.

Lastly, Sha (2024) presented the hybrid model of GA and LSTM networks for time series stock price forecasting. (Sha, 2024). The researchers stressed that GA could optimize LSTM parameters to improve predictive performance. This integration demonstrates that GP has the flexibility to utilize deep learning models for financial forecasting, with potential for further improvement.

Research gaps

The collective study highlights that deep learning models, especially LSTM, GRU, and CNN-BGRU, have the potential to capture market dynamics and even improve forecasting in the NEPSE stock market. However, genetic programming also presents a promising alternative to forecasting

From traditional SARIMA models to advanced hybrid deep learning approaches, such as LSTM for news sentiment and CNN-BGRU architectures, Nepal's stock market forecasting has progressively achieved greater accuracy. Models now reach up to 98% prediction accuracy, revealing optimal architectures and parameters for NEPSE's unique conditions

Genetic Programming (GP) consistently outperforms traditional methods in global stock forecasting—demonstrating accuracy, adaptability to volatility, and synergy with AI techniques—yet remains unexplored for Nepal's unique market dynamics

stock prices, as it enables adaptive modeling and optimization to uncover complex patterns in financial data. In terms of the Nepal Stock Market, there are two research gaps:

- **GP Implementation in the Nepalese Stock Market** The NEPSE market has been substantially studied using DL Algorithms, but the implementation and performance of GP have yet to be explored in the Nepalese Stock Market.
- **Sector Coverage of Research** No existing research has included forecasting for all stocks across all sectors in the Nepal Stock Market. Previous research generally uses a single stock or uses 1-2 industries for predicting.

Methodology

The conceptual framework outlines the relationship between input data, predictive models, and output in stock price forecasting. The framework illustrates how input data are processed and utilized to train predictive models, providing accuracy metrics and actionable insights to support managers in informed decision-making.

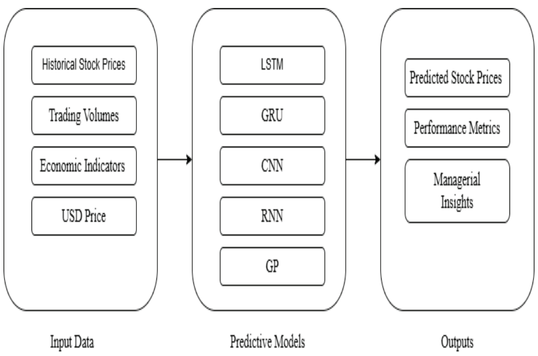

Figure 1 Conceptual Framework

This diagram illustrates a framework for predicting stock prices **using machine learning models**. Here's a breakdown of the three components and their interpretation:

1. Input data

This section includes the types of data used to train predictive models:

- **Historical Stock Prices** Past prices of stocks, which are essential for trend analysis.
- **Trading Volumes** The number of stocks traded indicates market activity and interest.
- **Economic Indicators** Broader economic variables like GDP, inflation, interest rates, etc.
- **USD Price** The currency exchange rate (USD), which can impact markets, particularly in globally interconnected economies.

These inputs provide a diverse and rich dataset to feed into predictive models.

2. Predictive models

This section lists machine learning or deep learning algorithms used for forecasting:

- **LSTM (Long Short-Term Memory)** A type of RNN that effectively handles long-term dependencies in time series data.
- **GRU (Gated Recurrent Unit)** A lightweight, faster alternative to LSTM, suitable for sequence prediction.
- **CNN (Convolutional Neural Network)** Primarily used for spatial data, but also effective in capturing patterns in time series.
- **RNN (Recurrent Neural Network)** Suited for sequential data but can suffer from short memory issues.
- **GP (Gaussian Process)** A non-parametric, probabilistic valuable model for small datasets and uncertainty estimation.

These models are applied to the input data to generate forecasts.

3. Outputs

These are the results or insights derived from the predictive models:

- **Predicted Stock Prices** The core output, forecasting future stock prices.
- **Performance Metrics** Evaluation results (e.g., RMSE, MAE, accuracy) to measure model effectiveness.
- **Managerial Insights** Strategic information from the analysis to support business or investment decisions.

Data collection

The stocks with at least 500 daily records, having a minimum of 2 years of active trading history, are selected to capture market trends. The stocks suspended or delisted are not selected for training. Stocks are then clustered into 15 sectors, with 10% of the stock from each sector, to ensure diversity and representativeness. After the collection criteria, a total of 29 stocks were selected. Historical stock prices and Today's opening price are sourced from the Merolagani website, and the historical USD price is taken from NRB's official website from 2014 to 2024. The Historical stock prices include the previous day's stock data (LTP, Percentage Change, High Price, Low Price, Opening Price, Previous Closing Price, and turnover).Tools & frameworks

The deep learning models—LSTM, GRU, CNN, and RNN were implemented using TensorFlow, Keras, and scikit-learn. Genetic programming was implemented using the learning library. Pandas library are used for preprocessing the data.

The SciPy library performs the Man-Whitney U test, which determines whether the performance differences between the DL models and GP are statistically significant. Matplotlib and Seaborn create visualizations, such as bar charts, line graphs, and heat maps.

Model training & validation

Given that the stock price is a time series of data, the sequence of the data is more important than the individual records for finding the sequence. The data is grouped into ten days and split into ordered datasets for training and testing. The data is then divided into 80% training data and 20% testing data. Finally, training is done for each model using the following parameters shown in the figure below:

A rigorous, sector-diverse dataset of 29 NEPSE stocks (2014-2024) powers comparative analysis of Deep Learning (LSTM/GRU/CNN/RNN) and Genetic Programming models, with statistical validation (Mann-Whitney U test) ensuring robust insights into Nepal's market-specific forecasting

Table 1 Deep learning parameters

Model	Layers	Hidden units	Dropout	Optimizer	Loss functions	Metrics	Output layer
LSTM (Long Short-Term Memory)	LSTM(100 uniuts return sequence) Droupout LSTM (50 units)	250	2	Adam (lr=0.001)	MSE	MSE, MAE	1 Unit (Dense)
RNN (Simple Recurrent Neural Net-work)	SimpleRNN(100 uniuts return sequence) Droupout SimpleRNN(50 units)	250	2	Adam (lr=0.001)	MSE	MSE, MAE	1 Unit (Dense)
GRU (Gated Re-current Unit)	GRU(100 uniuts return sequence) Droupout GRU (50 units)	250	2	Adam (lr=0.001)	MSE	M S E , MAE	1 Unit (Dense)
CNN (Convolutional Neural Network)	Convid(3 filters 100 kernel size, ReLU) Droupout Convid(3 filters 100 kernel size, ReLU) Dropout Flatten	250	2	Adam (lr=0.001)	MSE	M S E , MAE	1 Unit (Dense)

Table 2 Genetic programming training parameters

Category	Field	Value	Details
Population Configuration	Population Size	Initially: 3,500	Ensures diverse initial candidates.
	Population Size	Increased to: 5,000	For Hydropower, Life Insurance, and Trading sectors.
	Generations	Initially: 35	Number of generations for optimization.
	Generations	Increased to: 50	Applied to Hydropower, Life Insurance, and Trading sectors.
	Stopping Criteria	Fitness score < 0.001	Indicates the target accuracy for terminating the evolutionary process.
Operator Probabilities	Crossover Probability	0.7 (70%)	Chance of exchanging genetic material between two parents to generate offspring.
	Subtree Mutation Probability	0.1 (10%)	Replaces a randomly chosen subtree to diversify the population.
	Hoist Mutation Probability	0.05 (5%)	Alters a single point within the expression to introduce variation.
	Point Mutation Probability	0.1 (10%)	Changes a single point in the expression to enhance variability.
Model Settings	Verbose Mode	2	Gives detailed feedback during each training generation.
	Parsimony Coefficient	0.001	Encourages more straightforward and more interpretable solutions.
	Random State	42	Fixes the random seed for reproducible results.
Optimization Details	Default Loss Function	MSE	Primary loss function for evaluating the model.
	Evaluation Metrics	MSE, MAE	Metrics for measuring performance and accuracy.

This table compares four deep learning model architectures used for a regression task, as inferred from using MSE and MAE loss metrics and a dense output layer with 1 unit. Here's a breakdown of the table:

Operating definitions of the terminologies used in Deep learning.

Hidden layers: Neurons in the layers between the input and output layers—collectively called hidden layers—are called hidden units in a neural network.

Dropout: Dropout is a regularization method that keeps neural networks from overfitting. On each iteration during training, a random percentage of neurons in a layer are disabled (dropped). Because the network can no longer depend on certain neurons being active all the time, it is forced to learn more resilient and universal properties.

Loss function: The loss function calculates how much the actual values differ from the model's predictions. The aim of training is to reduce this loss. Metrics: The model's performance is assessed using metrics. In contrast to the loss function, metrics are only used for monitoring, not for learning.

Output layer: The last layer in a neural network that generates the prediction is called the output layer. The nature of the issue determines its shape and activation function: Each of these is measured using the standard unit listed in the table. Explaining them in detail is outside the scope of this essay.

Operational Definitions of terms used in genetic programming

Configuration of the Population: This is the initializing and managing the population of potential solutions in algorithms like Differential Evolution or Genetic Algorithms (GA). Operator probabilities: Operator probabilities are the odds attributed to genetic operators like selection, crossover, and mutation. Model setting: This describes the precise setup of the optimization or machine learning model employed during the run. Specifics of optimization: This section covers the control techniques and fine-tuning parameters used during the optimization process. Each of these is measured using the standard unit listed in the table. Explaining them in detail is outside the scope of this essay.

Results and analysis

The key performance metrics are calculated for each algorithm and selected stocks. All further analysis uses these values.

Average performance of algorithms

the following table summarizes the performance metrics of various predictive models used for forecasting stock prices, explicitly focusing on Root Mean Square Error (RMSE), Coefficient of Determination R^2 and Mean Absolute Percentage Error (MAPE):

Table 3 Average performance of models

Algorithm	RMSE	R^2	MAPE
GP (Gaussian Process)	26.79209	0.986501	0.020011
CNN	52.86093	0.669396	0.055188
GRU	40.3325	0.843351	0.035889
LSTM	43.29142	0.741601	0.040696
RNN	56.58934	0.613057	0.053737

The table presents the **performance comparison of five predictive algorithms (CNN, GRU, LSTM, RNN)** used for stock price forecasting. **GP comes under Genetic Programming,** It uses **three evaluation metrics**: **Metrics Explained are:**

- **RMSE (Root Mean Square Error)**: Lower values indicate more accurate predictions.
- **R^2 (Coefficient of Determination)**: A value closer to 1 indicates a better fit of the model to the actual data.
- **MAPE (Mean Absolute Percentage Error)**: Lower percentages indicate better accuracy.

The interpretation is presented in Table 4 based on the explained criteria.

Table 4 Interpretation of each model's performance

Algorithm	RMSE	R^2	MAPE	Performance Summary
GP (Gaussian Process)	**26.79**	**0.987**	**0.02**	• **Best overall**: Lowest RMSE and MAPE, highest R^2; most accurate and reliable.
GRU	40.33	0.843	0.0359	• Excellent performance; second-best after GP. Efficient and accurate.
LSTM	43.29	0.742	0.0407	• The model achieves decent performance, outperforming both CNN and RNN.
CNN	52.86	0.669	0.0552	• Weaker performance; struggles more with time-series patterns.
RNN	56.59	0.613	0.0537	• The lowest-performing model is the least accurate and unsuitable for stock prediction.

Statistical validation

For statistical validation, the Mann-Whitney U Test is used.

Hypothesis for mann-whitney U Tests

Null Hypothesis (H□): There is no significant difference between the GP and the deep learning models regarding performance metrics.

Alternative Hypothesis (H□): GP performs better (i.e., lower RMSE, lower MAPE, and higher R^2) than the deep learning models.

The significance Threshold(α) is **0.05**. We will reject the null hypothesis if the p-value is less than 0.05, indicating that GP performs better than the deep learning models.

Table 5 U test based on RMSE, MAPE, and R^2

Metric	Comparison	P-Value	Conclusion
RMSE	LSTM vs GP	0.013411308	Reject H□ ($p < 0.05$)
RMSE	GRU vs. GP	0.035779443	Reject H□ ($p < 0.05$)
RMSE	CNN vs. GP	0.000391578	Reject H□ ($p < 0.05$)
RMSE	RNN vs GP	0.00268741	Reject H□ ($p < 0.05$)
MAPE	LSTM vs GP	1.46952E-07	Reject H□ ($p < 0.05$)
MAPE	GRU vs. GP	3.98395E-07	Reject H□ ($p < 0.05$)
MAPE	CNN vs. GP	8.94E-10	Reject H□ ($p < 0.05$)
MAPE	RNN vs GP	3.43162E-09	Reject H□ ($p < 0.05$)
R^2	LSTM vs GP	8.8796E-11	Reject H□ ($p < 0.05$)
R^2	GRU vs. GP	1.81735E-10	Reject H□ ($p < 0.05$)
R^2	CNN vs. GP	7.22101E-11	Reject H□ ($p < 0.05$)
R^2	RNN vs GP	7.22101E-11	Reject H□ ($p < 0.05$)

Genetic Programming (GP) demonstrates statistically significant superiority over all tested deep learning models (LSTM, GRU, CNN, RNN) across RMSE, MAPE, and R^2 metrics ($p<0.05$), establishing it as a transformative approach for Nepal's stock market forecasting

Overall conclusion

- Across all three performance metrics (RMSE, MAPE, R^2), **GP outperforms all other models** with **statistically significant differences**.
- The **null hypothesis (H□)** — that there is no difference between GP and the other models — is **rejected in every case**.
- This finding strongly supports the selection of **Gaussian Process (GP)** as this study's best predictive model for stock price forecasting.

Conclusion

This analysis highlights the exceptional performance of Genetic Programming (GP) in predicting stock prices. Regarding predictive accuracy and model reliability, GP outperforms traditional deep learning models, such as LSTM, GRU, CNN, and RNN. While GP is the most robust model overall, LSTM remains a reliable option in specific sectors such as manufacturing and life insurance, where its performance is comparable to GP's. However, GP's consistent accuracy across all industries and performance metrics, especially RMSE and MAPE, positions it as the most reliable and effective tool for stock price prediction in Nepal's financial market.

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