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Original Paper : Cross-Sectional Research – Methodology Study Paper

Stock Market Price Forecasting Using LSTM And GRU Networks

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Abstract: Because of the inherent volatility and complexity of the financial markets, accurately predicting stock prices is a challenging task. By assessing the performance of many predictive models, including Random Forest, Stacked LSTM, Stacked GRU, ARIMA (Auto Regression Integrated Moving Average), network with long short-term memory (LSTM) and support vector machine (SVM), the study seeks to tackle this challenge. We thoroughly evaluate these model's performance by looking at their capacity for generalization and prediction accuracy. The GRU model outperformed the LSTM model with a substantially lower validation loss of 0.0101 and a training loss of 0.0067, whereas the LSTM model obtained a validation loss 0.5048 with a training loss of 0.0130. The SVM with Support Vector regression (SVR) demonstrated a much larger Mean Squared Error (MSE) of 2878.20, whereas Random Forest model produced an MSE of 85.57. The GRU and LSTM models were further improved by the stacked architectures; the Stacked GRU achieved loss of 0.0361 and the Stacked LSTM achieved a validation loss of 0.9658. Despite being simpler, the ARIMA model yielded a Mean Squared Error of 11.8594. The results of this through investigation show that the GRU and Stacked GRU models perform the best.

Keywords: Res-Next CNN, RNN, Deep Neural Network, Computer Vision.

1. Introduction

Precise forecasting of stock prices is a cornerstone of modern financial decision-making, providing essential insights for optimizing investments and managing market risks. Financial markets, characterized by intrinsic unpredictability, dynamic fluctuations, intricate nonlinear trends, present formidable obstacles to traditional prediction methodologies. While classical statistical models such Auto Regression Integrated Moving Average (ARIMA) have been widely used to identify linear patterns in historical data, their rigidity in addressing the multifaceted dynamics of stock markets has spurred the adoption of advanced computational approaches. This study investigates the performance of cutting-edge machine learning and deep learning frameworks to overcome these limitations, offering a comparative analysis of their predictive accuracy in volatile trading environments. Emerging innovation in artificial intelligence, particularly Long Short-Term memory (LSTM) and Gated Recurrent Unit (GRU) networks, have revolutionized time series analysis by effectively capturing temporal relationships while addressing gradient-related challenges in training. These architectures excel in modeling sequential dependencies, enabling robust prediction even in noisy, non-stationary markets. Complementing these, ensemble techniques such as Random Forest and Support vector Machine (SVM) leverage nonlinear pattern recognition, while hybrid stacked models (e.g., Stacked LSTM/GRU) combine hierarchical feature extraction for enhanced precision. The metrics like validation loss and Mean Squared Error (MSE), this analysis quantifies the predictive accuracy, scalability and computational efficiency of each approach. Key goals include determining optimal model architectures for real-world financial datasets.

2. Background

Stock price forecasting is a crucial part of financial research and investment. Strategy, motivated by the requirement to forecast market trend and arrive at well-informed conclusions. Conventional Models like Auto Regression Integrated Moving average (ARIMA) have long been used because of their ease of use and efficiency in capturing linear relationships. However, more advanced methods are frequently required because to the intricacy and nonlinearity of financial time series data. Promising alternatives are provided by recent advancements in machine learning and Deeping learning.

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Some models, such Gated Recurrent Unit (GRU) networks and Long Short-Term (LSTM) networks, are appropriate for handling temporal connection and identifying complex patterns in sequential data forecasting tasks. Because of their ability to maintain long-term associations, LSTM and GRU. Which are well-known for their effectiveness and reduced computational complexity. Notable improvements in prediction accuracy when compared to traditional methods. By using several prediction models to improve accuracy, ensemble approaches like Random Forest and Support Vector machine (SVM) can offer insightful information. The limits of model performance are further pushed by stacked architectures, which include many layers of LSTM or GRU units. In order to intricacies of financial data, this study investigates how these sophisticated models predict stock prices.

3. Related Works

Analyze forecasting Accuracy: To compare and assess the forecasting accuracy of various models, such as Random Forest, Auto Regressive Integrated Moving Average (ARIMA), Support Vector Machines (SVM), Gated Recurrent Unit (GRU), Stacked LSTM, Stacked GRU. This involves looking at performance metrics like validation loss and Mean Squared Error to see which model generates the best accurate forecasts.

Examine the Performance of the Model: To assess the benefits and drawbacks of each model in terms of its ability to capture the intricacies of stock price fluctuations. This involves assessing how well these models manages temporal relationships and nonlinearity in financial data.

Examine Advanced and Conventional Methods: To compare the effectiveness of traditional models (ARIMA, Random Forecast, SVM) and advanced machine learning approaches (LSTM, GRU, Stacked LSTM, Stacked GRU) in the context of stock price forecasting. This seeks to demonstrate how contemporary methods have improved predicted performance.

Assess the Useful Consequences: To provide useful standards for choosing and applying the best forecast model in actual financial situations. This entails giving investors and financial analysts information about each model limits and practical applicability.

4. Material and Methods

Accurate stock price forecasting is essential for reducing financial risks and improving trading methods. However, stock valve forecasting is quite challenging due to the non-stationary and unpredictable nature of financial markets. Traditional time series models like the Auto Regression Integrated Moving Average (ARIMA) have trouble capturing the complex and nonlinear connection seen in financial data. ARIMA models perform well for linear time series, but their shortcomings become apparent when dealing with intricate pattern of stock price movement.

4.1. Scope of This Paper

Comparing the performance of several models, including Random Forest, Support Vector machine (SVM), Auto Regression Integrated Moving Average (ARIMA), Gated Recurrent Unit (GRU), Stacked GRU, Long Short-Term Memory (LSTM) networks. This means assessing each model's accuracy, loss metrics, generalization capability.

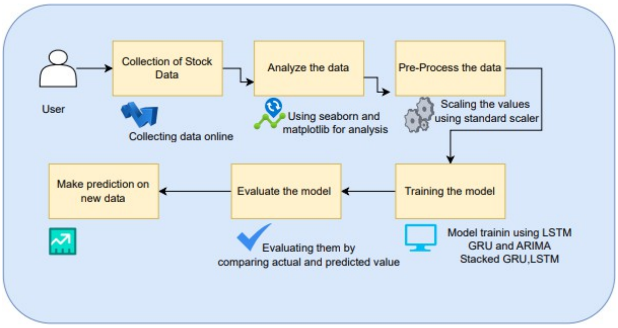

Figure.1 Architecture

Data Range: Historical stock price data to train and evaluate the models, ensuring a trustworthy evaluation across a range of conditions. Patterns and seasonality will be taken into throughout the datasets preprocessing.

Metric for Evaluation: Evaluating each models prediction accuracy using a variety of performance criteria, including as validation loss and Mean Squared Error (MSE). This aids in determining which models provide the most accurate prediction.

Data Collection: This module gathers historical stock price data via the internet. It ensures that the dataset contains key variables such as Adj Close, Open, High, Low, Close and Volume.

Preprocessing: The data is cleansed and ready for modeling at this point after it has been collected. Data must be scaled or normalized, missing values processed, separated into training and testing sets in order to ensure accurate model assessment.

Modeling: This topic focuses on developing and refining machine learning models. It involves implementing techniques such as Random Forest Regressor, Support vector Regression, GRU, Stacked GRU, LSTM, Stacked LSTM. The models are adjusted and modified the get the

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best stock price prediction outcomes.

Prediction: After models have been trained, this module generate prediction generates predictions based on new or unknow data. It produces forecast stock prices and uses measures such as Mean Squared Error (MSE) to assess the model's performance and validation loss.

4.2. Methodology and Problem Statement

Accurate stock price forecasting is essential for reducing financial risks and improving trading methods. However, stock value forecast is quite challenge due to the non-stationary and unpredictable nature of financial markets. Conventional time series models, such as the ARIMA (Auto regressive Integrated Moving Average), have trouble capturing the complex and nonlinear relationship seen in financial data. ARIMA models perform well for linear time series. when dealing with intricate patterns f stock price movement.

Recent development in deep learning and machine learning may provide answer to a number of problems. Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) networks are designed to better handle sequential input and store long- term dependencies, therefore addressing the shortcoming of older models

.4.3. Dataset Description

Adjusted Close (Adj Close): This column shows the closing price of Amazon stock dividends and stock splits are subtracted.it is a floating-point figure that is crucial to comprehending the stocks actual worth following modifications.

Open: On each trading day, this feature shows the price at which Amazon stock started trading. It is essential for examining the stocks opening trend and early market sentiment and is recorded as a floating-point number.

High: This column records the highest price at which Amazon shares were traded each day. This floating-point number aids in determining the market's volatility and peak trading price.

Low: This feature shows the closing price of Amazons shares on daily basis. This floating-point figure aids in determining the lowest trading value and market volatility.

Close: This column shows the price at which Amazons stock close at the end of each trading day. It is essential for assessing daily performance and end-of-day trends because it is a floating-point number.

Volume: The total number of shares of Amazons stock traded daily is shown by this integer column. Understanding market activity and liquidity requires the use of volume statistics.

5. Result and Discussions

(a). Long Short-Term Memory (LSTM) Networks

Long short-term memory (LSTM) networks in recurrent neural networks (RNNs) are designed to recognize longer patterns in sequential input. By keeping data in a memory cell over prolonged periods of time, address the vanishing gradient issue differently than traditional RNNs address this problem. The three primary parts of an LSTM cells are known as gates.

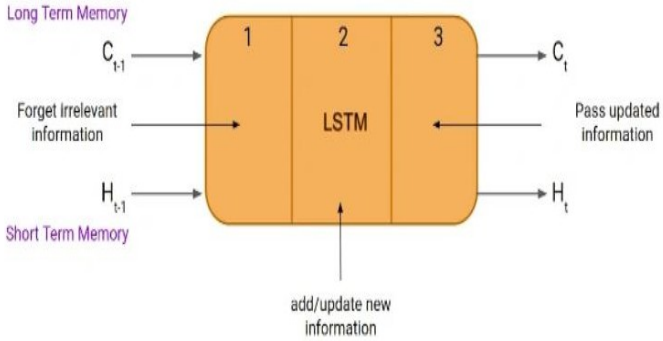

Figure.2 Architecture Low of Information

Similar to a basic RNN, an LSTM network include two hidden states: HtH_tHt at each time step and Ht-1H_{t-1} Ht-1 at the previous time step. Additionally, the numbers Ct-1C_{t-1} CtC_tCt, respectively, for the cell states of the previous and current time steps, while the hidden state represents short-term memory.

(b). GRUs, or gated recurrent units

GRUs are a similar variant of LSTMs that also address the vanishing gradient problem with fewer parameters. By combining the hidden state, cell concealed state into one entity, they reduce the complexity of computation.

Architecture: The reset entrance decides how much of the past data to disregard, while the update gated chooses how much of the fresh data to merge.

State Update: Unlike LSTMs, GRUs do not have a unique cell state. Instead, they use the reset and update gates to directly change the concealed state.

Training: GRUs and LSTMs are trained in a similar manner by using backpropagation through time (BPTT) to update the weight based on the loss function.

Internal processes are primary difference between training

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a simple recurrent Neural Network (RNN) and a Gated Recurrent Unit (GRU) network. Back-Propagation Through Time (BPTT) is used for training in both, but GRUs include gating procedures that alter the computation of gradients. In GRUs, gradients are aggregated over time steps to update the model's weights, and the error is computed as the difference between actual and predicted values. Compared to simple RNNs, the gradient computations in GRUs are altered by these social gating mechanisms.

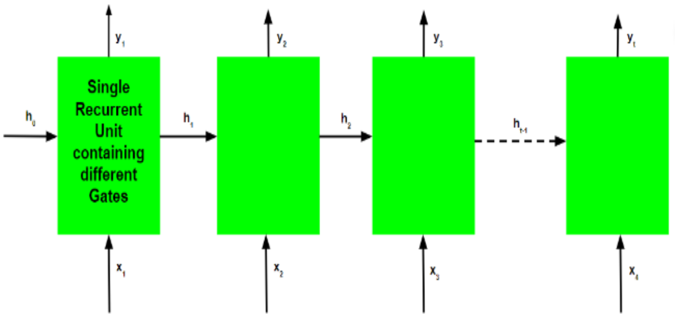

Figure.3 GRU's

(c). Stacked LSTM

Multiple layers of LSTM units make up stacked LSTM networks, which enable the model to extract more intricate pattern and hierarchical characteristics form the input. The primary benefits of stacked LSTMs are their ability to model intricate sequences and improve performance in applications like as voice recognition, machine translation, time-series forecast. Although stacked LSTMs need more processing resources because to their additional components, they are more accurate than gated recurrent unit (GRUs) in capturing long-term relationships. They are therefore a very useful tools for examining sequential data.

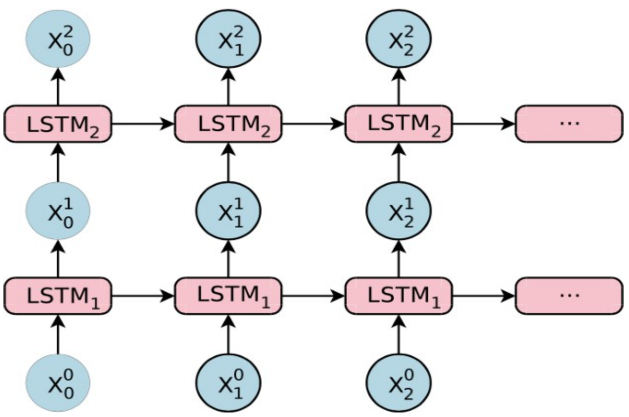

Figure.4 LSTM

(d). Stacked GRU

Like stacked LSTMs, stacked GRUs are made up of many GRU layers. They capture intricate temporal relationships while utilizing the effectiveness and streamlined structure of GRUs. The main advantages of stacked GRUs is their enhanced comprehension of complex temporal correlations, which qualifies them for use language modeling, speech recognition, time- series forecast, among other applications. Although stacked GRUs outperform single-layer GRUs, they need more processing resources and are more likely to overfit if improperly managed. In some applications, among stacked GRUs might be faster to train and deploy than LSTM networks because of their simpler design, which has fewer parameter and no separate memory cell.

(e). ARIMA (Auto Regressive Integrated Moving Average)

ARIMA is a traditional time series estimation model that incorporates auto regressive (AR) components, differencing (I) to stabilize the series, moving normal (MA).The Integrated (I), Auto Regressive (AR), Moving Average (MA) are the three main parts of the ARIMA model. The link between the historical and present data is captured by the AR component, which highlights the importance of previous values. In order to attain Stationarity. Which stabilizes the mean and variance by elimination trends and seasonality the component entails differencing the time series. The relationship between a observation and the residual error from a moving average model applied to lagged values is the main focus of the MA component.

(f). Evaluation Metrics

In assessing the performance of LSTM and GRU models for stock price prediction, key evaluation metrics include Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which quality the average deviation of predicted prices from actual values. Mean Absolute Error (MAE) provides an interpretable measure of average prediction error magnitude, while Directional Accuracy (DA) evaluate the model's ability to correctly predict upwards or downwards price trades. Additionally, R-squared (R2) assesses the proportion of variance in stock prices explained by the models.

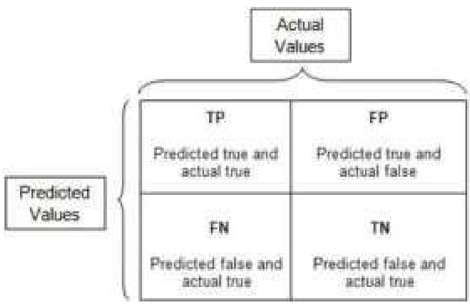

Figure.5 Accuracy Value

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

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Mean Squared Error (MSE)

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Root Mean Squared Error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Directional Accuracy (DA)

$$\mathrm{DA} = \left(\frac{1}{n}\sum_{t=1}^{n}\mathbf{1}\left(\mathrm{sign}(\hat{y}_t - y_{t-1}) = \mathrm{sign}(y_t - y_{t-1})\right)\right) \times 100\%$$

R-squared Error (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

These metrics collectively gauge the proportion of variance in stock prices explained by the model. These metrics overall model reliability, ensuring a comprehensive evaluation of LSTM and GRU architectures in financial time-series analysis.

(g). Accuracy Comparison

Table.1 Algorithm Performance Metric

Algorithm	Model	Accuracy	MSE	MAE
Random Forest	Random Forest Regressor	0.8600	424.0100	**15.9900**
SVM	SVR	0.3463	232.6406	**11.5442**
LSTM	LSTM	0.7983	71.7857	**6.6633**
S-LSTM	S-LSTM	0.7273	71.7857	**8.2540**
GRU	GRU	0.7499	88.6861	**7.7797**
S-GRU	S-GRU	0.9281	25.4863	**3.8941**
ARIMA	**ARIMA**	**0.9660**	**11.8594**	**2.5032**

6. Conclusion And Future Scope

This study investigates advanced techniques for predicting stock prices by evaluating various machine learning and deep learning models. The research focuses on comparing the effectiveness of different approaches, including Random Forest, Gated Recurrent Units (GRU), Stacked LSTM, Stacked GRU, Support Vector Machines (SVM), and Auto Regressive Integrated Moving Average (ARIMA). Historical stock data from Amazon, comprising adjusted close, open high, low, close prices, and trading volume, was used for analysis. The goal was to determine which models deliver the most accurate forecasts in the highly volatile stock market environment.

Traditional machine learning models, such as Random Forest and SVM, recorded higher MSE values, indicating their limitations in Modeling the non-linear and sequential nature of stock price movements. ARIMA, while effective for linear trend analysis, fell short in accuracy when compared to deep learning approaches. The findings suggest that advanced neural network architectures, particularly GRU-based models, offer superior forecasting accuracy for stock prices. Future research could explore hybrid models or addition feature engineering to further enhance predictive performance.

Future Research Directions

Model Optimization: Future studies should prioritize refining the architecture and training parameters of LSTM and GRU models to enhance their predictive accuracy. This could involve exploring advanced regularization method, optimizing layer depth, and experimenting with dynamic learning rate adjustments to minimize validation loss.

Feature Engineering: Incorporating novel data sources, such as real-time sentiment analysis from social media, geopolitical event indicators, or sector-specific economic trends, could enrich input datasets. Additionally, testing feature selection techniques to identify the most impactful variables may improve model efficiency.

Hybrid Models: Developing integrated framework that merge neural networks (e.g., GRU or LSTM) with traditional machine learning approaches, such as gradient boosted decision trees or Bayesian optimization, could leverage the strengths of both paradigms to better capture complex market dynamics.

Extend Data Sets: Expanding research to include diverse asset classes (e.g., cryptocurrencies, commodities) or global stock markets would validate model generalizability. Cross-sector and cross-regional analysis could uncover universal patterns and improve.

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