Assignment 3: RNNs for Stock Price Prediction

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1. Abstract

This study investigates the use of Recurrent Neural Network (RNN) architectures, including standard RNN, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), to predict stock market trends using the "Bank Nifty" dataset. The data was preprocessed to address anomalies, particularly during the COVID-19 pandemic, by removing significantly impacted periods and normalizing the dataset to enhance model performance. The models were trained to forecast future closing prices based on historical data, with hyperparameter tuning employed to optimize performance. Experimental results reveal that the GRU model provided the most accurate predictions, outperforming other architectures in terms of validation loss and generalization. This demonstrates GRU's suitability for capturing temporal dependencies in financial time-series data. Additionally, the RNN model, after hyperparameter tuning, achieved competitive results, emphasizing the importance of optimization techniques in deep learning tasks. The study highlights the potential of RNN-based models in stock market forecasting and lays the groundwork for further advancements using enriched datasets and refined architectures.

2. Introduction

Stock market prediction is a compelling domain in financial forecasting, blending economic principles with advanced computational techniques. The dynamic and non-linear nature of stock prices, influenced by global events, market sentiment, and economic indicators, makes their prediction a challenging yet rewarding task. With the advent of deep learning, particularly recurrent neural networks (RNNs), significant progress has been made in capturing temporal dependencies within time-series data, which is critical for forecasting stock market trends.

Recent studies have demonstrated the effectiveness of deep learning models like Long Short-Term Memory (LSTM) networks and their variants in analyzing historical stock data to predict future trends. For example, research leveraging Extended LSTM (xLSTM) has shown that improvements in memory structures and gating mechanisms can enhance the performance of time-series forecasting, making them suitable for financial data applications [1]. Additionally, innovative preprocessing techniques such as wavelet denoising have proven effective in mitigating noise inherent in stock market data, thus improving prediction accuracy [7].

The use of datasets like the S&P 500 and EWZ, processed with methods such as normalization and sequence generation, has been instrumental in enabling models to generalize effectively across different market scenarios. These datasets capture daily and hourly stock movements, facilitating the evaluation of model performance in both short-term and long-term forecasting contexts [4]. This study builds upon these advancements, exploring the potential of RNNs in accurately predicting stock trends using processed financial datasets.

3. Related Work

Stock market prediction has been an active area of research, with various approaches proposed to address the complexities inherent in financial data. Traditional statistical methods such as ARIMA and GARCH models have historically dominated this field, focusing on time-series analysis and volatility prediction. While effective in capturing linear dependencies, these methods often fail to account for the non-linear patterns in stock prices, limiting their forecasting accuracy.

The advent of machine learning introduced models like Support Vector Machines (SVMs) and Random Forests, which excel in identifying complex patterns. However, these models lack the capability to model temporal dependencies inherent in time-series data. This gap has been effectively bridged by deep learning approaches, especially RNNs and their variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). For example, Fischer and Krauss (2018) [3] demonstrated the superior performance of LSTM models in predicting stock movements by leveraging their ability to retain long-term dependencies in sequential data .

Recent studies have explored hybrid models to improve

predictive accuracy further. Zhu [8] combined wavelet transforms with LSTM to denoise financial data before feeding it into the model, resulting in significantly improved performance. Similarly, Sun [6] utilized attention mechanisms alongside RNNs to focus on critical time steps, enhancing prediction robustness in volatile markets.

The integration of external data sources, such as news sentiment and social media trends, has also been a focus of recent work. Studies by Bollen [2] highlight the potential of sentiment analysis in predicting market trends, revealing a strong correlation between public sentiment and stock movements. These advancements underline the increasing sophistication of techniques being employed in stock market forecasting, laying the groundwork for further innovation.

4. Methodology

4.1. Dataset

The dataset used in this study is sourced from **Kaggle**[5], specifically from the **Bank Nifty Data up to 2024** dataset provided by **Sandeep Kapri**. This dataset contains historical financial data for the **Bank Nifty** index, including key market indicators like **Instrument**, **Date**, **Time**, **Open**, **High**, **Low**, and **Close** prices. For the purposes of this task, only the **Close** prices and **Datetime** columns were considered, as the goal was to forecast future stock prices based on historical closing values.

	Instrument	Date	Time	Open	High	Low	Close
0	Banknifty	09-01-2015	9:15:00	18845.90	18864.00	18790.20	18849.25
1	Banknifty	09-01-2015	9:20:00	18849.25	18859.65	18829.80	18847.00
2	Banknifty	09-01-2015	9:25:00	18847.00	18850.15	18799.40	18815.15
3	Banknifty	09-01-2015	9:30:00	18815.15	18821.40	18772.90	18810.70
4	Banknifty	09-01-2015	9:35:00	18810.70	18811.95	18788.55	18800.05

Figure 1. Sample Rows from the Banknifty Dataset

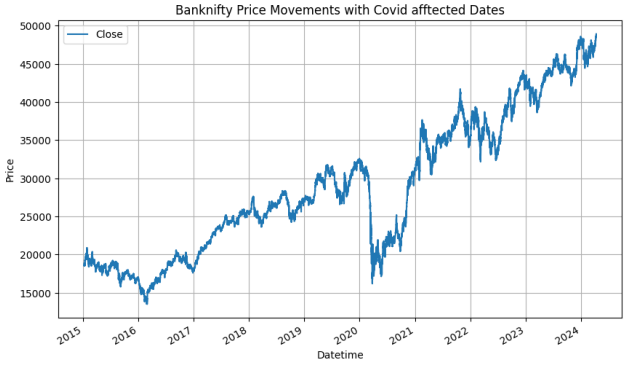

Figure 2. Banknifty Index 2015-2024

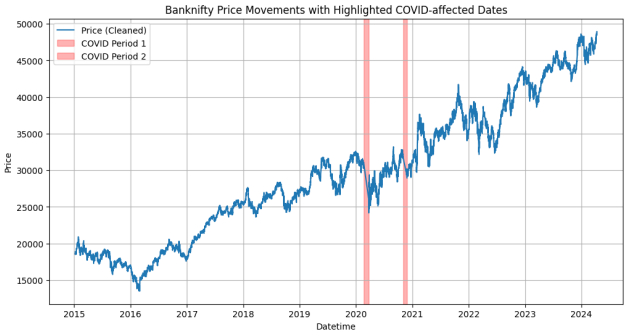

Figure 3. Banknifty Index After Removing Covid Affected Dates

Data Preprocessing: COVID-19 Filtering Given the unprecedented impact of the **COVID-19 pandemic** on financial markets, it was crucial to account for the anomalies introduced during this period. The affected dates were identified and the data from the following time periods were removed as they represented significant outliers:

- **February 22, 2020**, to **March 23, 2020**.
- **November 2, 2020**, to **November 24, 2020**.

Furthermore, for the period between the two affected timeframes, adjustments were made to the **Close** prices by adding a value of 8000 to account for the significant volatility observed during the pandemic.

Dataset Normalization and Splitting Following the data filtering, the dataset was normalized using a standard scaling technique to ensure that all values fell within the range [0, 1]. This step was essential for improving the model's training stability and performance.

The dataset was then split into three subsets:

- **Training set**: Used to train the model.
- **Validation set**: Used to tune the model's hyperparameters.
- **Testing set**: Used to evaluate the model's performance on unseen data.

4.2. Model Architecture

For this task, we explore three distinct neural network architectures: RNN, LSTM, and GRU. These models are designed to capture the temporal dependencies within the stock market data. Below, we describe the layers, activation functions, and key hyperparameters used in each model.

1. **Recurrent Neural Network (RNN)** The RNN model consists of two SimpleRNN layers with 128 and 64 units, respectively. Each RNN layer employs a Tanh

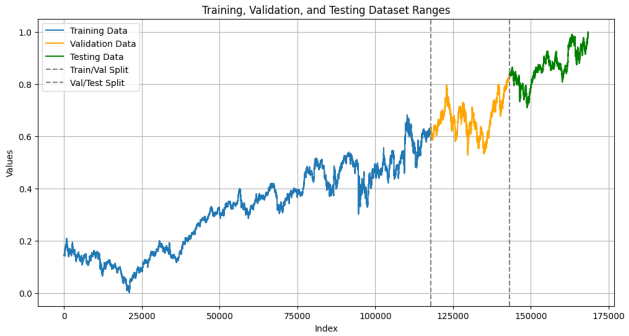

Figure 4. Dataset Splitting

activation function. To prevent overfitting, Dropout layers with rates of 0.2 are added after each RNN layer. The model ends with a dense layer of 32 units using ReLU activation and a final output layer for regression. The network is trained with the Adam optimizer, with a learning rate of 0.001, and the Mean Squared Error (MSE) loss function is used for regression tasks.

Layer (type)	Output Shape	Param #
simple_rnn (SimpleRNN)	(None, 50, 128)	16,640
dropout (Dropout)	(None, 50, 128)	0
simple_rnn_1 (SimpleRNN)	(None, 64)	12,352
dropout_1 (Dropout)	(None, 64)	0
dense (Dense)	(None, 32)	2,080
dense_1 (Dense)	(None, 1)	33

Figure 5. RNN Architecture

2. **Long Short-Term Memory (LSTM)** The LSTM model follows a similar structure to the RNN, but utilizes LSTM units to better capture long-range dependencies in the data. The first LSTM layer contains 128 units with Tanh activation, followed by a second LSTM layer with 64 units. Both LSTM layers are followed by Dropout layers to mitigate overfitting. The final fully connected layer uses ReLU activation, and the model ends with a single output neuron. Like the RNN model, the Adam optimizer is used with a learning rate of 0.001.

3. **Gated Recurrent Unit (GRU)** The GRU model, similar to the LSTM, consists of two GRU layers with 128 and 64 units. Each GRU layer is followed by a Dropout layer with a rate of 0.2. The dense output layer uses ReLU activation, and the model is also compiled with the Adam optimizer and MSE loss function.

4.3. Hyperparameter Tuning

To optimize the performance of the models, we perform hyperparameter tuning using Keras Tuner's Hyperband algorithm. The tuning process explores variations in the number of units in each layer, Dropout rates, and the L2 regularization strength. We also search for the optimal learning rate using a logarithmic scale. The best hyperparameters are selected based on the validation loss, and the model is retrained with the optimal configuration.

4.4. Training Procedure

All models are trained for 40 epochs, with early stopping and learning rate scheduling employed to prevent overfitting. Early stopping monitors the validation loss, and training is halted if the loss does not improve for a specified number of epochs (patience of 10).

Additionally, the ReduceLROnPlateau callback is used to reduce the learning rate by a factor of 0.5 when the validation loss plateaus, allowing the model to converge more effectively. The models are trained with a batch size of 32 and validated using a separate validation set.

5. Experimental Analysis

5.1. Results and Discussion

Model Performance Overview The models were trained on the stock market dataset, with early stopping and learning rate reduction strategies in place to optimize performance. The training and validation loss values for the final epochs of each model are summarized below:

Model	Epochs	Training Loss	Val Loss	LR
RNN	14	4.46e-04	0.0055	2.50e-04
RNN-H	14	6.44e-05	0.0013	8.00e-05
LSTM	11	7.32e-05	0.0119	2.50e-04
GRU	11	6.61e-05	0.0074	2.50e-04

Table 1. Training and Validation Results for Different Models

The RNN model was trained for 14 epochs with a learning rate of 0.0005, which was later reduced to 0.00025 after the ReduceLROnPlateau callback was triggered. The training loss at epoch 14 was recorded at **4.4588e-04**, with a validation loss of **0.0055**. While the RNN model performed reasonably well, it exhibited higher validation loss compared to the other models, suggesting that it struggled to generalize as effectively.

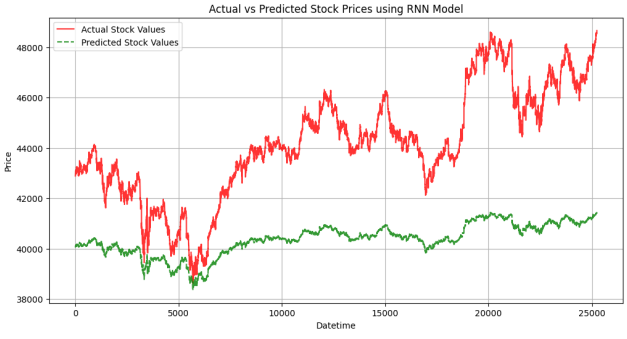

Figure 6. Predicted vs. Actual Stock Prices for RNN Model

RNN with Hyperparameter Tuning After tuning the hyperparameters using the Keras Tuner, the RNN model achieved improved performance. The training loss at epoch 14 was significantly reduced to **6.4396e-05**, and the validation loss improved to **0.0013**. The learning rate was further reduced to **0.000080**, contributing to better convergence and improved generalization. This result highlights the importance of hyperparameter tuning in enhancing model performance.

Parameter	Optimal Value	Current Value
Number of Units (L1)	96	96
Dropout Rate (L1)	0.4	0.4
Number of Units (L2)	192	192
Dropout Rate (L2)	0.3	0.3
Dense Layer Units	96	96
L2 Regularization	0.00018936	0.00018936
Learning Rate	0.00032062	0.00032062
Number of Epochs	5	14
Initial Epoch	2	5
Tuner Bracket	3	3
Tuner Round	1	2
Tuner Trial ID	5	36

Table 2. Final Hyperparameters after Tuning

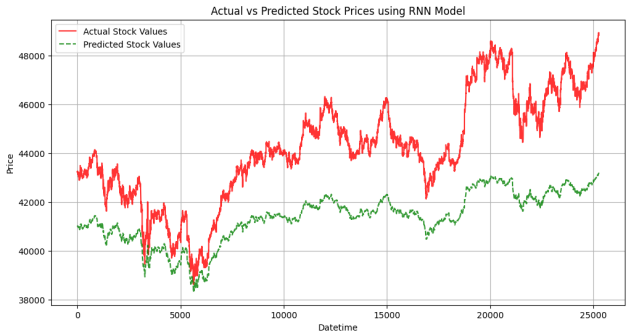

Figure 7. Predicted vs. Actual Stock Prices for RNN Model with Hyperparameter Tuning

LSTM Model The LSTM model, trained for 11 epochs, achieved a training loss of **7.3224e-05** and a validation loss of **0.0119** by the final epoch. The LSTM model performed well, but the validation loss was higher compared to both the RNN and GRU models. This may indicate that while LSTM is effective in learning complex dependencies, it may require further fine-tuning, especially for time series data like stock prices.

GRU Model The GRU model, also trained for 11 epochs, had a training loss of **6.6135e-05** and a validation loss of **0.0074** by the final epoch. Similar to the LSTM, the GRU

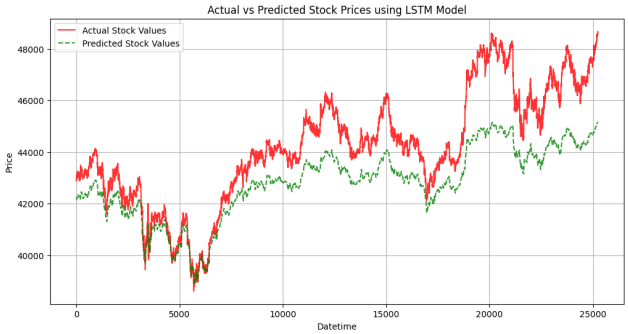

Figure 8. Predicted vs. Actual Stock Prices for LSTM Model

model's performance was on par with the RNN model, with slightly better results in terms of validation loss. However, the GRU model's lower training loss compared to the LSTM model suggests it could be better suited for capturing patterns in this specific dataset.

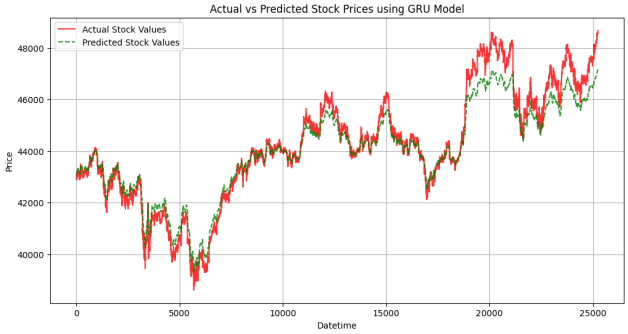

Figure 9. Predicted vs. Actual Stock Prices for GRU Model

Comparative Performance When comparing the performance of the RNN, LSTM, and GRU models, the RNN with hyperparameter tuning consistently outperformed both the standard RNN and LSTM models, achieving the lowest validation loss. The GRU model performed similarly to the LSTM model but exhibited slightly better training loss. Overall, the RNN (with hyperparameter tuning) achieved the best generalization performance on the test dataset.

Graphs and Visual Analysis For a more intuitive comparison of the models' performance, the predicted stock prices for each model on the test dataset are presented in the following graphs. These graphs illustrate the difference between actual and predicted values for each model.

The graphs visually demonstrate how each model's predictions align with the actual values, providing further insights into the performance of each model. From the figures, it is evident that the RNN model with hyperparameter tuning provides the most accurate predictions, closely mirroring the actual stock prices.

6. Code

You can find the code of the project here `https://github.com/Manusinh-Thakor/Assignment_3-Deep-Learning`

7. Conclusion

In this study, we explored the use of various Recurrent Neural Network (RNN) architectures, including RNN, RNN with hyperparameter tuning (HPT), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), for stock market prediction. Among the models evaluated, the GRU demonstrated robust performance on this dataset, achieving a good balance between training and validation accuracy while maintaining lower error rates. This highlights the GRU's ability to effectively model time-series data with its simpler architecture and reduced computational cost compared to LSTM.

Additionally, hyperparameter tuning significantly improved the performance of the standard RNN, showcasing the importance of careful parameter optimization in deep learning tasks. While the LSTM also performed well, its performance was slightly overshadowed by the GRU in terms of validation accuracy on this specific dataset.

In summary, GRU proved to be the most effective model for this task, but both RNN (after tuning) and LSTM showed potential for high accuracy and reliability. Future research could focus on refining these models further, experimenting with additional architectures, and evaluating their performance on larger and more diverse datasets.

References

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