Stock Return Prediction using Deep Learning

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Abstract

Predicting stock market returns comes with own set of challenges and risks due to its highly volatile and non-linear nature of data. Traditional methods used to forecast often could not catch non-linear behavior of time series data. Deep learning techniques has proven to be efficient in capturing such non-linear behaviors and forecast for longer duration compared to traditional methods. This project highlights how we can use LSTM model to forecast stock return for weekly, monthly and 3 months into the future. The model architecture is evaluated using RMSE and co-efficient of determination. The lower value of RMSE and higher value of the latter determines the model performance.

1 Introduction

Stock market is dynamic and mostly unpredictable. The company valuation of stock hugely depends on external factors such as global economy, financial report, competitive industry performance, political situation etc. Hence, forecasting task is one the most challenging task in financial industry. To maximize one's profit and minimize loss advancement in deep learning has helped to analyze data from history to predict the future stock movements. In literature there are two types of analysis namely, fundamental, and technical analysis. Fundamental analysis involves analyzing company's future based on current financial performance. Technical analysis assumes, future behavior of stock is dependent on past behavior and there is a probability of history repeating itself and use this notion to predict future stock returns. In particular there are 3 methods that help in stock forecast. First being, traditional methods which use ARIMA, SARIMA models to forecast. The second being traditional machine learning techniques. Random forest regressor (RF), support vector machine (SVM) and linear regression are used. In deep learning area, artificial neural network (ANN), convoluted neural network (CNN), Recurrent neural network (RNN), Long short term memory (LSTM) and gated recurrent unit (GRU) has shown promising results in these areas. Especially RNN, LSTM and GRU benefits greatly out of the sequential nature of time series data of stock market and is shown to work better compared to others. In this project we use, multivariate time series model to predict future value.

1.1 Related Work

In 2019, Mehar Vijh, Deeksha Chandola, Vinay Anand Tikkiwal, Arun Kumar [1] applied ANN to forecast stock price and compared the work with Random Forest. In 2014, Yunus et al used ANN to predict closing price of NASDAQ [5]. Similarly, in 2018-2019 Chau Tsun Man, Suen Heung Ping, To Cheuk Lam, Wong Cheuk Kin [2] worked extensively used LSTM to predict the trend of closing price for next 10 days. Sidra Mehtab, Jaydip Sen and Abhishek Dutta in their paper[3], used different architecture of LSTM an extended further to encoder-decoder LSTM and did a comparative study taking both univariate and multivariate stock data to predict open value of NIFTY 50 stock index. In this work, instead of stock price prediction stock return prediction is done and extended to different timelines (week ahead, month ahead and 3 months ahead). A comparative study is carried out for four companies and evaluated based on model performance.

Figure 1: Closing price of stock

2 Methodology:

The historical data for four companies is collected from year 1990-2019 for Intel and Apple, 1991-2019 for Qualcomm and 1999-2019 for Nvdia from Yahoo finance. The data contains the daily data of stock price. The dataset contains information about High, Low, Open, Close and Volume. Initial modelling with original features did not enhance the model performance and therefore, enhanced features was considered. Six new variables were considered as below.
Stock High-Low (H-L)
Stock Open-Close(O-C)
Simple moving average of last 3 days (SMA_3days)
Simple moving average of last 10 days (SMA_10days)
Simple moving average of last 30 days (SMA_30days)
Stock price's standard deviation for the past 5 days (Std_dev)
Stocks' relative strength index (RSI) for past 14 days (RSI)

These values were used to define 3 tasks, weekly, monthly and 3 months stock return. The target variable i.e. weekly stock return was calculated as [(close price a week ahead / close price today) -1]. Similarly monthly and 3 months stock returns was calculated for every company.

2.1 Stationary vs non-stationary:

A typical time series encounters two aspect of any time series problem, i.e., trend and seasonality. Trend refers to a linear increase or decrease of value in time and seasonality refers to repeating pattern in time series. Converting such non-stationary time series to stationary if often recommended to improve model performance. Typically, using first order difference or percent change helps removing both trend and seasonality and making it stationary. A common statistical test known as Augmented dickey fuller test is also used to check if a time series is stationary or not. Here, since stock return is used as target variable for prediction, which is in percentage form, doing the augmented dickey fuller test gives p-value less than critical value of 0.05 and hence we can consider it being stationary.

2.2 Long short-term memory:

Recurrent neural netwrok (RNN), given its capability of handing back propagation through time (BPTT) is a good fit for time series problem. However, RNN suffers from vanishing and exploding gradient. While exploding gradient can be handled using gradient clipping, for vanishing gradient LSTM architecture is proposed because of its nature to forget irrelevant details of past and only pass-through important information. The architecture used in this project consist of four LSTM layer, two fully connected layers and one dense layer at the end to output one value at the end of time-period considered. The last layer uses linear activation function to output stock return value. The hyper parameters used were tuned using grid search technique.

Timestep: how many past days were taken into consideration for 1 training sample
Future_to_predict: how many days ahead we want to predict

Neurons used: 100 in each layer
Batch size: 64
Layers: 4 LSTM layers and 2 fully connected layers
Epochs: 100
Learning rate: learning rate schedule within initial learning rate being 1e-3
Loss function: Mean squared error
For weekly forecast: feature value of last 10 days was used
For monthly forecast: feature value for last 40 days was used
For 3 months forecast: feature value for last 100 time-step was used.
Optimizer: Adam was used as it showed better model performance

2.3 Gated Recurrent Unit

GRU works similarly as LSTM except it has two gates, update and reset gate. GRU uses less parameters and therefore uses less memory. It executes much faster than LSTM but provide less accurate results compared to LSTM for longer sequence. This architecture was used with three layers of GRU and one dense layer to see if it provided better results than LSTM.

2.4 Metrics

To find the effectiveness of model, the evaluation metric is compared for all four companies using Linear regression, Random Forest, LSTM and GRU models.

$$RMSE = \sqrt{\frac{\sum (O_i - F_i)^2}{n}} \tag{1}$$

where 'O_i' refers to actual return, 'F_i' refers to predicted return and n refers to total no. of samples.

Coefficient of Determination (R squared): R-Squared is a statistical measure that tells the proportion of the variance in the target variable that is explained by the independent variables. R squared value ranges between 0-1. The closer to 1 the better the model.

$$SS_{res} = \sum y\_true_i - y\_pred_i \qquad \mathrm{SS}_{tot} = \sum y\_true_i - y\_mean$$

$$R_{squared} = 1 - \frac{SS_{res}}{SS_{tot}} \tag{2}$$

3 Results

Figure 2 shows the weekly stock return for all the four companies using LSTM.
Similarly, Figure 3 and 4 shows monthly stock returns and 3 months stock returns respectively.

3.1 Figures

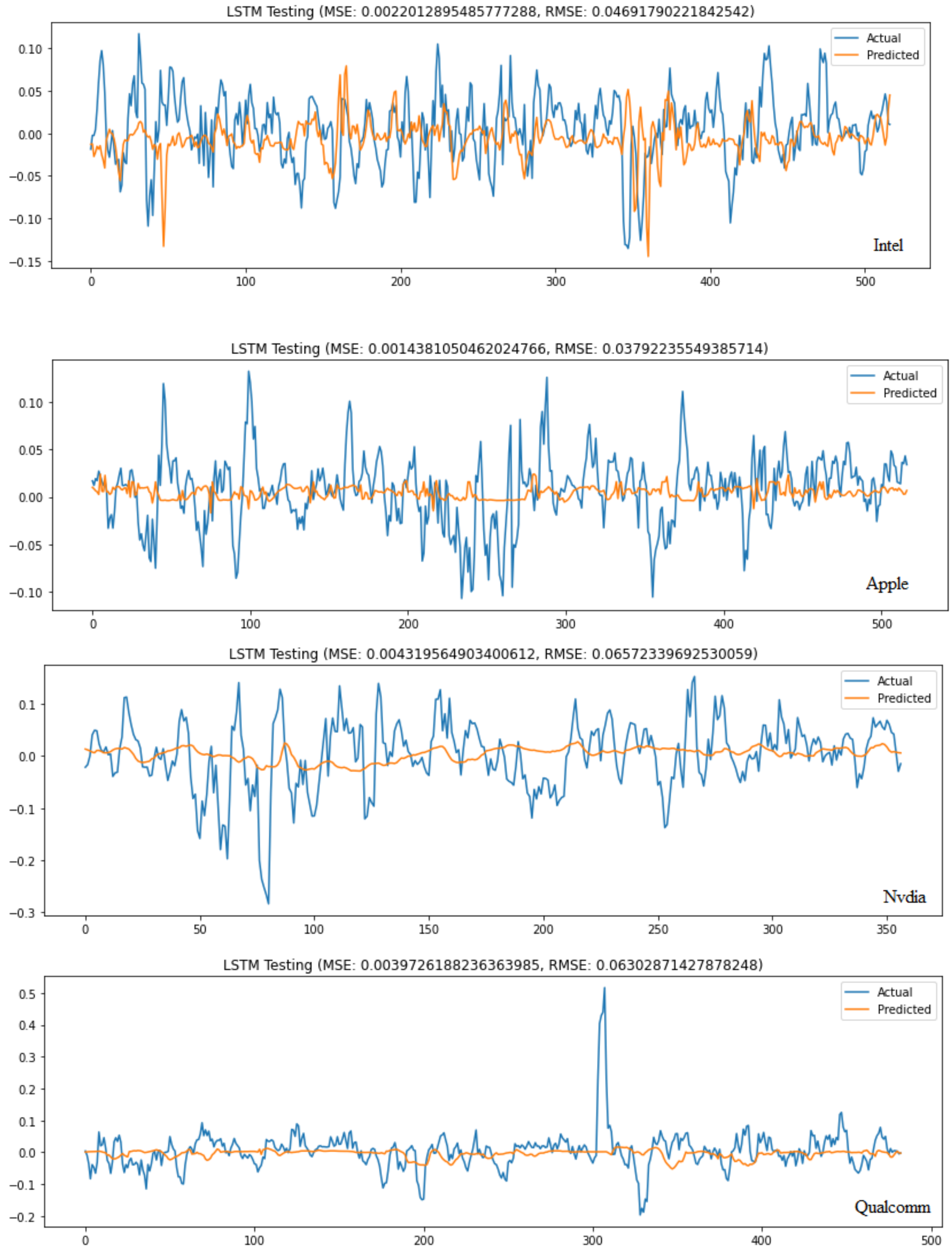

Figure 2: Weekly predictions

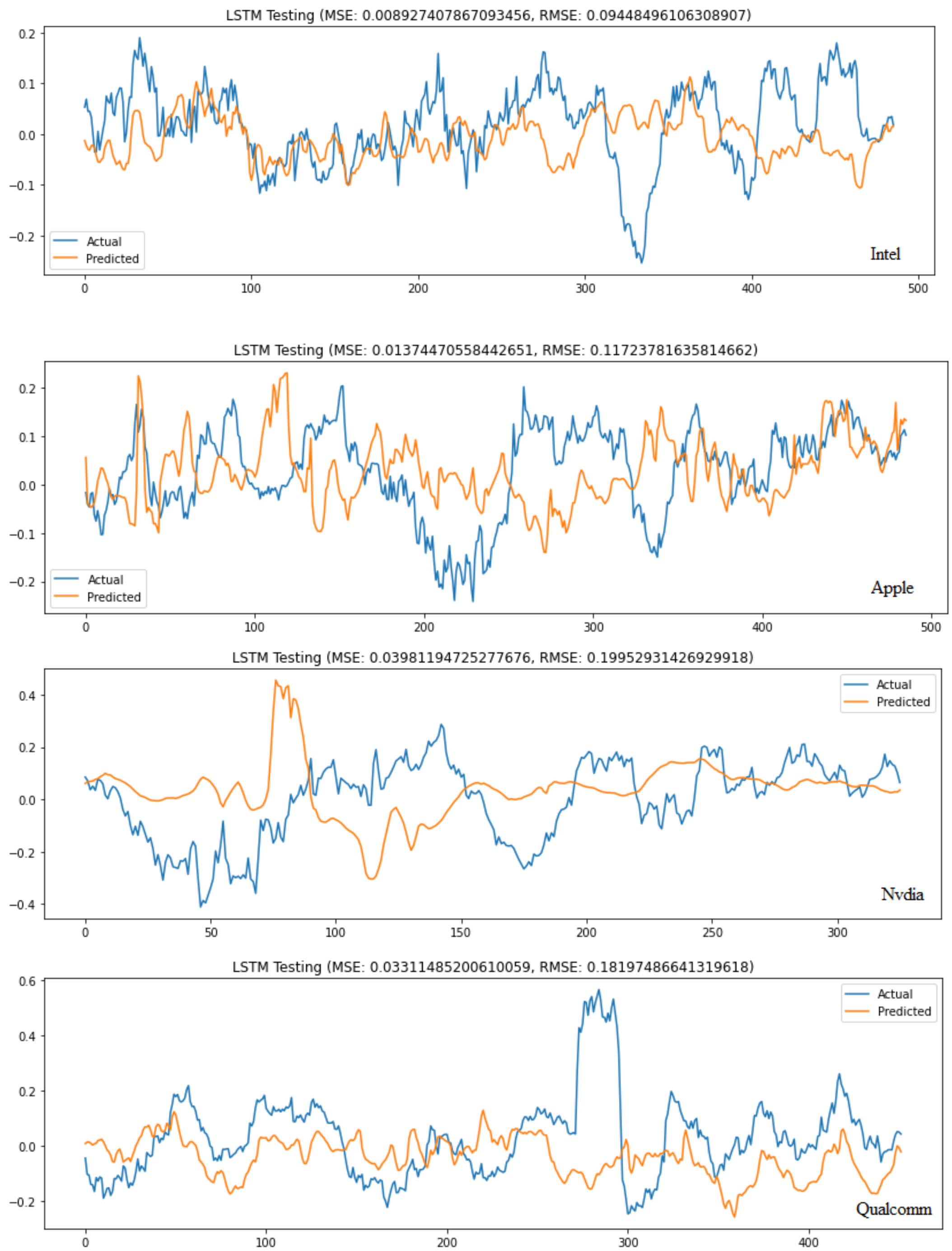

Figure 3: Monthly predictions

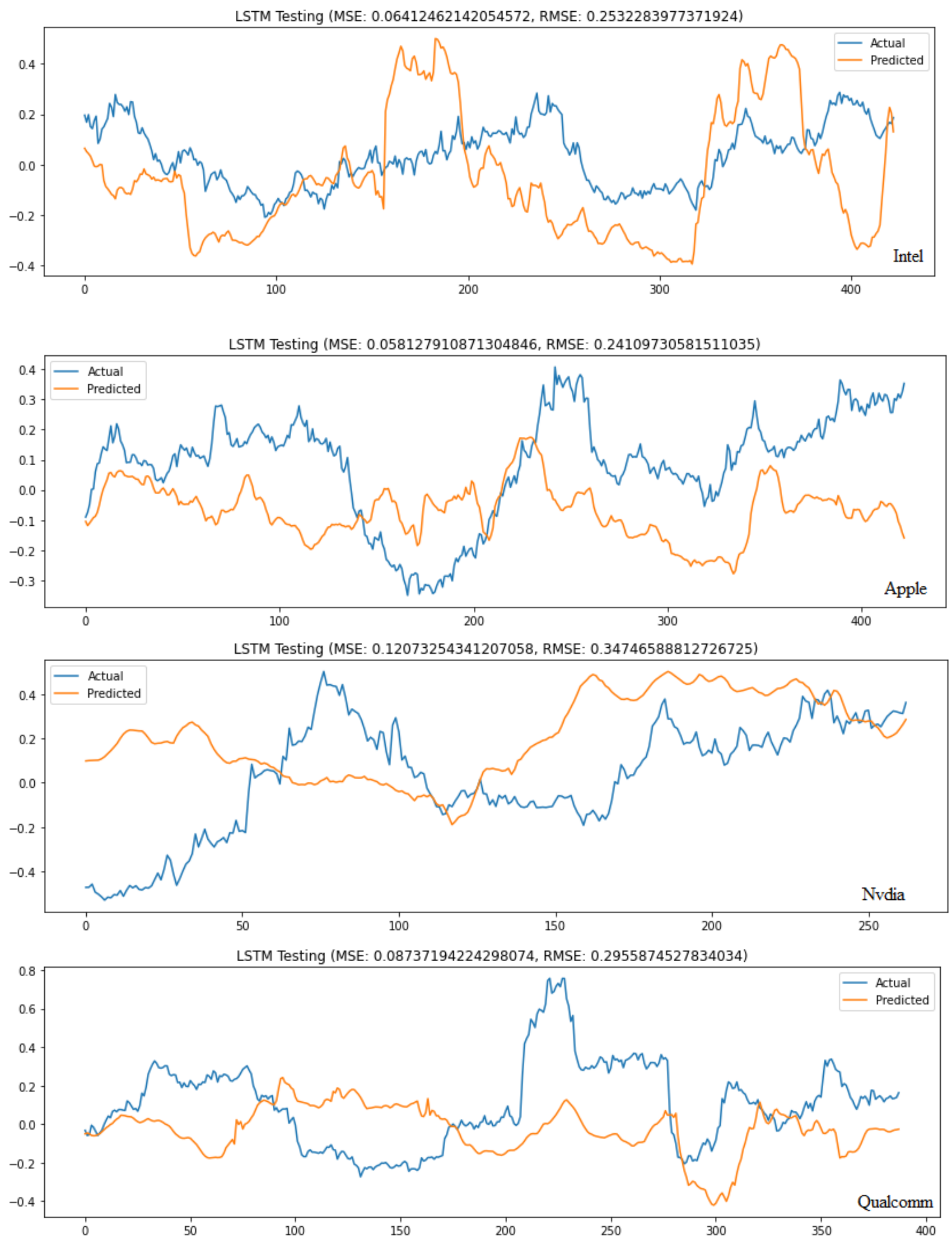

Figure 4: 3months predictions

3.2 Tables

Table 1: Weekly stock return evaluation metrics

	RMSE				R_squared			
Weekly	**LR**	**RF**	**LSTM**	**GRU**	**LR**	**RF**	**LSTM**	**GRU**
Intel	0.0437	0.0806	0.0469	0.0541	-0.1639	-2.913	-0.3254	-0.7678
Apple	0.0379	0.0401	0.0379	0.0449	-0.0542	-0.1833	-0.0176	-0.469
NVDIA	0.0664	0.069	0.0657	0.0702	-0.0238	-0.1051	-0.0204	-0.1176
Qualcomm	0.0627	0.0636	0.063	0.0742	-0.0517	-0.0834	-0.0455	-0.4516

Table 2: Monthly stock return evaluation metrics

	RMSE				R_squared			
Weekly	**LR**	**RF**	**LSTM**	**GRU**	**LR**	**RF**	**LSTM**	**GRU**
Intel	0.0985	0.3319	0.0944	0.117	-0.6495	-17.7189	-0.4422	-1.2133
Apple	0.0958	0.1517	0.1172	0.1418	-0.17	-0.8354	-0.6362	-1.3959
NVDIA	0.151	0.1826	0.1995	0.0702	-0.1064	-0.6166	-0.7656	-0.4962
Qualcomm	0.1534	0.1466	0.1699	0.172	-0.1385	-0.0405	-0.3037	-0.3367

Table 3: 3 months stock return evaluation metrics

	RMSE				R_squared			
Weekly	**LR**	**RF**	**LSTM**	**GRU**	**LR**	**RF**	**LSTM**	**GRU**
Intel	0.2266	0.4737	0.2532	0.2715	-2.2225	-13.0808	-3.2595	-3.8976
Apple	0.1837	0.2186	0.241	0.2737	-0.346	-0.9049	-0.9519	-1.5157
NVDIA	0.336	0.3999	0.3474	0.4983	-0.8236	-1.5828	-0.774	-2.649
Qualcomm	0.2721	0.2369	0.2955	0.3336	-0.5811	-0.1982	-0.6823	-1.3327

4 Conclusion

Predicting stock return is a complex task and heavily dependent on various external factors. The dataset used here had few features which were further extended to generate technical indicators ideally used in stock market. The results shows, compared to all models, LSTM performed well for weekly prediction and relatively okay for monthly and 3 months prediction. Linear regression seemed to provide better results than LSTM many times. The GRU model did not improve model performance compared to LSTM which could also be because every hyper parameter was not tuned to full extent. Since, stock return is very volatile, additional financial indicators such as exponential moving average, bollinger bands, MACD etc could help enhance model performance. In addition to that, external factors such as quarterly financial reports, sentimental analysis done on news articles could provide more insight for predictions[7].

5 References

[1] Stock Closing Price Prediction using Machine Learning Techniques Mehar Vijh, Deeksha Chandola, Vinay Anand Tikkiwal & Arun Kumar.

[2] Stock Price Prediction App using Machine Learning Models Optimized by Evolution By CHAU Tsun Man, SUEN Heung Ping, TO Cheuk Lam, WONG Cheuk Kin.

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[4] https://www.investopedia.com/terms/r/r-squared.asp

[5] Yetis, Yunus, Halid Kaplan, and Mo Jamshidi. (2014) “Stock market prediction by using artificial neural network.” in2014 World Automation Congress (WAC)

[6] Robust Analysis of Stock Price Time Series Using CNN and LSTM-Based Deep Learning Models, Sidra Mehtab, Jaydip Sen, Subhasis Dasgupta

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