Incorporating Financial News Sentiments and MLP-Regressor with Feed-Forward for Stock Market Prediction

Junaid Maqbool, Preeti Aggarwal and Ravreet Kaur

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Junaid Maqbool[1], Preeti Aggarwal[1], Ravreet Kaur[1]

[1] UIET, CSE Department, Panjab University, Chandigarh
maqbooljunaid@gmail.com

Abstract.
Stock Market being very volatile depends on various political, environmental, and internal factors. The stock price prediction using news data is an interesting research topic. In this paper, an approach is proposed that represents textual news data as sentiment metrics using VADER sentiment analysis and price data scaled down between 0 and 1. The output predicted price of a stock on a particular day is fed forward to the next level of MLP*-Regressor to train as well predict the prices of following days. Experiments have been conducted on 10-year financial news as well price data of Reliance Company using the proposed model. The results show that the model because of feed-forward was able to learn the trend and the depths were followed more closely than the spikes. The model was tested on the news data of the same date as well as on the previous date separately. The model is an improvement made to MLP-Regressor whose results are also compared. The MLP-Regressor with feed-forward was able to learn long-term trends and also predict with an accuracy of .714 for the upcoming 7 days.

***MLP- Multilevel Perceptron**

Keywords: Stock prediction, News sentiment analysis, MLP Regressor, forecasting

1 Introduction

The price of a single stock fluctuates more frequently compared to the stock indices and other metrics because of its dynamic and non-linear manner. The stock prices are very unstable and uncertain due to the dependence of its price on an uncountable number of parameters. The stock trade is done online dynamically. Traditionally the prediction decisions are based on the historical trend as known by the trader and the current market knowledge[1]. The stock market is often influenced by political, financial, environmental factors and the psychology of the investors[2]. The investors buy and sell their stocks based on all these events which let them predict possible up or down in the market. As the financial news is one of the most important factors which has the power to influence the psychology of traders to invest in a particular stock. The traders can gain profits if they will be able to predict correctly the stocks whose prices are going to increase in near future and buy them and sell the stocks whose prices are going to decrease [3]. The prediction of stock prices has attracted researchers from computer science, statistics, economic and operations research [4].

Different models of machine learning like Bayesian Networks [5], Artificial Neural Networks[6], Support Vector Machines[7], Multi-Level Perceptron (MLP) [8], and Recurrent Neural Network especially Long Short Term Memory (LSTM) [9] have already been utilized to predict the trends and the future stock prices. As the stock market exhibits natural chaotic behavior as different world markets react with different intensities to the period of crisis hence cannot be predicted by simple trading strategy [10].

The motivation for this study is to build a model which will be able to learn and predict the upcoming stock prices based on the sentiments calculated from financial news articles. The stock market being one of top most money investing destination, hence it will help investors to earn more profits and invest with more possibility of gains. This will help and encourage new investors to invest in stock market with limited information about market.

The main objective of this paper is to predict the future stock prices as well the trend of the direction of the stock price in which it will move based on sentiments [11]of news data provided for the same day and the previous day. This paper takes into consideration a new parameter called **label** which signifies if that particular date any news regarding the given stock is present. This paper will also check the effect of this new parameter “label” on the stock prediction. The machine learning models in[5][6][7][8] do not take into consideration the previous day prices thereby model learns only the fluctuations based on the change in sentiments while [9] do not take the sentiment of the news thereby predicting using historical trend and not taking in consideration the sentiment. Our model MLP-Regressor with feed-forward takes into consideration the previous day's price which given short-term historical support and news sentiments to predict the trend in the stock prices. Our model was able to follow the trend in long term.

This model is tested and trained on the stock data of reliance industries. The model is tested on the sentiments of the present day and the previous day separately. The model is compared with the MLP Regressor without taking the previous day's price into consideration. The model was also tested with and without the label parameter and in turn, these models are evaluated in terms of Mean Absolute Percentage Error (**MAPE**), precision, recall, accuracy, and F1 measure.

The problem statement of this paper is to check the prediction accuracy of stock prices while incorporating financial news articles along with historical stock data using MLP Regressor.

The paper is organized as follows: Section 2 briefly discusses existing work in the related field. Section 3 discusses the approach followed in this paper, models implemented and the results derived from the experiments. Section 4 concludes and discusses future scope.

2 Related Work

There are two traditional approaches for stock prediction: Technical Analysis and Fundamental Analysis[12]. Most of the models made employ these two traditional approaches for prediction where fundamental analysis takes into consideration the overall financial conditions of the company, their management, and economy [1]. The models which employ a technical analysis approach generally take prediction as a classification problem where historic time series data is used to learn the market pattern. The models which work to predict exact stock price are termed as predictive regression in economic literature[13]. Though simple and naïve approaches mostly suffer from over-fitting when applied to real-world setups and are unable to learn the long-term trend. The Recurrent Neural Networks especially LSTM can work better on the long-term trend and prove to be superior to ARIMA (AR-autoregressive, I- integrated, MA- moving average) (Table 1) [9][14].

Table 1: Related work in stock prediction

Research work	Technique /Algorithm	Dataset	Observation
Stock Prediction using LSTM[9]	RNN LSTM on historical time series data.	NYSE [GOOGL]**	The LSTM model can predict the opening prices while learning the long-term pattern and performs better than ARIMA[9].
Stock price prediction using News sentiment analysis[14]	ARIMA, LSTM with stock price and textual information.	Standard and Poor's 500 (S&P 500), Online newspaper articles.	The models did fit the data with some considerable accuracy but did not perform well when the stock prices were less or excessively volatile[14].
Improved deep learning model for prediction using time series and sentiment [15]	Empirical wavelet transform(EWT), Outliner Robust Extreme Learning Machine (ORELM), LSTM, Particle Swarm Optimization (PSO)	S&P 500, Dow Jones Industrial Average (DJI)	The hybrid novel stock prediction model is introduced using EWT, ORELM, LSTM, and PSO. The proposed hybrid model has better accuracy than other deep learning models and any single model[15].
Ensemble of Deep Q-learning agents for stock market forecasting[10]	Q-learning, Double Q-learning ,	S&P 500, German DAX	The proposed model doesn't learn from market ups and downs, hence is flexible against the chaotic behavior of stock price rather it learns to maximize the return over time[10].
An integrated framework of deep learning and knowledge graph for stock prediction [16]	Attention based bi-directional LSTM,	Chinese stock Exchange market	The proposed model takes into consideration real transaction records data and utilizes CNN to

	Convolutional Neural Network (CNN), Deep Stock-trend Neural Network (DSPNN)	data	extract daily group trading vectors. DSPNN outperforms LSTM because of the attention mechanism and bidirectional structure of DSPNN[16].
A Multiplicative self-attention Bi-Directional LSTM for stock prediction [17]	Volume Weighted Average prediction using multiplicative self-attention layer	NIFTY 50	When lag and exogeneous features are considered, The proposed model has higher accuracy over LSTM and simple RNN[17].
Stock prediction using graph-based CNN-LSTM [18]	CNN ,LSTM , new method named Stock Sequence Array Convolutional LSTM (SACLSTM)	Historical data of stocks in Taiwan and America	Convolutional layer used to extract financial features combined with LSTM achieves better performance than any of method individually[18].
Stock price pattern using Neural Network and Back Propagation (BP) algorithm [19]	BP algorithm, Fuzzy algorithm	Gree electric, Maotai of shanghai mainboard	With improved training speed of BP algorithm the accuracy is still better than fuzzy algorithm to predict the closing stock price.

**NYSE = New York Stock Exchange, GOOGL – Google(historical stock price)

The LSTM models are now being extensively used for stock prediction because of their ability to store the historical trend in architectural memory. LSTM models clubbed with other deep learning techniques show promising results in stock prediction.

3 Proposed Methodology

This section will introduce our methodology; feedforward MLP-Regressor with sentiment analysis. The framework is shown in Fig 1. The training of the model on time series data was done in a sequential manner without shuffling the data. The output of each day was fed as an input to the next day too.

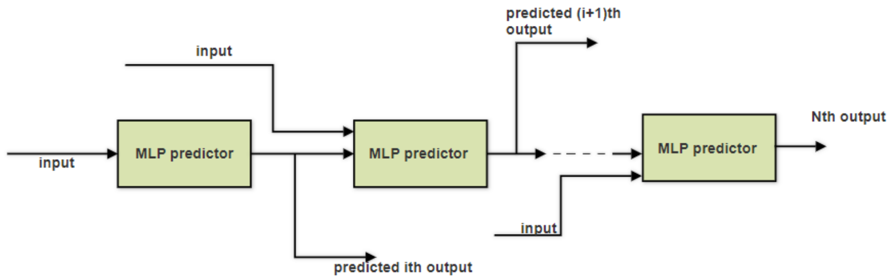

Fig 1: Feed-Forward MLP-Regressor

During training, the output of the first prediction was fed into the input for the second prediction which helped the model to predict temporally for each day. The predictions have shown because of feed-forward the model was able to predict the trend for a longer period.

3.1 Problem definition

To predict the stock price for an individual stock using the news sentiments, label, and historical stock price data. The task is to predict the movement of the stock price after analyzing the sentiments of the financial news and the previous stock price for the next trading day and also predict the trend of the stock prices for upcoming n days. The problem has two tasks 1) what is the direction of the trend 2) what is the amount by which the trend changes.

Direction of trend: If the stock price for the next day will be more than the stock price on the day preceding it the trend is positive, and if the stock price is less on the next day than the preceding day then the trend is negative. If the stock price remains unchanged then the trend is neutral.

$$T = closing(day\ i+1) - closing(day\ i) \quad (1)$$

$$\begin{cases} T > 0, trend = positive \\ T < 0, trend = negative \\ T = 0, trend = neutral \end{cases}$$

3.2 Data Collection

The stock price data of reliance (Fig 2) was collected from Jan 2010 to May 2020 from yahoo finance[20]. The closing price of each day along with the news sentiments applied on the financial news data of the same day using VADER sentiment analysis[21] from Natural Language Toolkit (NLTK) [22] and **label** were used to check the effect of the news sentiments on stock prices or future price of the stock.

Date	Open	Low	High	Close
Jan 19-2010	544.84	536.24	547.83	537.41
Jan 18-2010	548.30	540.85	552.98	544.59
Jan 15-2010	557.61	547.34	564.10	550.16

Fig 2: historical reliance stock data

Label defines the presence of the news of individual stock in the news collected on a particular day. Some important keywords related to the stock can be used to check the label. Label equals 1 when news about the same company is present and 0 when not present.

3.3 Evaluation metrics

The metrics are used to evaluate the way our model is performing as this model classifies the data as per future predicted trend as well checks the amount of change. so this paper employs metrics like MAPE to check the error in change detection which doesn't take the direction of change into consideration and Accuracy which checks the classification correctness without considering the rate of change.

Accuracy In classification, accuracy is among the popular metric used. It represents the ratio of the number of correctly classified values to the total number of classified values[10].

$$Accuracy(X) = \frac{X^{(+)}}{|X|} \tag{2}$$

Precision tells how many predictions are really positive among all positively classified predictions.
Recall represents the model's ability to predict correct positives among all positives in the list.
F1-score model score which is the function of precision score and recall score. It is the harmonic mean of precision and recall score.

*F1-Score = (2*precision*recall) / (precision + recall)* (3)

Mean Absolute Percentage Error (MAPE) It is average relative error of forecast predictions in percentage. It is one of the popular forecast prediction accuracy metrics [14][23].

$$MAPE = \frac{100}{n} \sum_{j=1}^{n} \left| (y_j - y'_j)/y_j \right| \tag{4}$$

Where y_j is the original value and y'_j is the corresponding predicted value.

3.4 Model used

This paper has used MLP Regressor[24] which previously have not shown promising results in learning the long-term trend [25]. The MLP models without feed-forward tend to lose the historical information unlike LSTM models [26][27][28]. Our model (Fig 3) uses feed-forward to remember the trend.

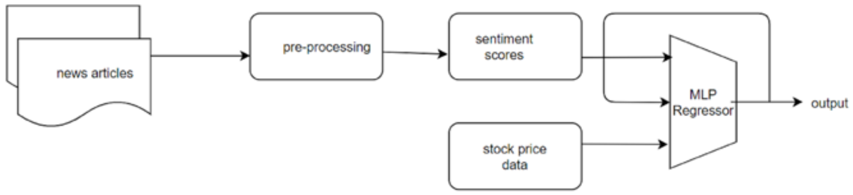

Fig 3: complete feedforward MLP Regressor with sentiment and stock input

The output of one prediction is used as an input to the next prediction helping to preserve the previous trend and predict the next output in relation to the previous output instead of making the model work independently on sentiment score. Sentiment score affects the stock price but the effect is always shown to the previous price, not to a general or average price. Accuracy is measured by checking the real trend and predicted trend for each prediction. MAPE is measured to understand the percentage change with which the predictions vary to original output.

3.5 Evaluation and results

The proposed model was checked against 10-year stock and news data. The training and testing data was divided into an 8:2 ratio. The models were evaluated based on the input data keeping the model specifications same. The model was tested with label and without label to understand the effect of label parameter on the prediction which showed slight variation in accuracy. Hence label parameter does play role in improving the prediction accuracy of the model. Then the model was tested against the sentiments available. The sentiments for same-day (Fig 4) were used in one case and sentiment score from the previous day (Fig 5) was used in the other model to understand the time effect of the news on the prediction.

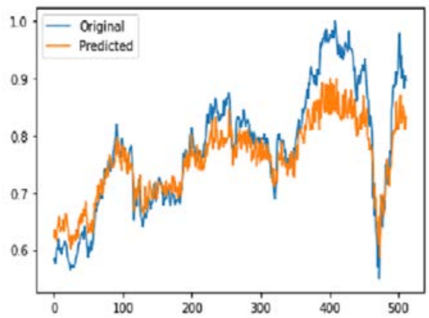

Fig 4: Prediction using same day news sentiment

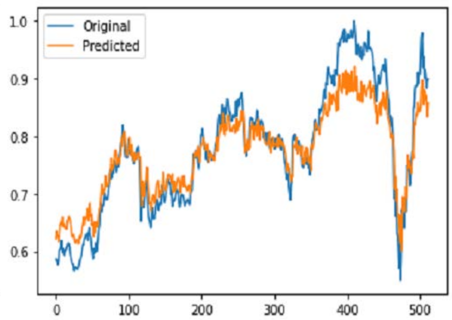

Fig 5: Prediction using previous day news sentiment

The model without label (Fig 6) was unable to predict as accurately as done by with model with label. The models were tested for 7 days (Table 2), 30 days (Table 3), 300 days (Table 4), and 512 days (Table 5). Fig 4 and Fig 5 show that both the models are able to learn the trend and follow it for a long time while previous day sentiment graph show more overlapping of predicted and original graph. The model, MLP Regressor without feed-forward (Fig 7) was also tested and it can be concluded that these models are not able to follow the trend.

Table 2: Accuracy metrics for different models for 7 days prediction

Models	Precision	Recall	Accuracy	F1-Score	MAPE
MLP feed-forward with previous day data	0.80	0.80	**0.714**	0.714	**4.62**
MLP feed forward with same day data	1.00	0.66	**0.714**	0.80	6.98
MLP without feed forward	0.50	0.40	0.28	0.44	infinite

For predicting stock price of the upcoming 7 days the model shows that using sentiments of same day (Fig 4) does not increase the accuracy but decreases MAPE by 2.36 percent. But without feed-forward, the accuracy is as low as 0.28 and MAPE is infinite (Table 2). The previous day prediction was used to predict the next day which helped the models to remember and follow the trend. All models are plotted together show models are able to learn the trend (Fig 8). The results suggest the MLP model with news sentiments from previous day shows better accuracy and lower MAPE (Fig 9).

Table 3: Accuracy metrics for different models for 30 days prediction

Models	Precision	Recall	Accuracy	F1-Score	MAPE
MLP feed forward with previous day data	0.56	0.64	**0.60**	0.60	**6.42**
MLP feed forward with same day data	0.58	0.50	**0.60**	0.53	7.18
MLP without feed forward	0.47	0.57	0.50	0.51	infinite

Table 4: Accuracy metrics for different models for 300 days prediction

Models	Precision	Recall	Accuracy	F1-Score	MAPE
MLP feed forward with previous day data	0.55	0.52	0.52	0.53	**6.56**
MLP feed forward with same day data	0.56	0.55	**0.54**	0.56	7.07
MLP without feed forward	0.49	0.44	0.46	0.47	infinite

Table 5: Accuracy metrics for different models for 512 days prediction

Models	Precision	Recall	Accuracy	F1-Score	MAPE
MLP feed forward with previous day data	0.53	0.53	**0.53**	0.53	**5.07**
MLP feed forward with same day	0.52	0.53	**0.53**	0.52	5.32

data					
MLP feed forwards without label for previous day data	0.50	.51	0.50	0.50	9.16
MLP feed forwards without label for same day data	0.50	0.50	0.50	0.50	8.09
MLP without feed forward	0.51	0.49	0.51	0.50	infinite

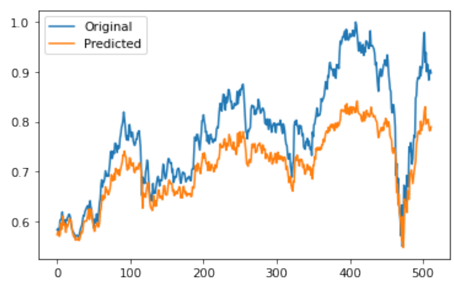

Fig 6. Feed-forward MLP Regressor without label on same day news data

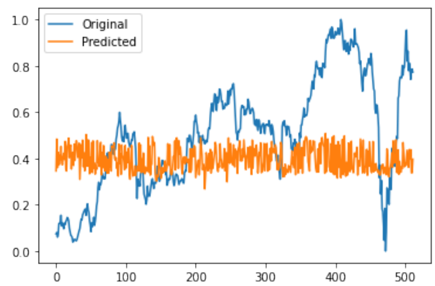

Fig 7**:** MLP Regressor without feed-forward on same day news data

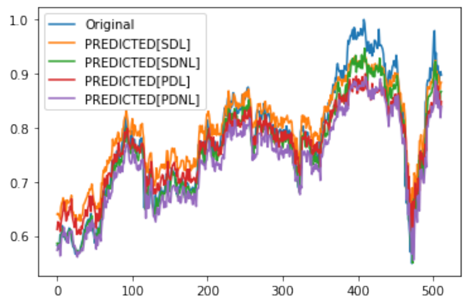

Fig 8: Predicted models**

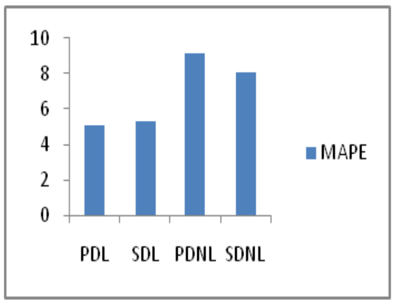

Fig 9: MAPE comparison of models** (512days)

**Same Day news data with Label (SDL), Same Day news data without Label (SDNL), Previous Day news data with Label(PDL), Previous Day news data without Label(PDNL)

When predicting for 30 days the accuracy in both feed-forward models the accuracy decreases by .11 while the MAPE doesn't show considerable change. And for the long-term prediction of 512 days the MAPE decrease by 1-2 % and accuracy by 0.07. While comparing the results with label and without label (Table 5) the accuracy decrease by 0.03 and MAPE increase by around 4% showing that the label has a considerable effect on the amount of change in price for a particular stock. The model without feed-forward is able to detect trend with an accuracy of 0.51. MAPE being infinite justifies Fig 7 about the model without feedback not being able to follow or predict trend anywhere.

4 Conclusion and future scope

In this work, the individual stock price was predicted using sentiments of financial news and the time-series data of the stock price. The graphs suggest that the label helps to fit the trend more accurately by decreasing the MAPE and show a high correlation between the stock price and news of a particular company than other news. The models were able to detect and follow a downward trend precisely while an upward trend was detected but the effect of the change was not followed when stocks were highly volatile. This paper shows that MLP-Regressor when employed with the feed-forward can provide promising results than MLP without feed-forward. The feed-forward can be used with more modifications in future work to predict the stock prices more accurately. There are various ways to predict stock price which can be explored in future work. Some of these include an ensemble of LSTM and other models where LSTM can be used to remember the trend and other models to predict the change rate. Different sentiment analyzing algorithms can be tested to check the compatibility of different sentiment scores against the ability to detect the trend of stock prices more accurately and tested against various models.

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