2021 18th International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE). Mexico City, Mexico. November 10-12, 2021

Effect of Rate of Change of Stock Prices with News Sentiment Analysis

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***Abstract*— Mapping the variations of stock prices in the market has proven to be a challenge to, considering impact of macroeconomic factors, such as news headlines on them. In this paper, a novel framework is implemented for predicting the effect of rate of change of stock prices through news sentiment by using a standard dataset with closing stock price rates for a chosen period. Random Forest classifier to extract the sentiments from day-today news articles to identify their polarity as positive, or negative. Bi-directional Long Short-Term models are implemented to map the sliding windows of prices along with corresponding sliding windows of sentiment scores of the articles. Thus, hybrid architecture that combines a Bi-LSTM based time series prediction model with a Random Forest based sentiment analysis model is developed and compared with some of the existing state-of-the-art methodologies. The polarity of news sentiment is determined with an accuracy of 84.92% and the price prediction model performs best with 10 headlines achieving a R-squared score of 74.84%.**

Keywords*— *Stock market, Price Prediction, News headlines, Sentiment Analysis, Event Embedding

I. INTRODUCTION

Stocks represent a share of ownership in the stocks issuing company, for the company to raise enough capital to invest back into the company [1]. Potential investors and traders choose their stocks carefully for better investment options that can provide inflation-beating returns and larger profits, over long periods of time [2]. The share prices are mainly determined by the forces of supply and demand, which is highly sensitive to the news of the moment [3]. Media sentiment [4] is also an important predictor of daily stock returns with decisions taken in the anticipation of an event, even before the actual event is reported in the news.

Social media provides an interactive and automated means of communication and information sharing in communities throughout the world in real time. News [5] plays a significant role in the investment world as it provides information to the investors to make decisions in the stock markets. It is capable of shaping and influencing the emotions and opinions of people, driving the decision to buy or sell in markets. An example of this is the world markets crashing in March 2020 [6] at the initial months of the COVID-19 global pandemic. The stock investors faced uncertain times owing to the lockdowns imposed worldwide, forcing businesses to close down and stop their ongoing activities. This led to the markets across the world crashing in March 2020, as seen in Figure 1.

Analyzing social media sentiment [7] through text analysis is subjective to the reader's opinion. By observing and studying such trends from users of these media, a number of applications of forecast business variables are delivered. Samuel P. Fraiberger of the World Bank had shown in is economic research paper [8] that news sentiment is an important predictor for daily stock returns in markets. Through sentiment analysis, the impact of global news and local news on their potential foreign and local investors were presented.

Sentiment analysis, or opinion mining, is a Natural Language Processing (NLP) technique to determine the polarity of the text sentiment (positive, negative, or even neutral) [9]. Using the sentiment from the text in an effective and efficient way helps in the analysis of the situation it is applied in. Machine learning architectures [10] such as Support Vector machines, Boosting and Bagging algorithms and Random Forests perform this analysis by assigning sentiment scores to the categories, within a phrase in a sentence used to determine its polarity.

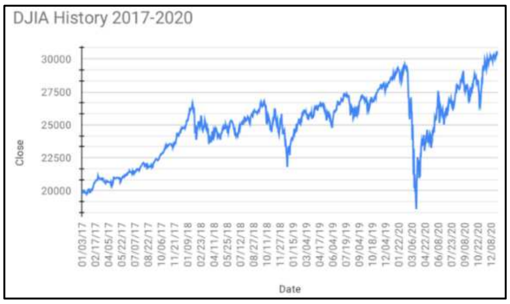

Fig. 1. The movement of the Dow Jones Industrial Average (DJIA) [12] is shown between January 2017 and December 2020, along with the pre-crash high on 12 February, and the subsequent crash during the COVID-19 pandemic and recovery to new highs later that year.

Random Forests [11] are built using multiple decision trees merged together for an accurate and stable prediction. This algorithm also adds randomness to the data for enhancing its performance, while training using the data bagging algorithm [12]. Having low bias and a property of high variance, the splitting of nodes is done by selecting the best performing feature from the generated subset of features. The versatility of this model helps in sentiment analysis by analyzing the importance given to each chosen feature to avoid overfitting the data.

Stock market price prediction models [13] have helped in the determination of asset investments for maximizing individual profits. The complexity of the time-series forecasting tasks are handled by Bidirectional Long Short Term Memory (BiLSTM) [14]. They aggregate the input information in the past and future of a specific time step through LSTM models in both forward and the reverse directions. They exhibit the ability to learn and predict the extracted features from the data.

In this paper, sentiment analysis is carried out on news headlines extracted from social media using Random Forest

978-1-6654-0029-9/21/$31.00 ©2021 IEEE

classifier to predict the polarity of the text, as positive and negative. Positive class is assigned to the text that preceded the day with no change or increase in the closing stock price and negative class for an observed decrease in the price. A deep neural Bi-LSTM architecture has been implemented for stock price prediction on data with and without headlines. This is recorded and the results of the impact of the text event embedding on prediction modelling are presented. Rate of change of stock prices with varying polarity of news sentiment is also studied.

The rest of the paper is organized as follows. Section II gives the summary of some of the best works in stock market price prediction modelling with deep neural modelling using macroeconomic factors like news headlines. The design of the system for market price prediction using news and the sentiment analysis model for prediction of rate change is given in Section III. The implementation details of the constructed deep neural models are given in Section IV. The results obtained from the implemented price prediction system and sentiment analysis model along with their analysis is present in Section V. The summarization of the project and the proposed future work are given in Section VI and section VII respectively.

II. Related Works

In this section, some of the recent works in stock market price prediction using deep learning architectures with sentiment analysis have been summarized.

There have been a number of studies for the prediction of stock market prices using big data sentiment analysis. Bourezk et al [15] had implemented machine learning algorithms for the analysis of the relationship between the general public view regarding a stock and its evolution within the Moroccan Stock Exchange. Malawana and Rathnayaka [16] had predicted the stock prices in the Colombo Stock Exchange by performing sentiment analysis on market related announcements in the news to extract positive, negative and neutral opinions. The Naive Bayes and Linear Regression models used for sentiment detection in text was used to predict sentiment class within a Big Data distributed Environment.

The analysis in our paper was carried out using DJIA indexed close stock price performance by the constructed BiLSTM model with and without the news headlines dataset to observe the effect of the textual data features on the prediction of the prices in the market.

A number of works have demonstrated the effectiveness and relevance of time series forecasting tasks for stock market price predictions and portfolio management. Chantona et al [17] modelled price prediction with deep recurrent Q-network using Recurrent Neural networks (RNN) in the foreign exchange (ForEx) trading market. Through the implementation of the word2vec module, the model was able to identify fundamental factors in the news headlines. The work demonstrated the impact of sentiment analysis of the news headlines to improve risk management and aimed to lower the maximum withdrawal point on the tested currency pairs.

Deep learning architectures can handle large volumes of multivariate data and have been proposed for time-series modelling of stock price data along with search trends, social media posts and global news headlines. LSTM-based multi-step multi-variate deep neural model was constructed by Aasi et al [18] to analyze the sentiment from the data features from a number of social media sources to forecast the actual stock price values instead of binary positive or negative output. The model trained with Google trend analysis predicted the overall directional movement correctly with the vast volume series.

Dependency parsing over the data helps in extracting grammatical relations between words in news articles. Wang et al [19] performed parsing on a dataset containing financial articles for performing sentiment analysis on the data using negation modifiers of sentiment words and identifying their corresponding modification scope. The relations between the news release and the corresponding market changes were analyzed with their time lag. In our paper, the effect of the identified positive and negative sentiment on the average price change in the market is studied for understanding the effect of public sentiment on the price prediction models.

In summary, we had developed a sentiment analysis model using Random Forest classifier for the positive and negative sentiment analysis of the chosen sets of news headlines with varying lengths. The most common occurrence of words in both these sentiments are presented along with the effect of the sentiments on average rate of change in close price in the stock market. A BiLSTM model was constructed to study the effect of the stock price prediction trend using day-by-say stock price analysis and then with data containing news headlines. The results obtained from these experiments are recorded and presented in further sections with their detailed analysis.

III. System Design

The hybrid architecture introduced to predict the rate of change of stock prices and to forecast the closing prices of stocks by taking into account the polarity of news articles is given in Figure 2. A multitask architecture is established to model the sentiment of the articles and the stock prices separately. Further, meta-classifier helps model the relationship between the sub-models.

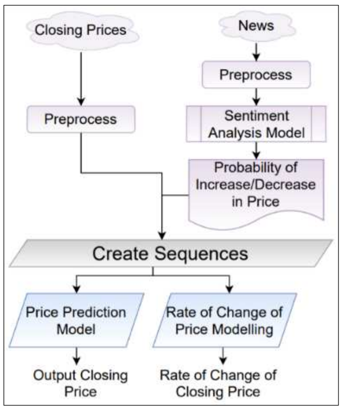

Fig. 2. Overall Multitask Architecture for Prediction

A. Data Set Description

A standard dataset comprising of pricing data for Dow Jones Industrial Average (DJIA) and news articles corresponding to each day in the period 2008-08-08 to 2016-07-01 is collected from [20]. The Dow Jones Industrial Average, Dow Jones, or simply the Dow, is a stock market index that measures the stock performance of 30 large companies listed on stock exchanges in the United States. The headlines were scraped from Reddit [21] and are ranked up to 25 based on user votes. The prices of the stock are obtained from Yahoo Finance [22]. The stock dataset has Open, High, Low, Close and Adjusted Close prices as well as Volume of stocks traded. The polarity of the headlines for each day is assigned as 0, when there is decrease in closing price of the stock compared to the previous day and 1 when the close price stayed the same or increased compared to the previous day.

B. *Preprocessing the Dataset*

The closing prices for the stocks is normalized to ensure that the prices are between 0 and 1. To perform sequential time series analysis on the data, the prices are remodeled such that prices for n days form the input sequence and the price on the $(n+1)^{th}$ day forms the output sequence. The prediction of output sequence prices forms a sub-task of the hybrid architecture.

The news headlines are cleaned to remove special characters, stop words, contractions etc. in order to remove unnecessary sections of the text and to ensure there are no null embeddings present. The text is converted to lowercase in order to make sure there is only one embedding per word. Each sequence of words in a sentence needs to be converted into a vector form that can be modelled. This is done by assigning a Term frequency - inverse document frequency (Tf-Idf) [23] score to each word that determines the frequency of occurrence of the word in the dataset.

Identifying the sentiment of news headlines forms one of the sub-tasks in the overall neural model implemented. A Random Forest classifier is built to determine the sentiment of a news headline which would indicate whether the stock price might decrease in the case of negative polarity, increase or remain the same in the case of positive polarity. The probabilistic sentiment scores for each day are converted to a sliding window corresponding to the sliding window of the price data. Figure 3 describes the creating of sliding windows of probabilistic news sentiment scores which will be mapped to the sliding window of prices. The determination of the positive and negative polarity scores forms two sub-tasks of the hybrid architecture.

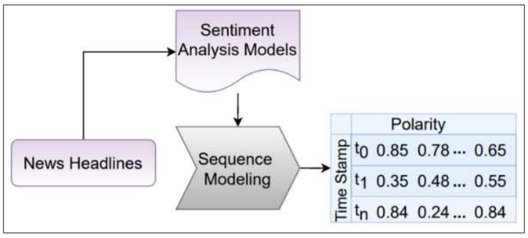

Fig. 3. Sliding Windows of Polarity Scores

C. *Multitask Learning*

Multitask learning [24] solves two different sub-tasks independently and then tries to correlate the learnings using a meta-classifier. Two different multitask models are built to predict the rate of change of stock prices and to predict the actual stock price itself. In both the models, the subtasks involve modelling the prices and identifying the sentiment of the news headlines and these subtasks act as Level-0 models.

D. *Close Price and Rate of Change of Price Modelling*

Sequential learning of time dependent data is performed using Recurrent Neural Networks (RNNs) [25]. RNN modelling can involve Long Short-Term Memory (LSTM) model and the modified Bi-Directional LSTM (Bi-LSTM) model. LSTM models determine the retainment of features within data by using gates. Each gate returns a value between 0 and 1. If the value is close to 0, it is dropped and if it is close to 1, it is retained. LSTMs consist of Forget gates, Update gates and Output gates as well as a memory cell that saves the sequential dependencies. Forget gate discards information from the previous cell state as seen in eqn. (4).

$$f(t) = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (4)$$

where, x_t is the input, h_{t-1} is the previous state of the memory cell and W_f , U_f , b_f are the weights and biases of the forget gate. The Update gate helps to determine which is the new information that needs to be added to the cell state and it is represented using eqn. (5).

$$u(t) = (W_u x_t + U_u h_{t-1} + b_u) \quad (5)$$

where W_u , U_u , b_u are the weights and biases of the update gate. The output gate determines the output information that needs to be passed on to the next cell and is represented using eqn. (6).

$$o(t) = (W_o x_t + U_o h_{t-1} + b_o) \quad (6)$$

where W_o , U_o , b_o are the weights and biases of the output gate. The cell state is determined using eqn. (7).

$$Ct = f_t \odot C_{t-1} + i_t \odot C_{temp} \quad (7)$$

where, W_c , U_c , b_c are the weights and biases of the cell state and C_{temp} is given by eqn. (8).

$$C_{temp} = tanh\,(W_c x_t + U_c h_{t-1} + b_c) \quad (8)$$

The output of the cell h_t is then calculated using eqn. (9).

$$h_t = o(t) \odot tanh(C_t) \quad (9)$$

Bi-LSTMs use the LSTM cells model sequences in both the forward and reverse directions. By passing the data in two different directions, it is possible to identify correlations in the past as well as the future.

E. *Layer-1 Meta-Classifier model*

The Layer-1 meta-classifier [26] learns features from both the subtask models mapping the interdependencies between the sub-tasks. The meta-classifier used is an Artificial Neural Network (ANN). This forms a method of ensemble learning, where there is a two-level optimization of the input data. This two-level architecture is used to predict both the stock prices as well as rate of change of prices.

IV. System Implementation

The implementation details of the system are given in this section. The sentiment analysis and price prediction models are set up on Google Colab with Intel(R) Xeon(R) CPU @ 2.20GHz Processor, 13 GB RAM and 12GB NVIDIA Tesla K80 graphics processor.

A. *Dataset Split*

1) *Sentiment Analysis of News Headlines*

The sentiment analysis model has top 25 news headlines for each day from 2008-08-08 to 2016-07-01. The dataset was divided in a train-test ratio of 80: 20 as seen in Table I.

2) Price Data

Prediction of rate of change of prices as well as prediction of closing prices is on the price data in the period between 2008-08-08 to 2016-07-01. The dataset was divided into a train-test ratio of 80:20 corresponding 1863 instances in the train set and 378 instances in the test set. A sliding window with input sequence length of 50 and an output sequence length of 1 is constructed.

TABLE I. DATASET SPLIT FOR NEWS HEADLINES

Data Type	Train Set	Test Set
Count of Days	1863	378
Count of News Headlines	50301	10206
Headlines with Positive Polarity	26865	5184
Headlines with Negative Polarity	23436	5022

B. Sentiment Analysis of News Headlines

The news headlines are cleaned to remove unnecessary characters such as punctuations, white spaces, operators etc. The Tf-Idf score is then calculated using sklearn's Tf-Idf Vectorizer [27]. Each day is labelled as 0 corresponding to a decrease in prices with respect to the previous day or 1 corresponding to the same price or an increase in price with respect to the previous day. A Random Forest model with 200 estimators is set up with entropy being used to determine the information gain.

C. Rate of Change and Price Prediction Model

The input closing prices and the difference between consecutive closing prices are first normalized using sklearn's MinMaxScaler [28] which ensures that all prices remain between 0 and 1. The hybrid architecture has three sub-tasks corresponding to the prediction of prices or rate of change of prices, modelling the news headlines to calculate negative polarity score and modelling the news headlines to calculate the positive polarity score. The sub-model to predict prices consists of an Input layer with shape (50,1) and 3 Bi-Directional LSTM layers with 128, 64, 32 nodes each interspersed with Dropouts of factor 0.2. The sub-models that learn the positive and negative sentiment of the headlines take in the prediction probabilities for the news headlines from the sentiment analysis model and they determine the association between these probabilities for the days within each sliding window. The sub-models have an Input layer of shape (50,1) and 2 Bi-Directional LSTM layers interspersed with Dropout layers of factor 0.2.

The outputs of all the three sub-models are concatenated and fed to a Level-1 meta-classifier. The information learnt by the individual sub-models is further optimized by the meta-classifier. This forms a stacking ensemble where an optimized relationship between Level-0 and Level-1 is obtained by training the outputs of the Level-0 model with the Level-1 model. The meta-classifier has 7 layers each with the ReLu activation function [29] having nodes 256, 128, 64, 32, 16, 8, and 4. The output layer has 1 node activated by the ReLu activation function that forecasts the predicted price or the predicted rate of change of price. The hybrid architecture is trained for 1000 epochs with a batch size of 8 using RMSProp [30] and MSE as the optimizer and loss function.

V. RESULTS AND ANALYSIS

The results obtained from the stock price prediction model and sentiment analysis models are presented in this section along with their analysis.

A. Training plot of the BiLSTM-based stock price prediction model with and without news headlines

The training of the Bi-LSTM for stock price prediction is performed for 100 epochs, with and without headlines in the data to analyze and compare their performance. In Figure 3. a), the training plot of the model trained using the daily stock price prediction to predict the value for the next day based on that day's price. In Figure 4. b), the model was trained with closing price of the stock and the news headlines on the stock market of that day to predict the closing price of that stock for the next day.

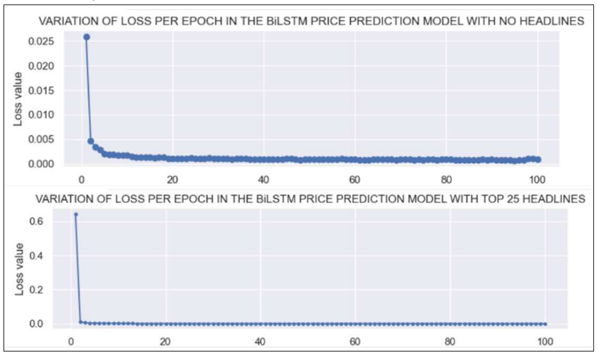

Fig. 4. a) Training plot of BiLSTM using price trend data without news headlines and b) with news headlines and price trend data

B. Evaluation Metrics of BiLSTM model stock price prediction model with varying number of headlines

The performance of the BiLSTM trained with a varying number of headlines is evaluated using metrics such as MSE (Mean Square Error) Value, MAE (Mean Absolute Error) Value and predictive R-squared value [31]. This is done to identify the interval of highest convergence on the training data for optimizing its data features for the best performance from the model. From Table II, it is inferred that the optimum training data required the number of headlines to be 10 for the prediction of the daily stock prices with the predictive R-squared value reaching 0.7484.

TABLE II. EVALUATION METRICS OF THE BILSTM MODEL WITH VARYING NUMBEBR OF HEADLINES

No. of news headlines	Evaluation Metric		
	RMSE	*MAE*	*Predictive R-squared value*
1	385.81	320.413	0.6244
5	390.53	357.331	0.5853
10	314.80	264.011	0.7484
15	529.46	466.723	0.2716
20	430.31	369.754	0.5242
25	412.90	354.707	0.5392

C. Plotting the real and predicted day-by-day stock price rates in the market

The daily stock prices are plotted in the graph in Figure 5 and compared with the predicted values from the BiLSTM model trained with and without news headlines for performance analysis. It is observed that the prediction results with Top 10 news headlines shows that the model is able to predict the positive or negative trend change on the next day with a high value of accuracy through NLP techniques.

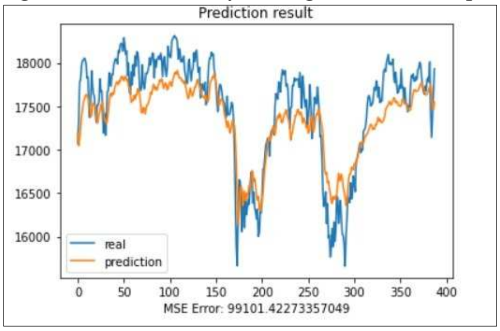

Fig. 5. Real and Prediction value comparison for the trained BiLSTM a) Without news headlines data and b) with news headlines data

D. *Calculating the prediction of rate of change of prices with news headlines*

The prediction rate of change calculates the average amount of variation between the actual stock price and the predicted stock price values over the testing dataset. This value is plotted in Figure 6 to identify the MSE and MAE values to record the performance of the constructed stock price prediction model. It is observed from Table III, that the model performed best with the Top 10 news headlines for the prediction of the stock price values.

TABLE III. EVALUATION METRICS VALUE FOR MODEL FOR AVG. RATE OF CHANGE OF PRICE WITH VARYING NUMBER OF HEADLINES

No. of news headlines	**Evaluation Metric**	
	RMSE	***MAE***
1	174.29	553.317
5	197.08	355.084
10	171.14	476.640
15	173.5	389.814
20	188.34	452.844
25	176.30	320.413

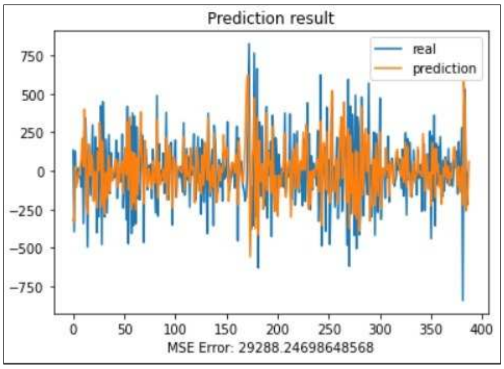

Fig. 6. Prediction Rate for real and predicted values by the Bi-LSTM model

E. *Analysis of the effect of news headlines on actual stock prices using sentiment analysis*

The analysis of the effect of the news headlines dataset is done by calculating the average rate of change in each probability range. This is done for both positive and negative sentiment to analyze their effect on the rate of change. In each probability range, the average rate of change is given in dollars. For negative sentiment in the probability range of 50-60, there was a high decrease in the rate observed. The higher probability ranges for the same sentiment the decrease was observed to be minimal.

In Table IV, the positive sentiment for the mid-range of probabilities has observed a significant increase in the average rate of change than the lower range of 50 to 60. The average rate of change was observed to have dropped slightly even when there was a high prediction for raise in the stock prices.

TABLE IV. EVALUATION METRICS VALUE FOR AVG. RATE OF CHANGE OF PRICE WITH VARYING NUMBER OF HEADLINES

Range of Probability		***Avg. Rate of change (in USD)***
LL	UL	
Negative Sentiment		
50	60	-181.6
60	70	2.59
70	80	8.93
80	90	4.42
Positive Sentiment		
50	60	-68.68
60	70	36.07
70	80	25.52
80	90	-17.73

F. *Comparison of the model with existing state-of -the-art architectures*

The performance of some of the existing state-of-the-art models that had used the standard dataset of stock prices with news headlines is given in Table V. The implementing novel framework hybrid model outperforms the other models with an accuracy of 84.92.

TABLE V. COMPARISON OF STATE OF THE ART ARCHITECTURES

Paper	**Model**	**Accuracy**
Our Paper	**Bi-LSTM with Embedded Random Forest Sentiment Scores**	84.92
Oncharoen and Vateekul [32]	Hybrid LSTM-CNN	69.86
Zhang and Lu [33]	Multi-Model Fusion	58
Liu et. al. [34]	GRU with GloVE Embedding	62.9

VI. CONCLUSION

The work explores the effect of public sentiment through news headlines on stock market prices, which has previously not been explored in detail. To accomplish that, a Random Forest classifier based sentiment analysis model is constructed using day-by-day news headlines dataset along with the variation of Close Stock price. The sentiment analysis model identified the headlines associated with positive and negative sentiment for further analysis. The constructed BiLSTM based stock price prediction model was used for predicting the close price rates with and without news headlines dataset to study the effect of change of sentiment on the average stock price rate in the market.

VII. FUTURE WORKS

The effect of the public sentiment on social media can be explored with a wider range of data collection such as Google trends analytics to build a price prediction model for forecasting stock price prediction rates and the investment periods. The constructed prediction model can be experimented with using trained weights from the sentiment analysis performed for optimizing the learning weights of the model further with attention-based deep neural architectures.

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