Optimizing Technical Parameters and Stock Price Prediction using: Linear Regressive MapReduce and Quasi-Newton Deep Learning

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Abstract. The Stock value forecast is a significant issue to determine the future direction of the financial Markets. Many research works are carried out and design many techniques to predict stock price of Individual stocks. But, the forecast precision/ of the regular methods was lower when taking the enormous size of the dataset. To address this downside, a Novel Deep learning based Broken-Stick Linear Regressive MapReduce Based on Quasi-Newton Deep Neural Learning (BLRM-QNDNL) method is proposed right now. BLRM-QNDNL technique targeting optimizing the parameters engaged with stock profit prediction. Quasi-Newton based Deep Neural Network Learning (Q-NDNL) is applied in the BLRM-QNDNL procedure for precisely foreseeing the stock prices dependent on the news with higher accuracy. Q-NDNL used several hidden layers in order to thoroughly examine the effects of emotions conveyed in news items on stocks with the least amount of time complexity. The BLRM-QNDNL method expands the stock price forecast performance with lower time complexity when compared with cutting edge works. The BLRM-QNDNL technique has been evaluated exploratory on metrics such as prediction accuracy, prediction time, and false positive rate with regard to different numbers of data. When compared to state-of-the-art studies, the experimental results show that the BLRM-QNDNL technique can reduce the time complexity of stock price prediction while simultaneously increasing its accuracy. The suggested BLRM-QNDNL technique reduces the false positive stock price prediction rate by 41% and 57%, respectively and decreases market price prediction time complexity by 9 percent and 29 percent relative to traditional DeepClue [1] and MFNN [2], respectively.

Keywords: Deep Learning; MapReduce, Quasi-Newton, Machine Learning, Stock Prediction.

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1 Introduction

The goal of stock market prediction is to estimate the future price of a company's stock that is traded on a market. Exact predicting of future stock values can result in substantial rewards. Many researchers have been introduced for stock market prediction. But expectation execution utilizing existing systems was not adequate while considering big data as input. Therefore, BLRM-QNDNL technique is designed in this research work to complete the effective stock price prediction process with minimal false positive rate.

A novel technique called BLRM-QNDNL is developed in this research work. Broken-Stick Linear Regressive MapReduce (BSLR MapReduce) is a statistical technique for simulating the relationship between two variables in a huge dataset. It is a variation of the linear regression algorithm that is well-suited for MapReduce environments, which are commonly used for processing large datasets in parallel.

The BSLR MapReduce algorithm works by dividing the dataset into smaller subsets, which are processed in parallel using MapReduce. Each subset is then analyzed using the Broken-Stick Linear Regression (BSLR) algorithm, which is a statistical method for identifying "change points" in a linear regression model. Change points are points where the relationship between two variables changes abruptly, indicating a change in the underlying data generating process.

The BSLR algorithm identifies these change points by segmenting the data and applying a linear regression model to each segment separately. The algorithm then uses a statistical test to determine if there is a significant difference between adjacent segments. If there is a significant difference, a change point is detected, and the algorithm fits a new linear regression model to the data after the change point.

BSLR MapReduce has several advantages over traditional linear regression algorithms. First, it can handle large datasets by dividing them into smaller subsets that can be processed in parallel. Second, it is robust to outliers and can handle non-linear relationships between variables. Finally, it can identify change points in the data, which can be useful for detecting regime shifts or other structural breaks in the data generating process.

Quasi-Newton methods are a family of optimization algorithms used to find the minimum of a function. They are particularly useful for deep neural learning because they can handle high-dimensional problems and can converge faster than other optimization methods, such as stochastic gradient descent.

Deep neural learning involves optimizing a complex, high-dimensional function, typically represented by a multi-layer neural network. The BFGS algorithm can be used to optimize the weights and biases of the neural network by minimizing the error between the predicted outputs and the actual outputs of the network. This can be done by computing the gradients of the error function with respect to the weights and biases, and then using the BFGS algorithm to update the weights and biases.

Overall, Quasi-Newton methods such as the BFGS algorithm can be a useful method for optimizing deep neural networks. They can converge faster than other optimization methods and can handle non-convex optimization problems.

In the upcoming section the work is structured as follows Section 2 explains the literature survey. In Section 3, the proposed BLRM-QNDNL technique is explained with the assist of the system architecture diagram. In Section 4, experimental settings are described, and the experimental result of the BLRM-QNDNL technique is discussed in Section 5. Section 6 shows the conclusion of the paper.

2 Literature Survey

The NLP machine learning approach was built in [3] Deep learning models are used to derive news from positive and negative opinions. Based on sentiment and time series data, stock market forecasting was performed in [4] by considering the financial microblog.

In [5] a hybrid model was introduced with the support algorithm and Hodrick – Prescott filters for the vector regression to optimize the stock market prices prediction. In [6], Network science was utilised to improve the accuracy of stock analysis market movements utilising a theoretical approach to knowledge.

In [7] a new approach was introduced by using the emotions of ordinary people through the news feeds and Sensex data to detect stock market behaviour. In [8], distributors were employed to measure sentiment by using company reports to forecast stock prices.

In [9] an improved feature representation was designed to achieve better accuracy in stock market prediction with the use of a basic linear regression model. In [10] the Support Vector Regression (SVR) was implemented with the purpose of calculating stock prices on various markets with up-to-date daily frequencies.

A new algorithm was built in [11], using PSO and the least square vector support machine (LS-SVM) to calculate the daily inventory prices at a lower time. A study of various stock market research methods was discussed in [12].

A CNN-based framework was introduced in [13] to predict the stock prices for extracting the features. But the time complexity was not reduced. Firefly algorithm with an evolutionary framework for OSELM was presented in [14,15] depended on feature reduction for determining the future stock price. However, the stock market prediction performance was poor.

3 Broken-Stick Linear Regressive Map Reduce Based Quasi-Newton Deep Neural Learning Technique

Broken-Stick Linear Regressive MapReduce and Quasi-Newton methods can be combined to develop an algorithm for stock price prediction using deep neural networks.

A novel technique called Broken-Stick Linear Regressive MapReduce Based Quasi-Newton Deep Neural Learning (BLRM-QNDNL) is introduced to achieve better accuracy for stock price predictions by collecting a significant volume of time-series data and analyzing it in relation to relevant news stories. This is achieved with the utilization of Broken-Stick Linear Regressive MapReduce Function (BLRMF) and Quasi-

Newton based deep Neural Network Learning (Q-NDNL) concepts. At first, Broken-Stick Linear Regressive MapReduce Function (BLRMF) is used for selecting optimal parameters to find the profits of stock. Then, Quasi-Newton based Deep Neural Network Learning (Q-NDNL) is applied to determine the best stocks depended on news articles with minimum time. The diagram of overall architecture of the BLRM-QNDNL technique is presented in Figure 1.

Once the dataset has been pre-processed using BLRMF, a deep neural network can be trained using a Quasi-Newton optimization algorithm. The neural network can be designed to take as input the pre-processed features, which may include stock market indices, company financial data, and technical indicators, and output a prediction of the stock price at a future time point.

During training, the Quasi-Newton optimization algorithm can be used to adjust the weights and biases of the neural network to minimize the error between the predicted and actual stock prices. The algorithm can converge faster than other optimization methods and can avoid getting stuck in local minima.

The BLRMF algorithm can be used to pre-process the new data by identifying change points and dividing it into smaller subsets. The pre-processed data can then be fed into the neural network, Then, Quasi-Newton based Deep Neural Network Learning (Q-NDNL) can be used to make predictions on new, unseen data, which can output a prediction of the stock price at a future time point. We achieved high prediction accuracy through the combination of BLRMF and Quasi-Newton method for stock price prediction using deep neural networks.

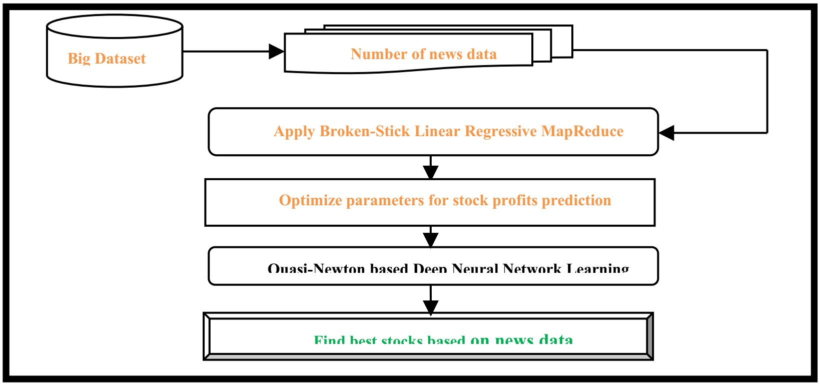

Fig. 1. Architecture Diagram of BLRM-QNDNL Technique for Stock Prediction

Figure 1 description: the overall processes of the BLRM-QNDNL Technique to identify the future price of company stock. The detailed process of the BLRM-QNDNL Technique is shown in the below subsections.

3.1 Broken-Stick Linear Regressive MapReduce Function

In BLRM-QNDNL Technique, Broken-Stick Linear Regressive MapReduce Function (BLRMF) is developed to optimize the parameters for effectively identifying profits of stock with minimum time complexity. On the contrary to conventional works, BLRMF is proposed by using the Broken-Stick Linear Regression and MapReduce Function. The BLRMF takes a set of parameters as input and then performs regression analysis to select the best parameters and thereby finds the best parameters to significantly find the profits of stock with higher accuracy. The process involved in BLRMF is shown in below Figure 2.

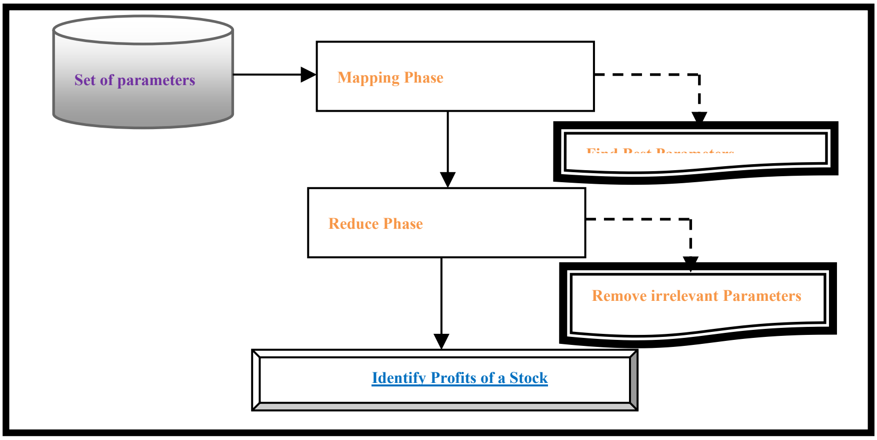

Fig. 2. Processes of Broken-Stick Linear Regressive MapReduce Function

Figure 2 description: The flow processes of the Broken-Stick Linear Regressive MapReduce Function are depicted in Figure 2. As exposed in the above figure, BLRMF includes two main processes, namely mapping and reducing. The BLRMF gets a set of parameters such as Stochastic Oscillator (SO), Relative Strength Index (RSI), Money Flow Index (MFI), Exponential Moving Average (EMA), and Moving Average Convergence/Divergence (MACD) as input. During the mapping process, BLRMF determines the relationship between input parameters and objective function. From the determined relationship, then optimal parameters are selected in BLRMF. During the reducing process, BLRMF accurately finds the profits of a stock with the chosen best parameters and removing the irrelevant parameters.

Let's start initially collecting numbers of parameters as data, and then testing out regression analysis. BLRMF is a specific form of linear regression that occurs when a single line is inadequate to model an input data. BLRMF splits the domain into several "components," fitting a separate line through each. The Broken-Stick Linear Regression Analysis is done as follows mathematically,

$$y = a_0 + a_1 \beta + a_2 (\beta - b)^+ + e \quad (1)$$

From the above equation (1),'b'represents the value of breakpoint and 'β'signifies input parameters whereas 'a_0, a_1, a_2 'point outs regression coefficients (represents the slope of the line segments). Here, 'e' denotes error vector and 'y' refers to the predicted output. By using the above mathematical equation, the relationship between input parameters and objective function (i.e. stock profitability) is measured. Thus, BLRMF selects parameters such as Relative Strength Index (RSI) and Moving Average Convergence/Divergence (MACD) as optimal to efficiently determine the profits of stock with help of TCS (Tata Consultancy Services) Wipro stock daily prices dataset.
In BLRMF, the Relative Strength Index (RSI) is a technical momentum indicator. RSI compares the magnitude of recent gains to recent losses to find out overbought and oversold conditions of an asset. The formula for measuring the Relative Strength Index is shown in below,

$$RSI = 100 - [100 / (1 + RS)] \quad (2)$$

RSI stands for average of x days' up closes / average of x days' down closes in the mathematical statement (2) above. Then, in BLRMF, Moving Average Convergence/Divergence (MACD) determines the variance between a price's short- and long-term moving averages. The mathematical expressions for calculating the MACD and its signal are as follows,

$$MACD = (0.075 - 0.15) * EMAofClosingprices \quad (3)$$
$$SignalLine = 0.2 * EMAofMACD \quad (4)$$

From the above mathematical equation (3) and (4),EMA indicates an exponential moving average. With the support of selected optimal parameters, BLRMF identifies the profits of stock with enhanced accuracy and lower time.

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Algorithm 1: Broken-Stick Linear Regressive MapReduce Function

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Input: set of parameters '$\beta_1, \beta_2, \beta_3, \ldots . \beta_n$';
Output: Select optimal parameters to find profits of a stock
Step 1: start
Step 2: **for** each parameter 'β_i'
Step 3: Apply Broken-Stick Linear Regression Analysis
// Mapping phase
Step 4: Determine relationship parameters using (1)
Step 5: Select optimal parameters
// Reducing phase
Step 6: Eliminate irrelevant parameters
Step 7: Accurately predict profits of a stock using optimal parameters
Step 8: **End for**
Step 9: End

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Algorithm 1 depicts step by step processes of Broken-Stick Linear Regressive MapReduce Function. With the above algorithmic processes, BLRMF effectively chooses best parameters to determine the profits of stock with minimal time and consequently removes the irrelevant parameters. From that, BLRMF enhance parameter optimization performance when compared to conventional works.

3.2 Quasi-Newton based Deep Neural Network Learning

The financial news stories are considered to have an influence on the return of stock prices. Previous research examined the latent association between word statistical trends and changes in the value of stocks by modelling news articles in the bag-of-words space. News sentiment, however, which is necessary to predict accurately stock price that is rarely affected in traditional works. Thus, Deep Neural Network Learning (Q-NDNL) based on Quasi-Newton is proposed to enhance the stock market prediction with lower false positive rate. Q-NDNL has used several hidden layers to evaluate input news articles in depth and thus identify best stocks with lower time complexity. Figure 3 illustrates the Q-NDNL framework for successful prediction of stock prices.

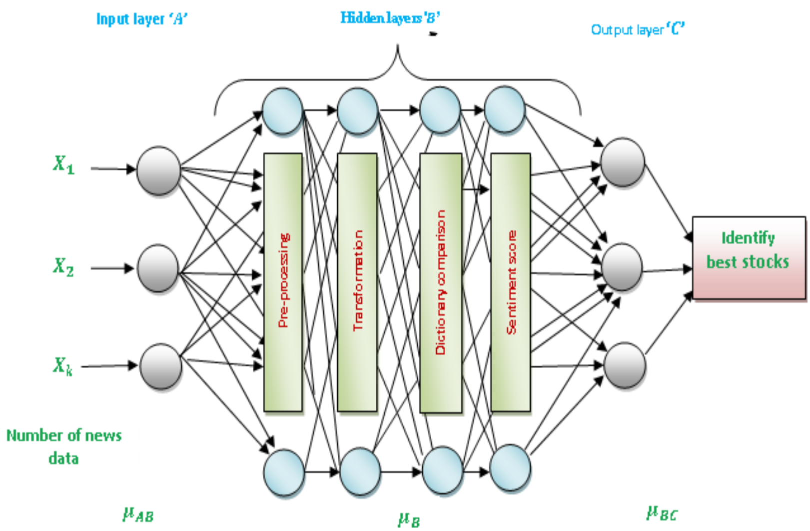

Fig. 3. Structure of Q-NDNL for Stock Price Prediction

Figure 3 illustrates: The Q-NDNL flow processes in order to accurately identify the best stocks with minimal time based on news articles. As seen in the figure above, Q-NDNL initializes a random weighted neural network. The input layer receives various news stories as input and routes them to hidden levels. The hidden layers in Q-NDNL thoroughly analyze news input data by executing Pre-processing, Transformation, Dictionary comparison and calculating the sentiment score, and then transfer the final result to the output layer. Instead, for each qualified news articles Q-NDNL tests the error rate. The error rate for each prediction outcome using Q-NDNL is then reduced by updating the adjusted weights with relation to the error rate. The cycle of Q-NDNL is repeated till the error value is negligible. The output layer in Q-NDNL finally delivers the best result in stock. Through Q-NDNL we achieved, improved efficiency in market price prediction as opposed to traditional works.

The algorithmic processes of Q-NDNL are shown in below:

Algorithm 2: Quasi-Newton based Deep Neural Network Learning

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//**Quasi-Newton based Deep Neural Network Learning Algorithm**
Input: Number of news data= $\{X_1, X_2, X_{3,\ldots}, X_k\}$'
Output: Enhanced accuracy for stock price prediction
Step 1: start
Step 2: Initialise a neural network with random weights
Step 3: **for** news data'X_i'
Step 4: **while** ('$e(t)$' is low) **do**
Step 5: 'X_i' is taken by input layer 'A(t)' and passed on to hidden levels through (5)
Step 6: using the first hidden layer proceed pre-processing (6)
Step 7: Second hidden layers performs transformation using (7)
Step 8: Third hidden layers performs dictionary comparison using (8)
Step 9: Fourth hidden layers measure sentiment score using (9) and (10)
Step 10: using 11 and 12 output layer "C(t)" produces a prediction result.
Step 11: Use (13) to calculate the error rate' e(t)'.
Step 12: Weights are updated using (14)
Step 13: Reduce 'e(t)' by using (15)
Step 14: **stop while**
Step 15: **if** ($C(t) == 1$), **then**
Step 16: **c**lassify Stock is best to buy
end if
Step 17: **else**
Step 18: **c**lassify Stock is not best to buy
Step 19: **stop for**
Step 20: stop

Algorithm 2 uses Quasi-Newton to carry us through the steps of deep neural network learning. In comparison to state-of-the-art work, Q-NDNL can identify the best stocks with more accuracy and in less time with the help of the mentioned algorithmic methods. Therefore, the BLRM-QNDNL methodology performs better in stock prediction when compared to state-of-the-art studies.

4 Experimental setup

Using a large dataset, such as the Daily News for Stock Market Prediction, the suggested BLRM-QNDNL approach is implemented in python in order to evaluate its performance. daily news dataset is collected from Kaggle (https://www.kaggle.com/aaron7sun/stocknews). For conducting the experimental process, BLRM-QNDNL Technique considers a diverse number of news data in the range of 500 to 5000. The efficiency of the BLRM-QNDNL Technique is decided in terms of prediction accuracy, time complexity, and false-positive rate with respect to the numerous types of news data.

5 Experiment comparison and analysis

In this section, the comparative result of the BLRM-QNDNL technique is discussed. The effectiveness of the BLRM-QNDNL Technique is estimated along with the following metrics with the help of tables and graphs.

5.1 Case 1: Prediction Accuracy

In the BLRM-QNDNL technique, the Prediction Accuracy 'PA' is measured mathematically, using the following,

$$PA = \frac{X_{AC}}{k} * 100 \tag{5}$$

'X_{AC}' reflects the number of properly classified news, 'k' symbolizes a total number of news data used for experimental process. The accuracy of prediction of stock price is measured in percentage (%).

Sample calculation for Prediction Accuracy:

- **Proposed BLRM-QNDNL Technique: T**he number of correctly classified news data is 455, and a total of 500 news data. The predictive accuracy is acquired as follows,

$$P \quad A = \frac{455}{500} * 100 = 91\ \% \tag{6}$$

- **Existing Deep Clue:** A total of 405 properly classified news data and a total of 500 news data. The exactness of the prediction is measured as follows,

$$PA = \frac{405}{500} * 100 = 81\ \% \tag{7}$$

- **Existing MFNN:** The Number of accurately classified news data is 345, and a total number of news data is 500. Precision prediction is determined as follows,

$$PA = \frac{345}{500} * 100 = 69\ \% \tag{8}$$

The performance result of accuracy is obtained during the processes of stock price prediction using three methods namely proposed BLRM-QNDNL technique and conventional Text-based deep learning models called DeepClue [1] and Multi-filters neural network (MFNN) [2] is presented in below figure 4.

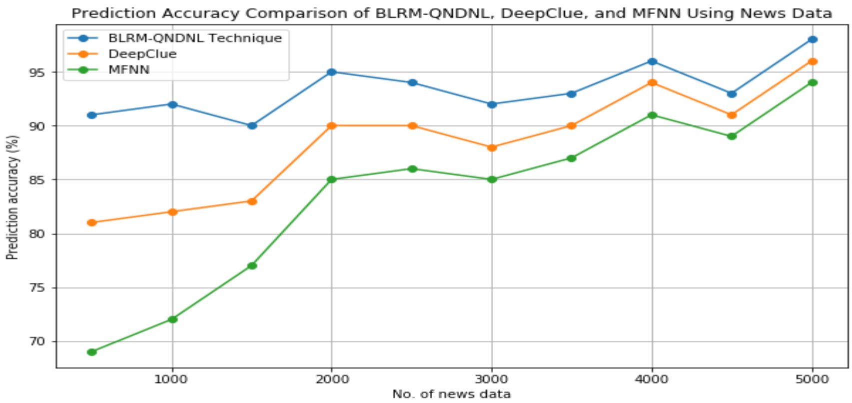

Fig. 4. Result of Prediction Accuracy

Figure 4 Description: presents the prediction accuracy of stock price forecasting with respect to a various number of news data in the range of 500 to 5000 using three methods, namely the proposed BLRM-QNDNL technique and conventional DeepClue [1] and MFNN [2]. Thus, the proposed BLRM-QNDNL technique enhances the accuracy of stock price prediction by 6 % and 13 % when compared to existing DeepClue [1] and MFNN [2], respectively.

5.2 Case 2: Time Complexity

In the BLRM-QNDNL technique, the time complexity 'TC'is determined by classifying news data as the amount of time taken to find the best stocks. The time complexity is measured mathematically, using the following,

$$TC = k * t\ (CSND) \tag{9}$$

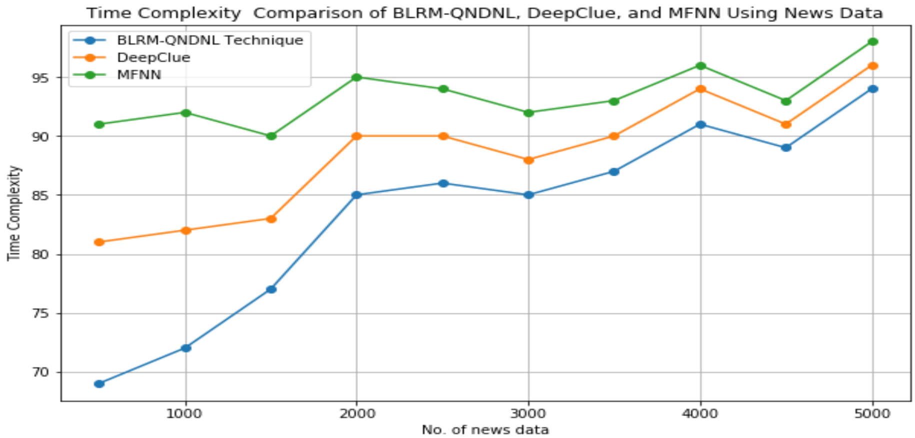

Fig. 5. Measurement of Time Complexity versus Number of News data

From the mathematical expression (6) referred to above, " t ($CSND$)'represents the time used to classify a single news item,'k' refers to a number of news items used for experimental work. The time-complexity of stock price prediction is calculated in milliseconds (ms).

Figure 5 demonstrates: Proposed BLRM-QNDNL technique decreases market price prediction time complexity by 9 percent and 29 percent relative to traditional DeepClue [1] and MFNN [2], respectively.

5.3 Case 3: False Positive Rate

False positive rate (FPR) in the BLRM-QNDNL technique calculates the ratio of the number of news data that were inaccurately categorised to the total number of news data that were input. The following formula is used to calculate the false positive rate,

$$FPR = \frac{X_{WC}}{k} * 100 \tag{10}$$

From the mathematical formula above (7), 'X_{WC}' denotes the number of times news has been incorrectly classified, where 'k' denotes multiple news items. The stock prediction's false positive rate is calculated as a percentage (%).

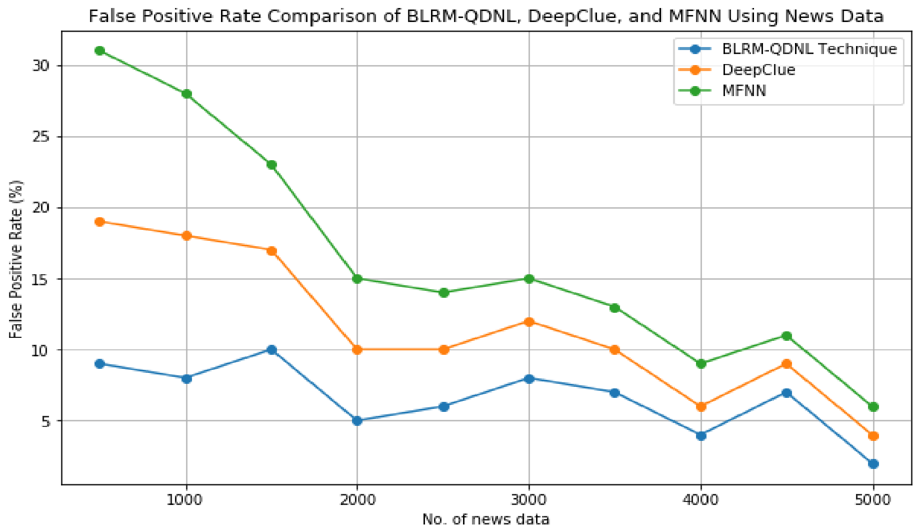

Fig. 6. Measurement of False Positive rate versus Number of News data

Figure 6 Description: shows the false positive rate of stock price detection along with the varied number of news data ranging between 500 and 5000 using three methods, the suggested BLRM-QNDNL technique reduces the false positive stock price prediction rate by 41% and 57%, respectively. In comparison to state-of-the-art DeepClue [1] and MFNN [2].

6 Conclusion

In this research paper, we proposed BLRM-QNDNL technique with the intention of increasing the output of the stock price by considering the technical parameters of a stock and classifying the news data. The goal of the BLRM-QNDNL technique is accomplished with the help of the algorithms Broken-Stick Linear Regressive MapReduce Function (BLRMF) and Quasi-Newton based Deep Neural Network Learning (Q-NDNL) as opposed to conventional works. The proposed BLRM-QNDNL methodology greatly decreases the number of parameters considered against current works to evaluate stock profitability. Furthermore, as compared to existing cutting-edge works for consistently predicting stock prices, the suggested BLRM-QNDNL technique reduces the amount of time consumed by applying the Q-NDNL algorithm and reduces the ratio of numerous erroneously classified news items to find the best stocks on the market in comparison to other works. The experimental results reveal that the suggested proposed BLRM-QNDNL technique performs better than cutting-edge studies in terms of effectiveness, accuracy, and time complexity for stock price prediction.

Disclosure statement

This paper has not yet been submitted to a journal, and none of the co-authors has a conflict that would prevent them from submitting and processing it in this.

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