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# Impact of COVID 19 on Stock Market performance using Efficient and Predictive LBL-LSTM based Mathematical Model

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**ABSTRACT: In this research work, Efficient Stock forecasting model using Log Bilinear and Long Short term memory (LBL-LSTM) is designed, considering external fluctuating factors to analyze impact of the pandemic COVID 19, on stock market performance using similar kind of historical records like past outbreaks of severe acute respiratory syndrome (SARS) virus occurred in 2002-2004. Earlier Machine learning (ML), based stock Market predictive models based on pre-epidemic reaction can become obsolete as theses models takes relatively longer historical training data as input parameters. These predictive ML models should be more robust to current happenings. Taking into account this problem, there is a need for model to be agile and flexible enough to sense external fluctuating factors. Model should be able to capture, adapt to rapid changes happening in economic dimension. Objective of this research work is to design and implement Log -Bilinear and Long Short term Memory based (LBL-LSTM) based model considering both long term and volatile short term external conditions. Experiments are conducted to analyze the performance of Proposed LBL -LSTM model, which shows significant performance improvement in terms of Root Mean Square Error (RMSE), Accuracy Score over existing ML based stock predictive models. Finally, after analyzing the effects conclusion can be made that markets will often react negatively to these incidents, in short term, but in the long term, the markets will eventually correct and improves.**

**Keywords:** COVID-19, sentiment Analysis , Stock Market Prediction, Long-Short Term Memory, Machine Learning Algorithms, stock market indices, Log Bilinear model.

## I. INTRODUCTION

**Effect of Covid 19, SARS virus, Spanish Flue comparison on Stock Market Crash:** The Covid-19 epidemic is an international pandemic that has swept the world. As of May 1, there are approx 3.4 million reported Covid-19 cases worldwide with approximately 240,000 reported deaths. When a new virus, an outbreak occurs, nobody fully knows what the long-term effect of the virus will be. There may be long-lasting effects on both public and public health. If we look back in time to 2003, when the SARS epidemic occurred, with another type of corona virus, in retrospect, with only 8096 reported cases and 774 deaths. However, it is not always the actual direct effects of a pandemic what drives the market. The stock market often moves with speculations and sentiments. Between January 2013 and mid-March 2013, the period of time that with an outbreak of SARS on the horizon, the Dow Jones index fell about 15% from peak due to the fear and uncertainty surrounding the virus. This may sound negative, but at the end of the year, the Dow Jones index rose by about 21% to date or about 39% from its lowest point of the year. In fact, it only took about 3 months since the Dow Jones hit rock bottom to return to it's own previous peak. For a relatively docile outbreak like SARS, there was a short-term market shock that reduced the value of stocks, but eventually stocks returned to previous levels and even hit new highs. SARS is the same type of virus as COVID-19, but the reaction to the viruses couldn't be different.

Currently it is not completely known what kind of long-term effects the virus can have on general economy. For this reason, it could be better look beyond the past into Spanish flu as a comparable pandemic. The Spanish flu was the deadliest pandemic in the world, the 20th century. At least one third of the world's population was estimated to have the disease and over 50 million people died. Thinking that, such a pandemic would have serious negative effects on the stock market. But this is not the case. The beginning of the Spanish flu occurred in early 1918 and the worst pandemic occurred in the autumn of 1918. However, if we really look at equity returns for that period, we will generally see that the market was not that largely affected. From the beginning of 1918 to the end of 1918, the stock market in general had an upward trend with some setbacks. At the end of the year, the Dow Jones closed 7% more than in the beginning. Furthermore, we see that in 1919, the market in fact, it recovered almost 50% until it collapsed in 1920. Of course, in the same period of time, World War II had just ended, which undoubtedly fueled a recovery in the market. For this reason, Spanish flu is not an apple for apples comparison of the COVID-19 pandemic in terms of the effects of the stock market, an important idea from which we can deduce looking at the Spanish flu influence; even with market shocks, stocks are doing well in the long run. If we conclude that the market will act similarly as in the past, then we can assume that there will be a short term stocks decrease but increase in the long term. This means that there is great potential for purchasing shares in strong companies, at discounted price.

Inter-relation of pandemic between countries: As from economic and globalization point of view, global financial market related impacts of SARS disease and 2014 EBOLA outbreak effect on stock markets crash, economic adverse effects affects from one country to another country. As the COVID 19 Outbreaks there is a sad investors sentiments across the stock market because half of world's population is in lockdown which affected investor's sentiments around the world resulted in slowdown of world's economy.

Effect on Indian Stock Market: Indian stock markets are also affected badly which will be continued in near future as Foreign direct investments ( FDI) declined caused a drop in Indian Stock Markets. On January 20, 2020, S&P BSE Sensex, was 42,273 points and on April 8, 2020, market collapsed to 29,894 points [11]. Taking examples of external fluctuating factors such as Sensex sank 53% in one year during "Harshad Mehta Scam" (1992) but recovered 127% in 1.5 years [12]. During "Tech Bubble" (2000), Sensex dropped down 56% in 1.5 years, but recovered back to 138% in 2.5 years [12]. When the United States faced the "Real Estate - Lehman" crisis in 2008, Sensex dropped 61% in a year, but recovered 157% in 1.5 years [12]. In current Covid-19 pandemic situation, market has collapsed by about 30% in less than three months [12].

Factors to be considered while designing Robust, Agile, Flexible Machine Learning (ML) based model sensing external fluctuations :

**1. ML based stock predictive models:** based on pre-epidemic reaction ML based models can become obsolete as these models takes relatively longer historical training data as input parameters which assumes somewhat stationary conditions. Hence there is a need to consider short term training data. In this research work we have considered LBL based model which mainly focuses on short term market conditions need to choose period of input training dataset considering lot of fluctuating factors for shorter periods of time.

**2. Agility and Evolutionary ML model:** Considering flexible behavior where short term adjustments are needed, there is a need to adapt to short term behavior of model, hence short term adjustments are needed taking into account training data. These ML models should be more robust to current happenings. Model should be able to capture, adapt to rapid changes happening in economic dimension.

**3. Test A/B:** Considering stock market's volatility, duration of A/B Testing should be long enough to allow volatility modeling. Hence benefits and costs of A/B tests during COVID pandemic must be assessed, balanced because conclusions drawn should not get invalidated after short term fluctuations.

**4. Change in certain sectors stock:** Pandemic has affected commercially on many sectors such as various industries, supply chain management, commercial sales etc. Some stocks related to certain industries are increasing such as communication sector, online education related sectors, medical sectors, entertainment whereas other financial sectors such as tourism industry, hospitality sector, international trade business has affected on a large scale.

## II. RELATED STUDIES

There are many research articles on stock market forecasting and LSTM. Many different functions and the attributes were used for the same purpose. There are three main categorizations of the stock market from analysis and forecasting point of view as (a) fundamental analysis, (b) technical analysis and (c) time series analysis. Most time series data forecasting techniques typically use a linear method. Such as AR, MA, ARIMA, ARMA, CARIMA, etc. [1, 2, 10] or nonlinear models (ARCH, GARCH, ANN, RNN, LSTM, etc.) [9, 10, 13]. The authors of [3] analyzed several macroeconomic factors for design a data warehouse that affects the movement of stock prices, such as the price of crude oil, the exchange rate gold price, bank interest rate [16], political stability, etc. Researchers from [4] have used frequent article series mining technique to find a delayed correlation between price movements between different sectors index in the Indian stock market. Roondiwala *et al.* [5] used the RNN-LSTM model in NIFTY-50 shares with 4 characteristics (high/closed/open/low price of each day). They used a 21 day window for predict price movements the next day. A total of 5 years of data were used for forecasting and RMSE as an error metric to be minimized with back propagation. Kim *et al.*, [6] proposed a model, the characteristic convolutional fusion of long-term memory Neural Network Model (LSTM-CNN). "They used CNN to learn the characteristics of the stock chart. images They found that candlestick charts are the best candidate for predicting future stock prices. movement. They then used LSTM and provided historical pricing data. They tried share the price per minute and the 30-minute sliding window used to predict the 35-minute price. They have tested on ETF on the S&P 500 with share price and trading volume via CNN. They use CNN and LSTM individually in different categorization of the same data and then used the combined function casting model for the same purpose. It is observed that the combined model surpasses the individual models with fewer prediction errors. So this work establishes the fact that different representations of the same data (raw price and trading volume and stock chart image) with combined models each individual model is optimized for a separate data format capable of learning more intrinsic data dynamics and features that are not logical for looking at the same object from different angles than gives a new vision. Hiransha *et al.*, [7], they used three different deep learning networks activities such as CNN, LSTM and RNN to predict the price of shares using the day's closing prices. Two IT companies (TCS and Infosys) and one from Pharma were considered sector (Cipla) for experiment. The uniqueness of the study is that they trained using models data from a single company and have used these models to predict future prices for five different stocks of NSE and NYSE (New York Stock Exchange). They claimed that linear models attempt to adapt the data. The pattern, but deep underlying networks of dynamic stock prices are discovered. According to his CNN's results outperformed all other models and classic linear models.

DNN could forecasts companies listed on the NYSE even though the model has learned from the NSE dataset. The reason It could be the similar internal dynamics of both exchanges. As discussed in our earlier research work [9, 13] modified back propagation neural networks, in that case, gradients values are used to update the NN weights. The 'Vanishing gradient problem' occurs when back propagation takes place, the gradient slows down or decreases quickly over short duration of time span [9,13, 20]. The ML model can not learn properly if gradient value becomes very small, as it doesn't contribute much to learning [20]. Gers and Schmidhuber proposed to Variation of LSTM introducing "peephole connections" [18]. In this model it is possible to see the door layers in the cellular state. In another case, the model matches the doors of oblivion and the entrance. In this case, the decision of add new information or forget it is taken together. Just forget when you need to insert something instead. This architecture inserts new values into the cell state when it forgets something older. Cho, *et al.*, [19] proposed another popular LSTM variant known as the Closed Recurrent Unit (GRU). What add both the forget and entry doors to an "update gate" proven batter than original LSTM. For this reason, this model is becoming popular day by day. These are not indicates an exhaustive list of modified LSTMs. There are many other variations, such as closed depth, Yao, *et al.,* [20] proposed "mechanical RNN" to address long-term dependencies in a completely different way.

*A. Log Bilinear-Long Short Term Memory Model (LBL-LSTM) Model*

Recurrent Neural Networks are State of the Art algorithms which can Memorize previous historical records, provided large time series data. RNN can be described as n number of copies of the same neural network, passing, messages from predecessor to successor nodes.

Log Bilinear (LBL) model proposed by Mnih and Hinton, in 2009 is the very unique language model [9, 24]. This feed-forward neural probabilistic model is simple with just one linear hidden layer and output layer [2, 14, 15]. LBL is used to model short term behavior of stock prices correctly [2], hence, stock buyers can determine when to buy and when to sell. Recurrent Neural Networks (RNN) can't learn short-term fluctuations in stock market [2]. Long Short-Term Memory (LSTM) networks is a type of RNN, can model long term behavior pattern in time series based sequential prediction problems such as complex problem domains like machine translation, speech recognition etc. [20, 22].

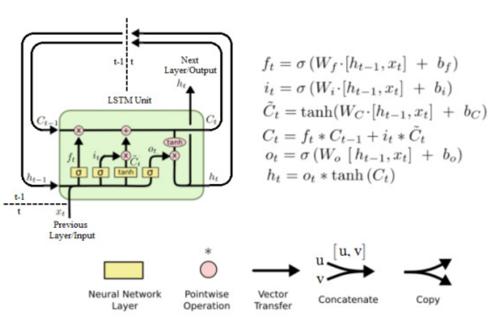


**Fig. 1.** Understanding LSTM Networks [13].

This work presents LBL based model with a hidden linear single layer. Hence it is a deterministic model [2]. If a long and short term fluctuating Financial time series (FTS) data is given for prediction LSTM suffer from carrying information from previous stage to the next stage. LSTM networks work better compared to traditional RNN since they overcome problem of 'Vanishing Gradient Problem' [10]. LSTM, in all cases, may not work well as they may leave some important part of information in short term dependencies, hence LBL based model is the solution. LSTM fails to establish short term dependencies, although it works well in case of long term predictions, because as errors are back - propagated to multiple layers of LSTM, performance obtained is poor which can be improved by combining LBL and external sensing factor. Hence proposed LBL-LSTM model can solve 'Vanishing Gradient problem which is the drawback of RNN while establishing long term relationships in time series forecasting models. Meanwhile aim is not to confuse the LBL-LSTM model by over fitting considering too many parameter, which may lead to reduced performance of the model .

**The Research work contribution is as follows:**

— Here, an attempt has been made to design intelligent predictive stock forecasting model which senses market fluctuations due to external parameters. Hence, Design of stock forecasting model based on LBL-LSTM is proposed, by combining LBL with LSTM which models both short term fluctuations and long term behavior pattern of stock market respectively.

— To study the effect of external fluctuating factors such as COVID 19 similar to previous outbreak of SARS virus on stock Market performance. Here, in our research External Fluctuating factor taken into account is, COVID 19 effect which is considered to be Crucial factor.

— Model designed is agile, flexible and adaptive in nature to market fluctuations. This model's performance is evaluated on data obtained from yahoo.finanace.com and sentiments of stocks are obtained from Yahoo Finance Message Board (YFMB) is used as external fluctuations sensing parameter.

— Comparative analysis with base paper [21] existing (LSTM model) is done. LSTM model implemented using PYTHON, Jupyter notebook and it's performance compared against LBL-LSTM model and other existing ML models in terms of accuracy score and RMSE and compilation time.

— Results obtained proves, that performance of the proposed LBL-LSTM based stock forecasting model is better than existing ML based stock prediction models evaluated in terms of train and test Root mean square error(RMSE), and accuracy score.

— Meanwhile, in our previous research work [9] RNN-LBL based model without considering external fluctuating factor for stock market predictions gives accuracy rate of 78%.This research work is an extension to that work and crucial factors affecting stock performance are addressed.

*B Design of proposed LBL -LSTM model*

In proposed research work, objective is to forecast stock price of a company, one step ahead, using historical datasets. Mathematical Formulation of the given problem is:

Let, set of basic indicators represented as $\boldsymbol{X_t}$. $Y$ denotes the stock's closing price value for short term period at the given time instance $t$ :

$t = 1, 2, \ldots, T$ (1)

where $T$ is maximum lagging time. Given the dataset parameters , $\boldsymbol{X}$ as described as in the equation

$\boldsymbol{X} = \{\boldsymbol{X_1}, \boldsymbol{X_2}, \ldots, \boldsymbol{X_T}\}$ (2)

previous close price value $\boldsymbol{Y}$ given as :

$\boldsymbol{Y} = \{\boldsymbol{Y_1}, \boldsymbol{Y_2}, \ldots, \boldsymbol{Y_T}\}$ (3)

Main objective is to predict $\boldsymbol{Y_{T+1}}$, the close price . Let us consider stock market as

$$\mathcal{U}\{u_1, u_2, \ldots\}, \quad (4)$$

Set of Stocks within given stock market as follows:

$\mathcal{V} = \{v_1, v_2, \ldots\}$. (5)

Then, output of the LBL-LSTM model is to predict future stock price of a particular company within a stock market.

**The LBL-LSTM model** comprises of multiple input, hidden and output layers, along with inner adjusted weight matrices.

Hidden layer's activation function:

$$i_\ell^v = f\left(\mathcal{X} i_\ell^v + \mathcal{D} s_{w_\ell^v}\right), \quad (6)$$

where, $i_\ell^v \in \mathbb{S}^e$ represents the hidden layer design of stock $v$ at time instance t at position $\ell$ in time series, $s_{w_\ell^v} \in \mathbb{S}^e$ represents the hidden illustration of $\ell^{th}$ input stock of a particular stock market $v$. The activation function (AF) is represented by $f(i)$ and transition matrix (TM) of present stock is given as follows [9]:

$$\mathcal{D} \in \mathbb{S}^e \quad (7)$$

and previous status is :

$\mathcal{W} \in \mathbb{S}^{e.}$ (8)

$\mathcal{D}$ stands for volatile stocks, short term fluctuating pattern of the stocks is fed externally with additional weight as soon as LBL -LSTM model senses steepest gradient and weight adjustments are done accordingly. These weight are having some external weighing factors which are fed as $Ext_{lr}$, for sentiment of stock is obtained from YFMB (Yahoo Finance Message Board)as external fluctuations sensing parameter. As soon as it senses fluctuations in the hidden layer considering non-stationary of short term records gradient becomes steepest, the negative of the gradient descent and this steepest gradient causes to change $Ext_{lr}$ parameter values and $\mathcal{X}$ represents propagation of time series signals. Weights and biases are optimized in the direction of negative gradient of the objective function [13]. The Eqn. (6) is iteratively invoked to calculate the updates in a time series signal sequence of each time instance. Algorithm updates LSTM network weights and biases in the direction in which the objective function decreases most quickly i.e., the negative of the gradient [13]. Usually earlier layers don't learn [20], which leads to short-term memory loss problem Hence, single execution can expressed as follows:

LBL-LSTM model is designed to compute derivative corresponding to weight and bias parameter [13]. External parameter which senses fluctuations $Ext_{lr}$ is optimized according to gradient descent as follows

$$\partial y = \frac{\partial \mathcal{P}}{\partial y} * m_s \quad (9)$$

Where $m_s$ is the learning rate. Hence learning rate considered here is considerably small 0.0001. It works on the formula given as :

**new weight = weight - learning rate*gradient**

So in LSTM layers where it gets a small gradient update, it will stop learning [13, 20]. At the next time instance, a predicted value can be derived using following equations, here j varies from 0 to $\sigma$

$$i_\ell^v = \mathcal{X} i_{\ell-1}^v + \sum_{j=0}^{\sigma-1} \mathcal{D}_j s_{w_{\ell-j}^v}, \quad (10)$$

where $\mathcal{D}_j \in \mathbb{S}^{e*e}$ illustrates the transition matrix for the particular time instance for short time behavior $Ext_{lr}$ and $\sigma$ is the number of elements considered in a time series. Log Bilinear model is shown in Fig. 2.

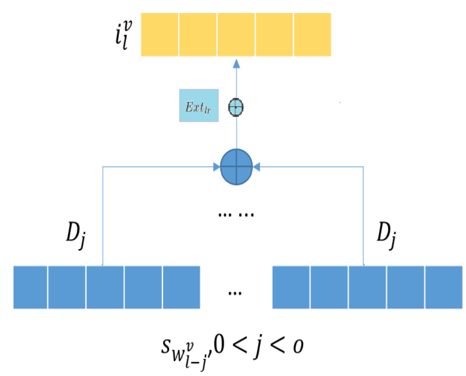


**Fig. 2.** LBL model Architecture .

In LBL, specific transition matrix [TM] is used to model every position in the time sequence. In general, LBL has difficulty in learning the long-term behavior model efficiently [9, 19]. To address previous research issues on value prediction, this research presents a value behavior model that simultaneously captures the long and short term behavior and external parameters in historical data, rather than considering only one component in each hidden level. Unlike RNN. This working model considers multiple components in every hidden layer and adds position centered matrices in LBL-LSTM model, as described in Fig. 3.

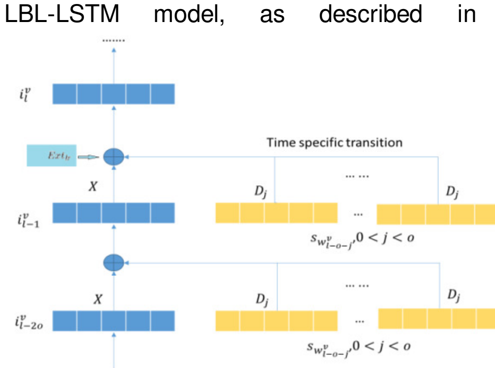


**Fig. 3.** Proposed LBL-LSTM based model architecture considering external factor.

Consider a stock $v$, the hidden layered description of the stock at time $\ell$ in the sequence is defined as:

$$i_\ell^v = \mathcal{X} i_{\ell-1}^v + \sum_{j=0}^{\sigma-1} \mathcal{D}_j s_{w_{\ell-j}^v}, \quad (11)$$

$j$ varies from 0 to $\sigma$, where number of input stock values represented by $\sigma$ in each layer of proposed LBL-LSTM model, is called as adaptive dimension. The TM which is position-centric described as follows:

$$\mathcal{D}_j \in \mathbb{S}^{e*e} \quad (12)$$

which is the factor for short term fluctuations, i.e. the $j^{th}$ score of the shares in each layer of the LBL-LSTM forecast model, the stock market pattern and the characteristics of the long-term records of the stock market. The values are learnt using LSTM. Furthermore, by considering only one input for every layer and set adaptive measurements $\sigma = 1$, result of the LBL-LSTM model will be same like RNN by ignoring nonlinear activations[9]. Important is that, for shorter patterns discoveries of adaptive dimension, the initial segment of a sequence, e.g. $\ell < o$, the Eqn. (12) can be reformulated as follows, j ranges from 0 to $\sigma$.

$$i_\ell^v = \mathcal{X} i_0^v + \sum_{j=0}^{\ell-1} \mathcal{D}_j s_{w_{\ell-j}^v}, \quad (13)$$

where $i_0^v = u_0$, showing the initial status of the stock market which will be same, $v_o$ which addresses cold start problem (i.e., new companies venturing into market) [9]. Experiments carried out to evaluate the performance of LBL-LSTM model shows performance improvement in comparison to existing machine learning algorithms, for which implementation part is explained in coming section Next we will discuss steps for implementation of this LBL-LSTM algorithmic framework.

**Implementation Steps**

**Step 1:** Original unprocessed Stock Market Dataset obtained from yahoo.finance.com. Historical records are obtained of selected companies are collected from the yahoo.finance.com, Bombay Stock Exchange (BSE), National NSE and moneycontrolexchange.com official website.

**Step 2: Pre-processing:** This step incorporates the following:

(a) **Data reduction:** a part of data reduction but with considering only important features, especially for numerical data

(b) **Data transformation- Normalization:** using minmaxscaler normalization technique to bring dataset on common platform. The output layer again consists of a dense layer with a linear activation RELU/SIGMOID activation function used. Weights are adjusted as soon as LBL -LSTM model senses steepest gradient and weights are adjusted accordingly.

(c) **Data Partitioning Train_Test_Split** After the dataset is transformed into a clean dataset, the dataset is partitioned as train, test, dataset using train_test_split function for the evaluation purpose. In this implementation we have used 60 timestamps and 1 output.

**Step 3: Feature Selection:** In this step, data attributes are chosen that are going to be fed to the LBL-LSTM based model. In this study Date & Close Price are chosen as selected features.

**Step 4: Training LBL-LSTM model:** The LBL-LSTM based model is trained by feeding the training dataset. The model is initiated using random weights and biases. Proposed LBL-LSTM model consists of a series of input layer followed by multiple LSTM layers and then a dense layer with activation function Sigmod and Relu.

**Step 5: Output Generation:** The LBL-LSTM generated output is compared with the target values and error difference is calculated. The algorithm calculates gradient steepest descent curve values so as to capture fluctuations in the market and weights and biases are optimized accordingly by minimizing error difference .

**Step 6: Test Dataset:** Step 2 is repeated for the test data set. RMSE values are calculated and the percentage of error of our predictions with respect to actual prices using deviation values is calculated.

**Step 7: Visualization:** Data visualization with respect to comparative analysis of compilation time taken by different algorithms and performance analysis with respect to RMSE is done by implementing various algorithms on the same platform using Keras, MatplotLib and related functionality predictions are visualized.

**Step 8: Investigation of results:** Repeat this process for different time intervals like quarterly , so that short term fluctuations in the market can be sensed

1. Like 4 years of training data then 1 year for predictions of closing prices.
2. 6 months training dataset to predict next 2 months.
3. Calculate percentage error in future prediction values

**Step 9:** The proposed LBL- LSTM based stock forecasting model and existing algorithms are designed using python programming language.

*C. Comparative Analysis using various existing Machine Learning (ML) algorithms and models*

This section presents evaluation of LBL-LSTM based model over existing Machine learning algorithms used for stock market prediction .

**Input Parameters:** This research work designed LBL-LSTM based model which considers stock market basic indicators such as open, volume, low, high, Adj. close parameter with *Ext*$_{lr}$ as Sensing the fluctuations using YFMB (Yahoo Finance Message Board).

**Evaluation of Results:** For performing prediction of stock returns for a particular company, dataset obtained from Yahoo finance [14]. We used similar experiment setup as base paper [21].

Further, for training historical dataset (2012 to 2018) are obtained from Yahoo finance and for sentiment of stock is obtained from YFMB (Yahoo Finance Message Board). For, testing COVID 19 epidemic outbreak related stock market conditions 2019-2020 APPLE company's stock data is considered and forecasting is performed for each month of year 2020.

As shown in Fig. 4, for SARS pandemic outbreak occurred from 2002-2004, dataset collected and observed ,shows that there is a sharp decrease in stock values during SARS pandemic. Training dataset obtained from 16th Nov 2002- 19th May 2005.

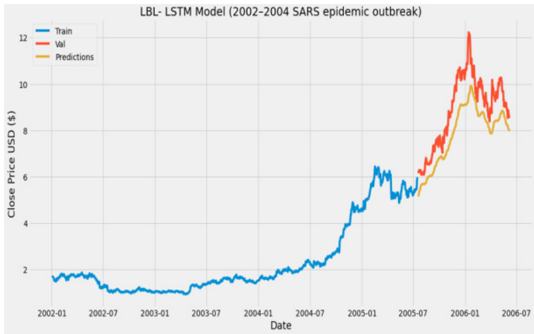


**Fig. 4.** Effect of SARS virus outbreak in stock market performance.

Here, Fig. 4 explains Apple company stock prices during severe acute respiratory syndrome (SARS) outbreak dated from 2002–2004 an epidemic involving using predictive LBL-LSTM model. Although it is observed from the Fig. 4 that stock prices dropping in 2002-2003 and It shows increase in stock prices after pandemic effects, increasing from 2004. Hence predictions are closer to the actual values.

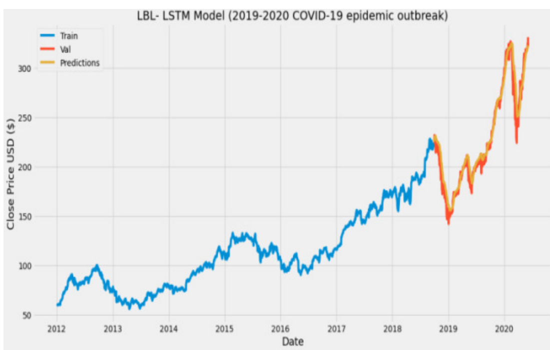


**Fig. 5.** Effect of COVID -19 virus outbreak in stock market performance.

Although it is observed from the Fig. 5 that stock prices dropping in late 2019 amidst Covid Outbreak and 2020 through-out year but again it improves slightly. Here Predictions are closer to the actual values using predictive LBL-LSTM model. It can be concluded from the Fig. 5 that market condition will improve after pandemic.

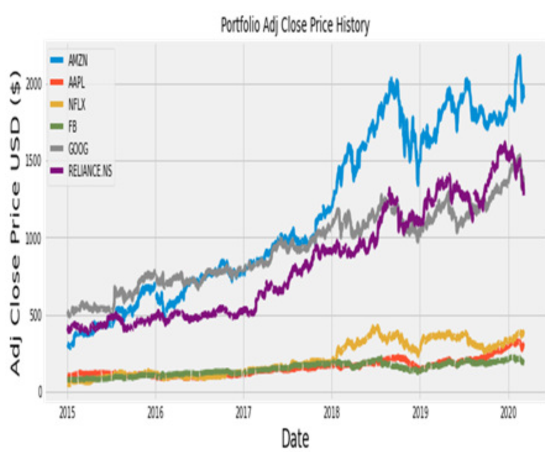


**Fig. 6.** Portfolio optimization.

Fig. 6 Portfolio optimizations for various stocks visualization of Amazon, Apple, Netflix, FB, GOOGLE and Reliance industries using LBL -LSTM model. Here dataset obtained from obtained from Yahoo. finance.com and from YFMB (Yahoo Finance Message Board) for sentiment of stock is obtained as external sensing parameter value. In terms of RMSE, performance of the various models is evaluated given as follows:

**Table 1: Comparative analysis of RMSE performance.**

| Algorithm | Train Score RMSE | Test Score RMSE |
|---|---|---|
| Simple linear Regress or model | 0.4303 | 0.28519784 |
| LSTM model | 0.01893715 | 0.03310835 |
| ANN | 0.0419 | 0.0485 |
| SVM | 0.0512 | 0.0450 |
| LBL-LSTM Model (Proposed) | 0.01706241 | 0.02048098 |

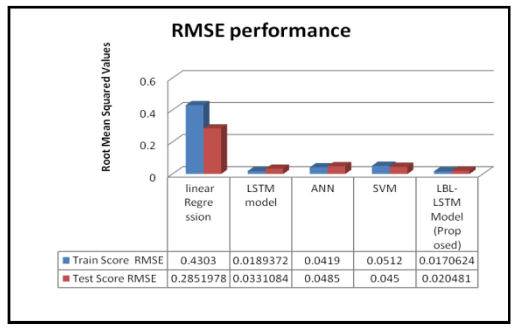


**Fig. 7.** RMSE performance for various algorithmic model.

Prediction outcome performance in terms of Training score and Testing score RMSE, Accuracy Score is shown in Fig. 7 and 8 respectively, Training score and Testing score RMSE 0.01706241 and 0.02048098 are obtained which shows performance improvement and accuracy score of 0.9443 over other existing stock market models. In Fig. 9 Compilation time analysis for various stock predicting models is done. It shows 0.122583628 ms is compilation time taken by LBL-LSTM model which is significantly higher compared to other models, which shows LBL-LSTM model achieves much better performance than existing predictive model.

**Table 2 : Performance analysis using Accuracy Score.**

| Existing Algorithm | Accuracy Score |
|---|---|
| Linear Regression | 0.35 |
| Logistic Regression | 0.518814139 |
| SVM | 0.88 |
| ANN | 0.519841 |
| RNN | 0.751954 |
| LSTM | 0.9017 |
| LBL-LSTM (Proposed) | 0.9443 |

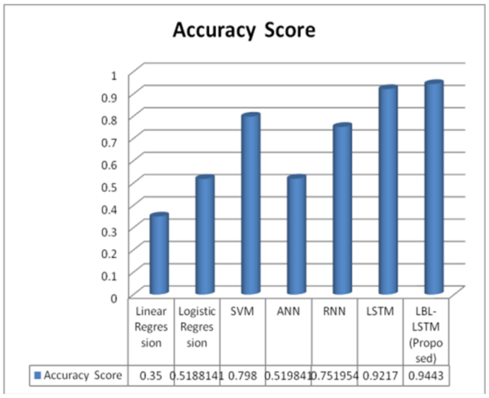


**Fig. 8.** Accuracy score comparison chart.

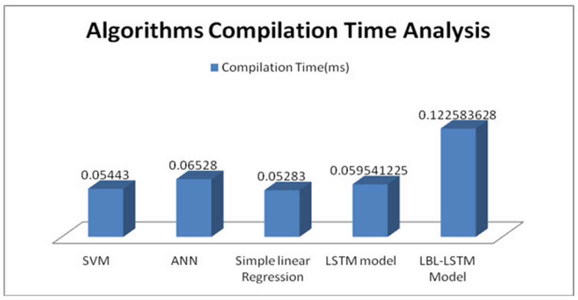


**Fig. 9.** Algorithm Compilation Time performance analysis.

According to statistics, mean absolute error is a measure of difference between two observed values and predicted continuous variables. The smaller the Root Mean Square Error (RMSE) the better the forecast, which gives accurate performance evaluation.

**Table 3: Comparitive analysis of Compilation Time.**

| Algorithm | Compilation Time |
|---|---|
| SVM | 0.05443 |
| ANN | 0.06528 |
| Simple linear Regression model | 0.05283 |
| LSTM model | 0.059541225 |
| LBL-LSTM Model | 0.122583628 |

$$RMS = \sqrt{{}^{1}/_{E} \sum_{v=1}^{E} (a_v - f_v)^2}$$

This method takes squared errors between actual value and predicted value and taking average of it for all predictions. The lower RMSE value, more accurate is the performance.

## III. CONCLUSION

Designing intelligent, adaptive and flexible LBL-LSTM based mathematical model considering external fluctuating factor is challenging. This paper presented intelligent and efficient stock forecasting model by presenting a LBL-LSTM based model. The performance of proposed LBL -LSTM based model and existing machine learning based forecasting models is evaluated in terms of RMSE and training and testing accuracy score. The experiments are conducted using yahoo.finance.com data sets and for sentiment of stock obtained from YFMB (Yahoo Finance Message Board) as external sensing fluctuating factors parameters. Proposed LBL-LSTM based design of an efficient stock forecasting model gives better performance than earlier existing machine learning models. Comparative analysis shows, accuracy of LBL-LSTM model is 94.43% which is highest compared to existing stock forecasting models and price prediction even in case of fluctuating external market conditions such as Covid 19, also reduced RMSE training score is 0.01706241 and testing score is 0.02048098 which is very less although compilation time taken by algorithm is 0.122583628 ms, which is slightly more than existing models. Hence, conclusion can be drawn, there is a strong correlations between Covid 19 infectious disease spread and investors negative sentiments which causes strong impact on their investments decisions and consequently on stock market prices.

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