Application of N-BEATS and BERT models for Stock market prediction

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Abstract

In this paper, an attempt has been made to predict the movement of the Indian Stock Market using a hybrid of deep learning models. A new model has been proposed in this paper called NB-B which stands for N-BEATS - BERT. The model makes use of social media posts, i.e, public sentiment along with historical stock market data and technical indicators to predict the movements of some highly volatile and high-volume stocks from different sectors of the Indian stock market. By generating a sentiment score for different stocks using the BERT model and by using N-BEATS to predict the prices of stocks through historical stock market data, the proposed model is tested on various stocks. Empirical study in this research has shown that the proposed model outperforms existing time series forecasting methods such as 1-D Convolutions, LSTMs and GRUs. The predictions of all the experimented models have been graphically compared. After a detailed discussion of the results, the impact of the work and future improvements in the model have been discussed.

Keywords: N-BEATS, BERT, volatile, volume, Forecasting, 1-D Convolutions, GRUs, LSTMs

1 Introduction

The stock market is a place where financial securities or shares of a company are issued and traded. Millions of investors from around the world invest in the shares of these publicly listed companies. For every country, there are a number of legal stock market exchanges where this trade of shares and securities takes place and is thoroughly monitored. In India, there are two prominent and active stock market exchanges – BSE (Bombay Stock Exchange) and NSE (National Stock Exchange). The BSE, Asia's oldest and world's fastest stock exchange saw 100,1,89,235 active traders in the year 2021-2022. An investor uses different trading strategies, risk managing agents and a lot of technical indicators to invest in this market and ensure a guaranteed return.

Analysis of a share is primarily divided into two parts – Fundamental analysis and Technical analysis. Both have their own upsides and downsides. However, along with the statistical outcomes of both of these analyses, the market also heavily depends on the public sentiment. Time and again it has been evident that a lot of external non-statistical factors such as pandemics, company board changes, war, etc. have influenced the market. The positive and negative impact of these occurrences can be predicted with the help of strong logic and proper knowledge. However, there is always a possibility of the public sentiment expressing the correct impact of these occurrences.

A lot of study has been done before on the– "Effect of public sentiment on the stock market". The authors in [1] showed that stock trend can be predicted using news articles and previous price history. The authors in [2] used the BERT NLP (Natural Language Processing model) to analyze investor sentiment in stock market and concluded that investor sentiment in online reviews had a significant impact on stock yield. The authors in [3] assessed the correlation between Twitter Sentiments Indicators and Stock Market Indicators, with reference to BSE and NSE in India and found from the correlation analysis that there was a relationship between Twitter sentiments indicators and stock market indicators. The authors in [4] analyzed the relationship between Twitter sentiments and stock market during two pandemics of 21st century, Influenza A (H1N1) outbreak and the Covid-19 pandemic. In both cases, they concluded that the markets reacted 0 to 10 days after the information was shared and disseminated on Twitter during the COVID-19 pandemic and 0 to 15 days after the information was shared and disseminated on Twitter during the Influenza A (H1N1) pandemic. Similarly, the authors in [5] concluded that public sentiment from social media holds significant predictive power for subsequent stock market movement.

Along with sentiment analysis and its effect on the stock market, the use of deep learning time series forecasting methods has also been researched widely. The use of prominent time series and sequence processing deep learning algorithms such as 1-D Convolutional Neural networks, LSTM (Long Short-Term Memory) networks, GRU (Gated Recurrent Units) networks, etc. is seen to predict the volume, closing prices, daily highs and lows of different shares in the stock market. The authors in [6] conducted various experiments where they trained four non linear deep learning models - LSTM network, Convolutional network, Recurrent Neral networks and MLPs to predict the movement of stock market using historical stock market data. They concluded that the deep learning models outperformed their linear counterparts such as the ARIMA model. The authors in [7] aimed to predict the movement of stock market using LSTM Netowks and concluded that the LSTM Networks were capable of tracing the evolution of opening prices for the assets that were a part of the research. The authors in [8] conducted several experiments where they aimed to predict the prices of a few companies in the Indian Stock Market using LSTM networks and Convolutional networks. They concluded that Convolutional network performs better than the LSTM network. The authors in [9] trained GRU networks to predict the movements in stock market, and they concluded that on the real-time dataset, their proposed method predicted the future prices successfully with good accuracy.

From the above discussion, it is evident that the stock market has unlimited uncertainties (since it is an open system), but the use of deep learning algorithms for time series forecasting and sentiment analysis can help investors gain some valuable insights about the market. Hybrid models, which make use of both – time series forecasting and sentiment analysis have also been researched widely. The authors in [10] used a hybrid of RNNs and dictionary based approach to predict the stock market movement using historical stock market data as well as public sentiment, and they concluded that the proposed hybrid model outperforms traditional RNN models. The authors in [11] used machine learning and sentiment analysis and found that their proposed model was able to predict the stock market movements. The authors in [12] used a hybrid of BERT NLP model and LSTM network for predictions on the stock market and concluded that their model was better than the traditional LSTM Networks. The authors in [13] used deep attentive learning model along with the USE (Universal Sentence Encoder) and received positve results. The authors in [14] used the BERT NLP model with a General Adversarial network (GAN) to predict the prices of stocks and their proposed model outperformed the traditional time series forecasting models. The authors in [15] used LSTM with Stock Prices and Textual Polarity to predict the stock market and achieved the best results with this model out of all experimented models. The authors in [16] used sentiment analysis through Naïve Bayes and Random Forest algorithms and Linear regression to predict the stock prices and received good results. The authors in [17] used Support Vector Machines and dictionary approach to predict the DIJA and S&P 500 using Twitter sentiment and historical data and received good accuracies. The authors in [18] used LSTM networks with polarity scores of public posts to predict the Indian Stock Market and obtained good scores. The authors in [19] used sentiment analysis with SVMs to predict the stock market with news data and market data and received promising results. The authors in [20] used the BERT NLP with LSTM networks and Fully connected layers along with sentiment and market data and concluded that BERT with Fully connected layers gave the best results. The authors in [21] analyzed news sentiment to get text polarity scores using Naïve Bayes and combined them with KNN algorithm to get good results. The authors in [22] used LSTMs with EMD (Empirical Mode Decomposition) due to its advantages of analyzing relationships among time series data and Convolutional neural networks to analyze sentiments and received good results. The author in [23] used MATLAB's NARX time series prediction toolkit along with NLP parser to predict the stock market movements and concluded that the hybrid model gave the best results.

2 Problem Statement

In this work, the problem that we aim to solve is "Predicting the movement of shares in the Indian Stock Market". As mentioned above, the volume of shares and the number of investors involved in the Indian Stock markets is tremendous. There are a considerable number of investors who face losses and miss out on various investment opportunities due to various incidents happening in the real world. The stock market, being an open system is influenced by countless factors and hence, it is very difficult for an investor to constantly keep a track of these incidents and invest in the market accordingly. The stock market is majorly influenced by two factors - historical data and public sentiment. The solution that we propose in this work extracts information from both - historical data of a stock and the public sentiment about the stock. Although extracting information from historical data of a stock is simplified by the use of various technical indicators, the extraction of information from public sentiment is still a challenge for many investors. The solution that we propose in this work can help investors in making insightful and knowledgeable decisions while investing and ensuring guaranteed returns.

3 Existing models

As discussed above, the field of stock market prediction using deep learning is a widely researched topic. Research and experiments on the use of various deep learning sequence processing models such as 1-D Convolutional Neural networks, GRU networks, Deep attention networks, Dense networks and LSTM networks to predict the movement of stock market are conducted quite frequently. For the comparative study of the performance of the proposed NB-B model, three models have been used in this project:

3.1 1-D Convolutional Layers

A convolution is an integral that expresses the amount of overlap of one function as it is shifted over another function. It therefore "blends" one function with another. 2-D Convolutional networks are widely used for image related tasks. 1-D Convolutional Neural networks are a subclass of 2-D Convolutional Neural networks. They are convolved with the input over a single spatial dimension to produce the output. The input that is given to a 1-D Convolutional layer is of the form [batchshape + (steps, inputdim)]. The architecture of the 1-D Convolutional model used in this research is given in Fig 1.

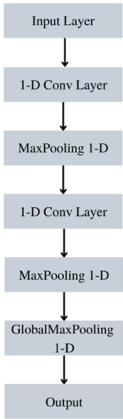

Fig. 1 Architecture of 1-D Convolutional Model

3.2 LSTM network

LSTM, is a variation of a Recurrent Neural Network (RNN) that is quite effective in predicting the long sequences of data such as sentences and stock prices over a period of time. LSTMs have a special unit known as a memory cell to withhold the past information for a longer time for making an effective prediction. In fact, LSTM with its memory cells is an improved version of traditional RNNs which cannot predict using such a long sequence of data and run into the problem of vanishing gradient. The architecture of LSTM network used in this research is given below:

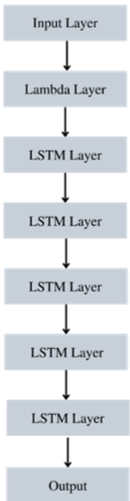

Fig. 2 Architecture of LSTM network Model

3.3 GRU network

A Gated Recurrent Unit is a variant of the RNN design and employs a gated process to control and manage the flow of information between cells in the neural networks. Introduced in 2014 by Cho et al., GRU facilitates capturing dependencies from huge sequential data without excluding information from the prior portion of the series of data. This is performed by its gated units that solve exploding/vanishing gradient problems of traditional RNN's. Such gates control the information that needs to be discarded or maintained on each step. GRU also utilizes gates such as LSTM, but only two. The architecture of GRU network used in this research is given below:

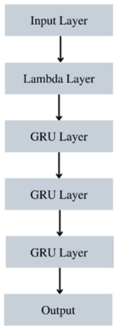

Fig. 3 Architecture of GRU network Model

4 Proposed Methodology

The research is primarily divided into two parts – getting and processing the data for both the models and building and training the proposed model.

The model is an ensemble of the M4 competition winner N-BEATS model and Google's BERT NLP model. The stocks that were selected for training and testing are from different sectors – Tata Steel Ltd. from industrial sector, ICICI Bank from the finance sector, ITC Ltd. from the tourism sector and Maruti Suzuki Ltd. from the automobile sector. The model has two different types of inputs – historical stock market data of the company and public posts from the forums of the company. The historical stock market data of these companies was obtained from Yahoo Finance [24]. The public posts of on these companies were obtained from moneycontrol [25]. The model was designed to take input of stock market data of the companies from the last seven days and moneycontrol posts from the last 1 day. The model predicts the closing price of the share for the next trading day.

Obtaining a clean, formatted public posts dataset from moneycontrol is not easy. Moneycontrol's api has a limit due to which the public posts for a stock from only the past three months can be downloaded and processed.

Also, although the data is cleaner and more relevant than other social media platforms such as Twitter, it still has a lot of spam posts. Hence, this adds a few more tasks to our project: to download public posts of the respective stock from moneycontrol, to check for spam and irrelevant data and filter it and to label posts as bullish or bearish.

The diagram shown in Fig 4 is the paradigm of the proposed methodology.

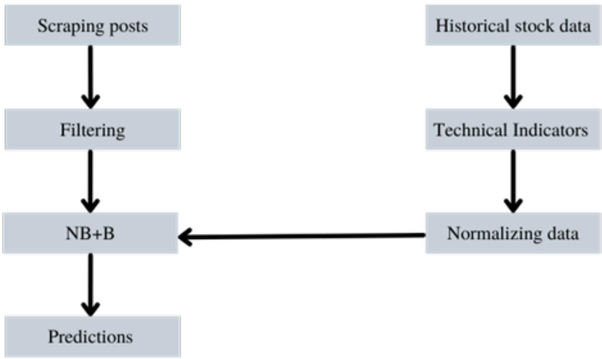

Fig. 4 Proposed model paradigm

4.1 Data collection and preprocessing

4.1.1 Stock market historical data

The stock market data for the four companies – Tata Steel Ltd., ICICI Bank, ITC Ltd., and Maruti Suzuki Ltd. was downloaded from Yahoo Finance. The stock market data was collected from 13 January 2021 to 11 February 2022. This data was then analyzed and four technical indicators were then calculated – Bollinger bands [26], RSI indicator [27], Aroon indicator [28] and MACD indicator [29]. These indicators were then added to the final stock market historical dataset. This data was then normalized. Since the N-BEATS model is built to take an input of seven days, a window of seven periods was slid over the entire dataset. At the end, the stock market dataset had 71 features.

4.1.2 Stock market posts

Training the BERT sentiment classifier requires a substantial amount of data to produce proper, useful results. However, since moneycontrol's api has a limit, i.e., it only allows the scraping of posts from the last three months, enough data was not available to train the BERT sentiment classifier. Hence, the BERT sentiment classifier was first trained on the Twitter stock market dataset [30] which is available on Kaggle. This dataset was selected because it has a good resemblance with the data that was scraped from moneycontrol. The model was then fine-tuned to fit on the data scraped from moneycontrol.

The public posts for the four companies – Tata Steel Ltd., ICICI Bank, ITC Ltd., and Maruti Suzuki Ltd. were scrapped from moneycontrol's forums for these companies. Public posts from 12 November 2021 to 10 February 2022 were scraped in this process for all the companies. The scraping code was developed using the Beautifulsoup4 [31] and requests [32] libraries. The data also had a lot of spam and irrelevant posts such as messages about irrelevant companies, spamming of a word, repeated messages, etc. Hence, the data was cleaned to prepare the dataset of clean and relevant posts. These posts were then labeled as bullish or bearish. The posts were then grouped in a way where all the posts from the previous day were used to make predictions on the next day. All the emojis were also removed from the data. Finally, after all the cleaning and removing of spam, these were the total number of posts collected for all the companies:

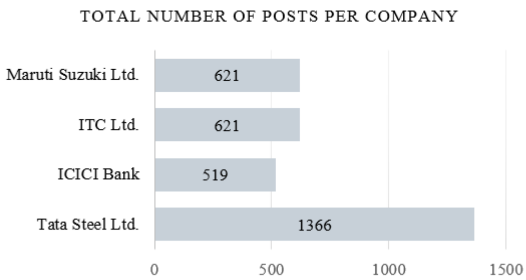

Fig. 5 Total number of posts per company

4.2 Building and training the NB-B (N-BEATS + BERT) model

4.2.1 N-BEATS model

The N-BEATS model was published in the N-BEATS paper [33]. The N-BEATS model given in the N-BEATS research paper was the winner of the M4 time series forecasting competition. N-BEATS uses a simple but powerful architecture of ensembled feed-forward networks with stacked residual blocks of forecasts and 'backcasts'. The N-BEATS model was built based on the architecture and hyperparameters given in the N-BEATS paper. Except for the batch size, no hyperparameter was changed. The batch size given in the N-BEATS paper was 64, but the batch size used during the training of N-BEATS model in this project was 32. The rest of the hyperparameters used are given in Fig 6.

The model was then trained with the Adam optimizer with a learning rate of 0.001. The data prepared was divided into training and testing data where 80% of the data was used for training and 20% of the data was used for testing. The loss function used for training was Mean Absolute Error. The

Neurons in each block	512
Number of layers	4
Epochs	5000
Number of stacks	30
Theta size	72
Input size	71
Output size	1
Output activation	Linear

Fig. 6 Hyperparameters in the N-BEATS Model

functions used to monitor the performance of the model were Mean Squared Error and Mean Absolute Error. The model was trained using two callbacks: EarlyStopping [34] and ReduceLROnPlateau [35].

4.2.2 BERT Sentiment analysis model

Bi-directional Encoder Representations from Transformers is a transformer based deep learning model which was developed by GOOGLE in 2018. It was deployed by GOOGLE in 2019. BERT's ability to process data from left to right as well as right to left, both at the same time is one of the many reasons why it is an effective and reliable Natural Language Processing model.

The BERT sentiment analysis model used for sentiment classification in this project was taken from Tensorflow-Hub[36]. All the hyperparameters remained constant. The hyperparameters used are given below:

Number of Transformer blocks	12
Hidden Size	768
Number of Attention Heads	12
Batch size	16
Epochs	5
Dropout rate	0.1
Output size	1
Output activation	Sigmoid

Fig. 7 Hyperparameters in the BERT Model

The model was trained with the Adam optimizer. The learning rate used was 1e-4. The loss function used was Binary Crossentropy. The metric used to evaluate the performance of the model was accuracy. The model was then fine tuned for another 15 epochs using a lower learning rate and the EarlyStopping callback. The model outputs sentiment score of the post that is given as input. The sentiment score is a float that has a value ranging from 0 (bearish) to 1 (bullish). The architecture of the BERT model used is depicted in Fig 8

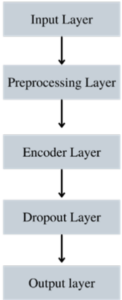

Fig. 8 Architecture of BERT Model used in the proposed work

4.2.3 Building the proposed model

The model takes two types of inputs – public posts on the stock and historical stock market data. These inputs are then processed by the BERT Sentiment analysis classifier and N-BEATS time series forecasting model. Hence, the final component of the model, which is a network of fully connected dense layers, receives two inputs – the final sentiment score of the stock and its predicted closing price for the next day. The final sentiment score of the stock is the mathematical mean of sentiment scores of all posts. Using this information, the final component of the model then predicts the closing price for the next day.

- Architecture of the model

The proposed NB-B model is an ensemble of the N-BEATS and BERT Sentiment classification model. The outputs of both these models are connected to three stacked fully connected layers with eight neurons each. These layers are then connected to the output layer with one neuron having the Linear activation function. The three stacked layers use the Selu activation function. The architecture is diagrammatically shown in Fig 9.

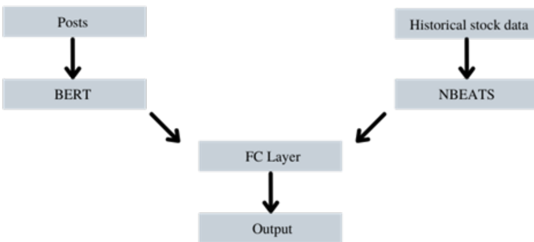

Fig. 9 NB-B Model

- Training phase

The final model was trained for 1000 epochs with the Adam optimizer having the default learning rate. The loss function used to fit the model was Mean Absolute Error and the metrics used were Mean Squared Error and Mean Absolute Error. The model was also trained with two callbacks – EarlyStopping and ReduceLROnPlateau. The hyperparameters used in the work are given in the Fig 10.

Number of Layers	3
Neurons in each Layer	8
Activation in hidden layers	SELU
Epochs	1000
Input size	2
Output size	1
Output activation	Linear

Fig. 10 Hyperparameters in NB-B Model

5 Results

All the experiments conducted in this work were run on a computer with Intel i-7 10875H with 2.3 GHz base frequency, RTX 2070 SUPER-MAXQ GPU and 16GB of RAM. All the experiments were run in the Python programming language using the Tensorflow deep learning library. The experiments were conducted on four models, namely the proposed NB-B Model, 1-D Convolutional model, LSTM Model and GRU Model. All models were evaluated on the same test data for different stocks. The metric used to evaluate the performance of the time series forecasting models is Mean Absolute Error (MAE). The architectures of all models were also kept the same for all stocks. Only a few hyperparameters of these models were changed to fit on different data while training.

5.1 Evaluating the BERT Sentiment Classifier

On the Kaggle's stock market dataset, the BERT Sentiment Classifier obtained an overall test accuracy of 80.17%. When this model was further fine tuned on the public posts' dataset collected from moneycontrol, it achieved an overall accuracy of 81.33%. The Receiver Operator Characteristics Curve for the model is shown in Fig 11.

The confusion matrix for the model before fine tuning it on the moneycontrol dataset is discussed in subsequent paragraph. From the confusion matrix shown in Fig 12, it can be concluded that in some cases, the model fails to identify bearish posts and it labels them as bullish. Overall the model successfully identifies true positives and true negatives in majority of the cases.

5.2 Evaluating the NB-B Model

The NB-B Model was evaluated on the test dataset which was kept the same for all time series forecasting models. The test results for the NB-B model have been given in Fig 13 and Fig 14.

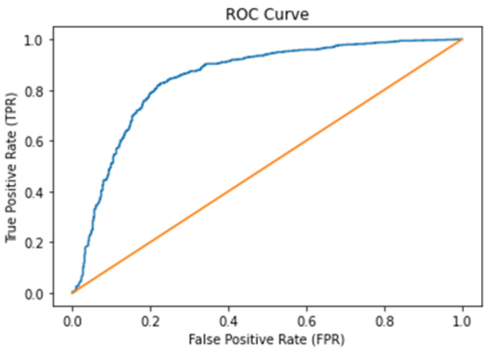

Fig. 11 ROC Curve for BERT Model

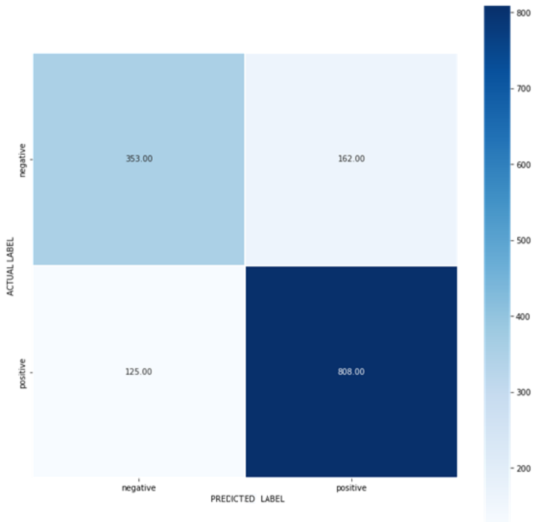

Fig. 12 Confusion matrix for BERT Model

ITC Ltd.	2.9299
ICICI Bank	10.6061
Tata Steel Ltd.	26.9819
Maruti Suzuki Ltd.	96.0099

Fig. 13 MAEs on different shares for the NB-B model

From the graph, it can be concluded that the proposed hybrid model is properly predicting the movement of the stocks with very low MAEs. The model is able to make use of all the technical indicators given as input along with the sentiment scores to identify and forecast volatile movements in these high volume stocks.

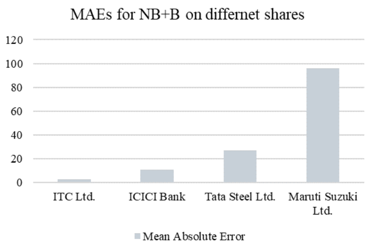

Fig. 14 Visualizing the MAEs on different shares for the NB-B model

5.3 Evaluating the 1-D Convolutional Model

The 1-D Convolutional Model produced the following results shown in Fig 15 and Fig 16 on the same test data for all stocks. The 1-D Convolutional model

ITC Ltd.	4.3033
ICICI Bank	16.6612
Tata Steel Ltd.	48.7429
Maruti Suzuki Ltd.	113.8570

Fig. 15 MAEs on different shares for the 1-D Convolutional network model

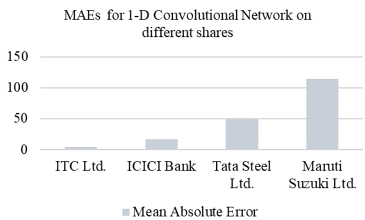

Fig. 16 Visualizing the MAEs on different shares for the 1-D Convolutional network model

used in this work is able to identify the uptrends and downtrends in the stocks properly with the help of historical data and technical indicators. However, the 1-D Convolutional model does not perform as good as the proposed hybrid model.

5.4 Evaluating the LSTM Model

The LSTM Model achieved the following results shown in Fig 17 and Fig 18 on the same test data for all stocks. LSTM network used in this work is predicting the movements in these stocks with a relatively higher MAE. The model's MAE scores are higher than both, 1-D Convolutional model and the proposed hybrid model.

ITC Ltd.	13.9198
ICICI Bank	106.6465
Tata Steel Ltd.	278.8986
Maruti Suzuki Ltd.	1062.3447

Fig. 17 MAEs on different shares for the LSTM network model

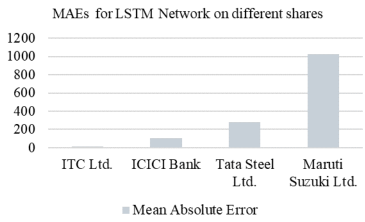

Fig. 18 Visualizing

5.5 Evaluating the GRU Model

The results for the GRU network model are given in the figures below. GRU

ITC Ltd.	11.3150
ICICI Bank	87.6500
Tata Steel Ltd.	229.5817
Maruti Suzuki Ltd.	530.4052

Fig. 19 MAEs on different shares for the GRU network model

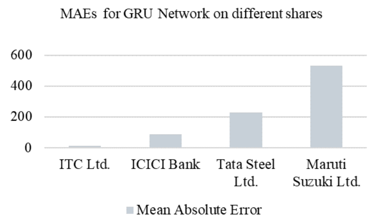

Fig. 20 Visualizing the MAEs on different shares for the GRU network model

model used in this research gave satisfactory MAEs. It performed better than the LSTM model but was not able to perform better than the proposed hybrid model and 1-D Convolutional model. GRU model was able to predict the movement in Maruti SUzuki Ltd. which is a very volatile stock with decent accuracy.

5.6 Final results

The graphs given below in Fig 21, Fig 22, Fig 23 and Fig 24 compare predictions of all the models.

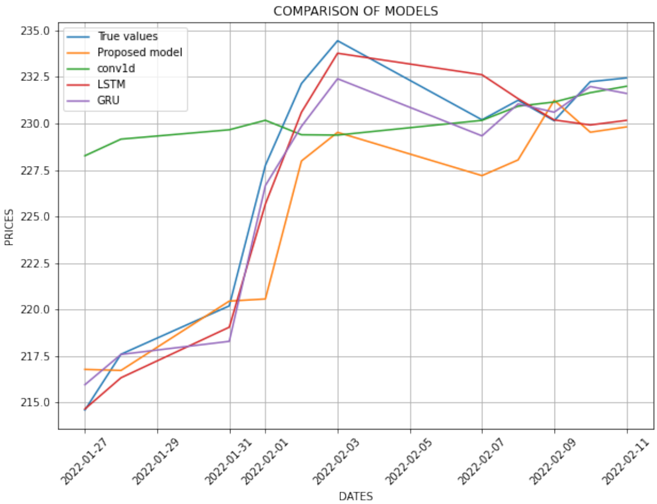

Fig. 21 Predictions of all models on ITC Ltd. share

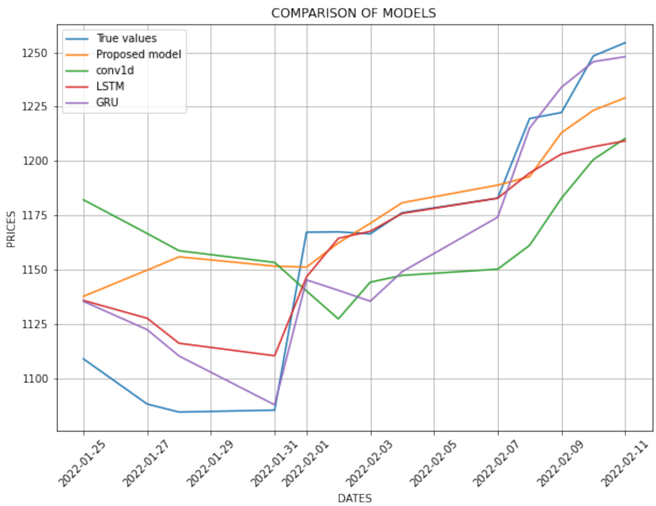

Fig. 22 Predictions of all models on Tata Steel Ltd. share

From these plots, it is evident that no model is perfectly fitting the data, due to the uncertainties involved in the entire stock market system. In all

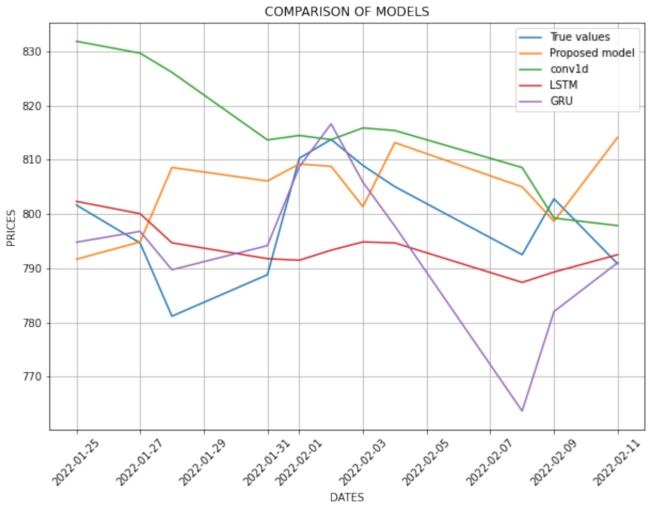

Fig. 23 Predictions of all models on ICICI Bank share

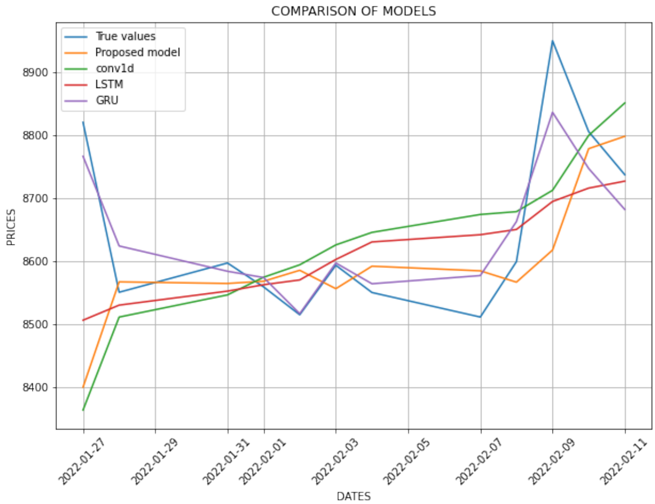

Fig. 24 Predictions of all models on Maruti Suzuki Ltd. share

the plots, it is also evident that the proposed model performs consistently to predict the movements in these highly volatile stocks. All the models were able to predict the movements in small value stocks such as ITC Ltd. and ICICI Bank. However, as the share value and volume in the stocks of Tata Steel Ltd. and Maruti Suzuki Ltd. were very high, the models were not able to predict their movements as well as the other low valued stocks. Here is the final tabular and graphical illustration of the MAEs of the different models:

	ITC Ltd.	ICICI Bank	Tata Steel Ltd.	Maruti Suzuki Ltd.
Proposed Model	2.9299	10.6061	26.9819	96.099
1-D Convolutional Model	4.3033	16.6612	48.7429	113.875
LSTM Network	13.918	106.6465	278.8986	1062.345
GRU Network	11.315	87.65	229.5817	530.4052

Fig. 25 Final MAEs of all models

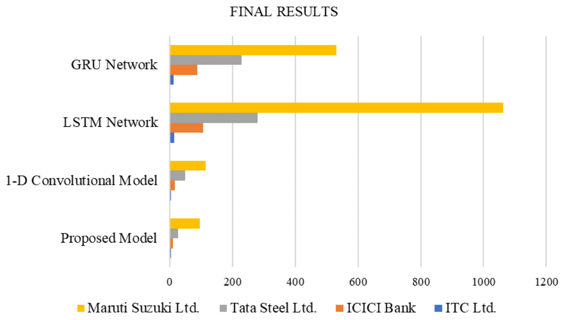

Fig. 26 Graph showing the final MAEs of all models

6 Conclusion

In this paper, a new hybrid model was proposed to predict the movement of stock market. The model was a hybrid of the M4 competition winner N-BEATS model and GOOGLE's BERT Natural Language Processing model. The model made use of public posts on the stock and the historical stock market data for the stock. Public posts from forums of different companies on moneycontrol were downloaded and historical stock market data of the companies was obtained from Yahoo Finance. From the series of experiments conducted, it can be concluded that new proposed hybrid model is able to predict the movement of stocks in the Indian stock market with good accuracy. The model also outperforms other existing deep learning models used for time series forecasting. Although the model achieves good accuracies, it will never be able to predict the prices of the stocks with extremely low error margins as the stock market is an open system. The efficient market hypothesis also states that stock price also depends on new information significantly making it difficult to predict it precisely. The proposed model displayed the dependency of the stock market on public sentiment and historical data. Further improvements can be made in this model to achieve better accuracies. These include better hyperparameter tuning, use of more public posts, experimenting with more technical indicators and replacing the fully connected dense layer in the model with other layers. The size of the public posts dataset can also be increased.

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