Methodology for Developing Deep Learning Models For Different Types of Stocks

Shaurya Gupta[1]
[1]*Bachelor of Technology in IT, VIT Vellore, Vellore*

***Abstract*—Stock market prediction provides an exhaustive domain of problems to be solved. The stock prices are affected by a large set of factors and their complex interrelationships. It becomes a difficult task for com- puters to generalize the trend and predict the market movement with hundred percent accuracy at all times. This project aims to develop an efficient system to predict stock price movement of a given stock. In the initial part of this project we review twenty papers from reputed journals to get the idea about the current advancement in the field of Natural Language Processing, Machine learning and Deep Learning applications in recent times. After the literature survey, we found that some statistical machine learning models are able to predict stock market data with good accuracy, mostly random forest models [12], but also found that deep learning models perform exceptionally well for stock market prediction due to their ability to understand nonlinear relation- ships. The project uses attention based Bi-LSTM with attention model[16] and different variations possible in the system to predict the stock prices for best results. Eleven different variants of LSTM based mod- els were trained and evaluated on their forecasting capabilities using Nasdaq 100 technology sector index data, and the best performing model was selected to forecast stock price for the next day in future.**

***Index Terms:* Stock Price Prediction, Machine Learning, LSTM, NLP**

I. INTRODUCTION

Inspired by the paper Event-Triggered Share Price Prediction [1] and Applying attention-based Bi-LSTM and technical indicators in the design and performance analysis of stock trading strategies [16].The aim of the project is to identify and map the inability of LSTM models to forecast stock prices with approaching zero errors to quantifiable reasoning. The project uses a subset of tickers listed across multiple exchanges.For preparing baseline models the project will be using Nasdaq 100 Technology sector index to train multiple vari- ants of LSTM models and evaluate their performance and find the best model architecture for forecasting stock prices. The reason to choose NASDAQ-100 Technology Sector index is the universal sense of the technology stock sector over a long time with strong investor reach and has shown a stable growth in the past. Also considering the scale of impact of the included companies in the index and the cumulative market cap of the companies in the index makes it an ideal stock with minimum outlier incidents and possibility of fabricated movement of stock prices. In this project, after reading the literature of state of the art systems for sentiment analysis, and certain improvements in the LSTM with introduction of bidirectionality for improved context ,deployment of attention models for solving the problem of previous features vanishing and stacking of LSTM layers to train model on more complex relationships.

II LITERATURE SURVEY

1. Event-Triggered Share Price Prediction:
The paper uses sentiment data as well as technical indicators as features to train the LSTM model, getting a broader and deeper and more granular con- text for prediction The paper demonstrates the use of LSTM, without any bi directionality and attention model, which leads the model to be incapable and not suitable for actual production use cases. The result showed that usage of sentiment data created noise in the short term prediction ie; one day predic- tion, but has a better accuracy when the prediction is for long durations for several months and years. The sentiment scores are pre assigned in the data used which might be too much abstracted and prone to errors which might magnify in the further processing and model training and lead to inconsistent and inaccurate results.
2. Unitary evolution recurrent neural networks: The paper discusses that recurrent neural networks are highly efficient with time series data but face some problems like vanishing gradient and exploding gradient.
3. TI-Capsule: Capsule Network for Stock Exchange Prediction: This paper studies ways to predict EUR/USD closing price behavior which may act as a crucial feature for predicting further behavior of any US listed stock that oper- ates world wide.The

study uses Capsule Network technique on finance texts and candle stick images, the model Text and Image information based capsule neural network is trained on both text and images. The study shows that inte- gration of various types of data including numerical, text and image data can lead to better model accuracy.The study emphasizes that the model accuracy of 91 % is achieved due to training the model on both text as well as image data. Advantages and Limitations: The highlight of the capsule network is the ability to keep the spatial relationships between images and semantic relationships between text data. They compared their model with LSTM, GRU, bi-GRU, in which their model outperformed all the given algorithms. The paper skips the sentiment analysis parts without any reasoning or verification and sometimes may be a driver for the stock, due to the mass reach of social media.

4. Attention Is All You Need: This paper introduces the Transformer model which is based on an attention mechanism,without any recurrent networks or convolutional networks.

5. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding: The paper introduces language representation based on the transformer model.The BERT(Bidirectional Encoder Representations from Transformers) is made to pre-train representations by jointly working on both right context as well as left context.

6. FinBERT: Financial Sentiment Analysis with Pre-trained Language Models: The pre trained BERT model is fine tuned on 3 datasets ,the TRC2- financial dataset subset with 46,143 documents,more than 29M words,and about .5M sentences, the second dataset being Financial Phrase bank data which consists about 4845 labeled sentences and third dataset being FiQA sentiment which include 1,174 financial news headlines and tweets with their corresponding sentiment score Advantages and Limitations: The model has been specifically fine tuned with financial data to process financial Language.

7. Leveraging BERT to Improve the FEARS Index for Stock Forecast- ing: The paper focuses on stock market prediction using BERT.The study uses Financial and Economic Attitudes by Search index semantics and uses BERT and develop self attention model for prediction.The study integrates the semantic information from ‘Financial and Economic Attitudes by Search index to predict the return of SP 500 index. The study method to predict is based on a self attention model which automatically allocates variable weights to different search terms, considering their impact on the target trading day. Advantages and Limitations: The model uses a self attention model, which enables the prediction at low error rates.

8. Time series forecasting using neural networks: The paper focuses on time series analysis methods by comparing the performance of neural network based architectures for prediction of currency exchange rates.The author preprocessed the data for observable and comparable results by removing the correlation between data and normalizing the data series. The study gives an insight into the performance of different neural networks.

9. Review of Data Pre-processing Techniques in Data Mining: The review paper reviews multiple data processing,data cleaning and data transformation techniques for data mining.The paper also defines use cases where different types of methods are suitable. The study gives the reader a broad perspective about data cleaning and normalization in different scenarios. As this is a review paper,limitations do not exist.

10. Application of support vector machines in financial time series forecast- ing: The paper examines the feasibility of SVM by forecasting and comparing it with multi layer back propagation neural network.As the result of the study the SVM out performs the NN architecture on the criteria of normalized mean squared error , mean absolute error,weighted directional similarity and directional similarity. The author also provide valid reasoning on why SVM must have outperformed the NN, which are described as follows, the SVM focuses on minimizing the generalized error rather than minimizing the training error.The SVM hosts fewer free parameters as compared to NN as it is a relatively difficult task to find the combination of most optimal parameters the gives best prediction.Also the gradient vanishing and exploding problems related to NN which leads to inability of the function to converge. The paper compares SVM and BPNN,as off the shelf classifiers like SVM are easy to setup,initialize and use.

11. A local and global event sentiment based efficient stock exchange forecasting using deep learning: The paper discusses stock market exchange prediction in depth, discovering multiple impacting aspect that affects stock market like global and local public sentiment,relationship between currency exchange rates and stock market,along with some of

the other major events like election in a developed nation etc.The author also elaborates on sensitivity and dependency of multiple markets with each other and each one of them tied to their own governing body with presence of political instability in the region which may impact the other markets. Due to this convoluted and non linear relationship these markets bear with them, the deep learning based models usually outperform machine learning based models,due to the ability of deep learning models to identify non linear relationships. The author gives a very real intuition of the markets and why statistical machine learning models generally fail to perform exceptionally well,when compared with deep learning models. The author does not take into account the domain of cryptocurrency and social media influencers which many times may lead to fabricating the state of the sentiment and news.

12. Predicting the direction of stock market prices using random forest: In this paper,the author treats the forecasting problem to be a classification problem as an objective to minimize forecasting error.In the study the accuracy ranged from 85-95The model proposed solves the non-linear nature of the problem with the advantage and ease of using linear discriminant type machine learning algorithm.

13. Time series forecasting using a hybrid ARIMA and neural network model: The paper proposes a novel method to combine Auto regressive moving average and Artificial neural networks in non linear as well as linear model- ing.The author points neither ARIMA nor ANN have the flexibility to be the universal best model in all the forecasting situations. The author combined both the linear and nonlinear model,to get different types of relationship in the data.The experiments conducted imply that the proposed model out performed both the ARIMA and ANN model.This model is useful for data with both linear and non-linear relation- ships.This also overcomes the overfitting problem faced by NN. The data with only a single type of relationship either linear or nonlinear,the hybrid model may be ineffective in that scenario.

14. A New Principal-Component Approach to Measure the Investor Sentiment: The paper introduces a methodology to develop a investor sentiment index using PCA.The components are turn over ratio,money flow,HIBOR,return if US and Japanese markets and short selling volume, and other composite indexes to include the broad influence from external factors combined as one as well.The Principal component obtained has a positive correlation with turnover,RSI and performance of 3 foreign stock markets, and negative association with short selling volume and HIBOR index.Using this investor sentiment index a trading strategy is devised. Advantages and Limitations: Investor sentiment is a good approach to determine abstract movement of the market. The indicator obtained is not reliable and robust towards all the market deflections.

15. BERT-based Financial Sentiment Index and LSTM-based Stock Return Predictability: The paper proposes a framework for financial sentiment analysis and predicting stock price using LSTM using the non linear relationships between multiple indicators. This is executed by combining BERT based sentiment index with other two types of sentiment indices derived from option implied information and PCA on market data to get another sentiment index. Option based index gives institutions attitude, the market index which is an overall index, and BERT gives state of the art sentiment analysis on individual investor level. The predictions are then predicted using LSTM with above 3 indices as input.The approach integrates all the aspects of the market to get meaningful predictions. Using LSTM on long term predictions may lead to inefficiency;to address, attention models can be used along with bi directional encoders.

16. Applying attention-based BiLSTM and technical indicators in the design and performance analysis of stock trading strategies: The paper introduces usage of attention based bidirectional LSTM time series models for prediction of stock prices.The paper also introduces some of the well known and effective technical indicators which have reached an accuracy of 68.83also discusses about exporting the output of given model probabilities to be used as signal for profitable trading of the stocks.The experimentation done using backtrading gave an return of 42.74 percent technical analysis with attention based BiLSTM.

17. Recurrent neural network and a hybrid model for prediction of stock returns: The paper proposes a hybrid model for stock market prediction.The hybrid model has 3 prediction model and a weight generator model.The two out of three models are linear models auto regressive moving average and exponential smoothing model and a non linear model RNN for prediction.The weight generator model works on Genetic Algorithm.The final prediction is calculated by processing the forecasts on weighted function.

18. Enhancement of stock market forecasting using an improved fundamental analysis-based

approach: The paper introduces a fundamental analysis approach by modularizing the system with the following components: Weight calculation of financial indicators, individual stock evaluation and selection, feature selec- tion of financial news, stock trading signal determination based on financial news and stock price trend forecasting component. In the experimentation the forecasting accuracy of adaboost (QGA-SVM) was better than the forecast- ing accuracy of adaboost (GA-SVM) and adaboost (SVM) without financial news. On using the financial news as the feature all the three models had their accuracy increased by 4 percent.

19. The paper introduces an all inclusive approach by studying macroeconomics,financial conditions, financial news of fundamental analysis and its usage to drive forecasting and trading activity. The sentiment analysis did not consider the long and short context of meaning for generating the feature.

20. Stock Price Prediction Using Attention-based Multi-Input LSTM: The author identified a problem while training models which was , during training multiple features/factors are are having negligible correlation with the pre- dicted forecast.To address this issue the author proposes a novel method to discard low correlated factors and their implied noise from the system.This is achieved by employing extra input gates.The author proposed MI-LSTM based on LSTM and attention mechanism which helps achieve extract important information and filter noise.The MI-LSTM units assign weights to different data streams, to keep the most impacting stream at priority while absorbing information from flow controllable input gates,the output further processed using self-attention.This helps model not only focus on current important feature but also adaptively capture important streams of data. Advantages and Limitations: The model is highly dynamic in nature in terms of selection of features. While filtering noise from the input factors, the model may miss cer- tain nonlinear and indirect relationships not recognizable during the data pre processing stage.

III. PROPOSED METHODOLOGY

The project tries to develop an ideal model for forecasting future stock prices and propose a methodology to determine the authenticity of the LSTM model, on the basis of predicting the error the model would have while forecasting the results. The project first focuses on setting a baseline with 11 different variants of LSTM models. Then the best performing model is considered as a baseline model for different stock tickers. Post training the selected model, test data from each of each stock ticker is pushed into the model and forecasted val- ues are plotted along with the error metrics. The errors for each stock ticker are calculated with 3 error metrics Mean Absolute Percentage Error, Mean Absolute Error, Median Absolute Percentage Error.On the basis of these error metrics, the stock tickers form clusters, which have correlation in terms of volatility, market sentiment, related sentiment scores from stock ticker related human synthesized text data from social media output sources including Twit- ter,Reddit,News,Blogs etc. There are multiple possibilities to develop different types of models with varying number of layers and neurons, but the paper Applying attention-based Bi-LSTM and technical indicators in the design and performance analysis of stock trading strategies[16], claims that using Bidirec-tional LSTM and Attention layer results in a better prediction accuracy. As a result of this claim, in this project, we try to develop LSTM models using the methodology proposed in the above given research work[16].

IV. MODEL DEVELOPMENT

All the eleven models are trained on last 21 Years of data of Nasdaq Tech- nology Sector Index (NDXT) with four features Open value, Close Value,High Value Close Value keeping the frequency to be one working day.The three per- formance metrics MAE, MAPE and MDAPE were used to evaluate the most suitable variant to be used to predict all the stocks in study.

The different variants of the LSTM model for stock’s closing price forecast are:

model0 : Stacked LSTM This model contains 2 sequential LSTM layers and 2 dense layers.

model1: Bidirectional LSTM This model contains 1 bidirectional LSTM layer and 2 dense layers.

model2: Bidirectional Stacked LSTM This model contains 1 Bidirectional LSTM layer and 2 LSTM layers stacked and 2 dense layers.

model3:All Bidirectional Stacked LSTM This model contains 3 bidirec- tional layers and 2 dense layers.

model4: Stacked LSTM with 1 attentional layer This model contains 3 LSTM layers stacked and 1 attention layer between 2nd and 3rd LSTM layer and 2 dense layers.

model5: LSTM with 1 attention layer This model contains 1 LSTM layer and 1 attention layer and 2 dense layers.

model6: Bidirectional LSTM with attention layer

This model contains 1 Bidirectional LSTM layer, 1 attention layer and 2 dense layers.

model7: Bidirectional Stacked LSTM with attention layer This model con- tains the 1st layer as Bidirectional LSTM and 1 attentional layer and 2 LSTM layers and 2 dense layers.

model8: Bidirectional stacked LSTM with 2 attention layers : This model contains 1 Bidirectional LSTM and 2 LSTM layers with 2 attention layers interleaved between the above 2 layers and 2 dense layers.

model9: All Bidirectional Stacked LSTM with 1 attention layer : This model contains 3 Bidirectional LSTM and 1 attention layer between first and second BiLSTM layer and 2 dense layers.

model10:All Bidirectional Stacked LSTM with 2 attention layers This model contains 3 Bidirectional LSTM and 2 attention layers interleaved between first and second and second and third BiLSTM layers and 2 dense layers.

The best performing model is selected to perform forecasting for stocks of different companies.

V. FORECAST MECHANISM

The project uses a multivariate LSTM for the prediction of close price of the (NDXT) stock ticker and the other stocks in study as well. For prediction, the model takes last n days data with all the 4 features and the model predicts the (n+1)th day closing price. Using a multivariate LSTM for forecasting closing prices of a technology stock requires all the features for the last n days (manually configured) (n = 50 in this project) , n signifies the last n days for which all the features are taken as input for prediction of stock closing price on (n+1)th day.

VI. RESULTS

The project developed 11 different types of LSTM models with variations, mentioned in section 3.1, and trained the models with the data of stock Open High Low and Close values from DateRange and then tested all the models on the Nasdaq 100 technology sector index data from date range. On evaluation on test data results, 3 models performed the best namely *names* ,out of the 3 models single layer bidirectional LSTM performed the best on all the 3 metrics MAE, MAPE, MDAPE, as a result we used only single layer bidirectional LSTM architecture for forecasting for single day prediction.

VII. OBSERVATION

The above observation from training different multivariate LSTM on NASDAQ-100 technology sector index, the top 3 models which performed the best to forecast the results on test data are Stacked LSTM with MAPE of 2.15 , Bidirectional LSTM with MAPE of 1.67 and All Bidirectional stacked LSTM with 2 attention layers with MAPE of 1.96

S.No	Model Name	Mean Absolute Error	Mean Absolute Error Percentage
1	Stacked LSTM	154.74	2.15%
2	Bidirectional LSTM	117.51	1.67%
3	Bidirectional Stacked LSTM	148.56	2.20%
4	All Bidirectional Stacked LSTM	179.11	2.49%
5	Stacked LSTM with attention layer	427.59	5.39%
6	LSTM with attention layer	347.49	5.46%
7	Bidirectional LSTM with attention layer	235.71	3.20%
8	Bidirectional Stacked LSTM with attention layer	428.98	5.23%
9	Bidirectional Stacked LSTM with 2 attention layers	548.39	6.74%
10	All Bidirectional stacked LSTM with attention layer	653.4	8.21%
11	All Bidirectional stacked LSTM with attention layers	2137.15	`

We can infer that the bidirectional LSTM is the best suited LSTM model to forecast the stocks prices in the sample universe.The model selection for forecasting the future closing prices of stocks is completed and we have selected 'model1', mentioned in the below table at sequence 2 to predict future prices of multiple stocks.

VIII. STOCK PRICE FORECAST WITH BIDIRECTIONAL LSTM

The project forecasts single day predictions on all the stock prices in study, 8 out of 10 stock prices were predicted within 4.26 percent of error and the other 2 were predicted within 9 percent of error. This results directs the project towards the following conclusions, first, almost all of the American technology stocks share some abstract relationships uninterpretable by humans, but can be captured by deep neural networks, second, majority of the information about the stock prices of a stock is contained in their 4 basic indicators Open, Low, High and Close prices, third, the most important part of a model architecture when forecasting stock prices is bidirectionality of the LSTM layer and not the depth, as it is evident a LSTM model with single bidirectional layer outperformed a stacked LSTM with multiple unidirectional LSTM layers on the same data.

IX. INFERENCE

The results show that some stocks formed clusters on the basis of the perfor- mance of the model in forecasting. The worst performing stocks were already having relatively high volatility indexes (assigned by rating agencies and IB firms) and vice versa.

1. Tesla and JP Morgan stock performs the worst on these multivariate Bidirectional Single Layer LSTM models having MAPE of 8.26 percent

and 6.58 percent for 1st April 2022 prediction respectively.

S.No	Stock Name (ticker symbol)	Actual Price as on 01-04-2022	Predicted Price on 01-04-2022	Error Percent-age
1	Apple (AAPL)	174.31	172.44	1.07%
2	Amazon (AMZN)	3271.2	3131.7199	4.26%
3	Tesla (TSLA)	1084.59	994.95	8.26%
4	Microsoft (MSFT)	309.42	322.41	4.19%
5	Adobe (ADBE)	458.19	463.7	1.13%
6	Nvidia (NVDA)	267.12	260.13	2.61%
7	Goldman Sachs (GS)	330.22	336.1499	1.79%
8	Morgan Stanley (MS)	86.99	88.97	2.27%
9	JP morgan (JPM)	135.31	144.2299	6.59%
10	Nasdaq 100 Technology Sector Index (N˜DXT)	8302.16	8229.1796	0.88%

2. The next worst performing stocks are Amazon, Morgan Stanley, Microsoft and Nvidia with MAPE ranging from 4.26 percent to 2.27 percent for 1st April 2022 prediction.
3. The relatively good performing stocks out of our sample universe were Nasdaq 100 Technology Sector Index, Apple, Adobe and Goldman Sachs with MAPE ranging in 0.88 to 1.79 percent for 1st April 2022 prediction.

The LSTM models, when trained on only quantitative data from the last 5 years, gave excellent performance with single digit mean absolute error percentages. This observation suggests that training models with sentiment data is not an optimal approach to consider for every stock, and addition of sentiment data may contribute to noise and might result in degraded performance of LSTM in terms of their forecasting accuracy .In contrast this is not true for each of the stock in the market, some stocks are more influenced by public opinion, sentiments and stock price movement is more sensitive to volatility and granular level busi- ness activities by some famous individuals. It is evident from our study, where 8 major technology stocks gave mean absolute percentage error less than 4.5 percent, there were 2 outliers which were predictable, the tesla stock(“TSLA”) and JP Morgan stock (“JPM”).The reason being tesla being the most famous stock among retail investors and the unpredictable executive board whereas the JP Morgan stock being so much volatile due to firm exponentially invest- ing in uncharted and unregulated markets of cryptocurrency. The above facts and reasoning help us document and design a dynamic framework where we train LSTM models using features that actually keep importance in the prices of the stock.

This project highlights the requirement of adopting a flexible methodology when developing and training deep learning models for different stocks, not every stock can be predicted by training the LSTM model on open, high, low and close values of the stock, although majority information is hidden in these given parameters. From here the future work in this domain can be of classifying stocks of similar nature given abstract relationships. Just like the Tesla and JP Morgan forecast had relatively high mean absolute percentage error rates when compared to other stocks in study. Also there is a possibility that LSTM model architectures can be hyper focused on a single stock, and carefully designed according to nature stock in study. A framework can be developed to identify stocks that strictly require sentiment analysis data to improve accuracy, or identify that the stock has a strong dependency on some other bond market or crypto currency or any kind of external factor that might have to be considered as a feature to develop and train an effective deep learning model.

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