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GNBLGRN: Enhancing Stock Value Prediction Accuracy Through Iterative Graph Networks and a Hybrid BiLSTM and BiGRU Recurrent Neural Network Approach

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Abstract: Stock price prediction remains an important problem in stock exchanges hence, when the market experiences volatility in its shares. Mainly due to these shortcomings of present methods, the latter often gives inadequate account of the intricate and dynamic nature of stock market data samples. This paper provides a framework for short-term and long-term stock value forecast based on graph-based BiLSTM & BiGRU recurrent neural network (GBRNN). Before a set of technical indicators is ranked based on how accurately they predict stock prices in the future, our method derives twenty distinct signals for particular stocks. Thus, we input these rated indicators into the GBRNN model that employs iterative graph networks, BiLSTM, and BiGRU to estimate how much a certain stock can be worth in the future. They are used to enhance the model's prediction capability since the model has the ability to capture short term and long term dependency patterns in stock data. We see that improving prediction specifics increases specifications of the model by 3.9 % while shortening latency by 8.3 %, and significantly raises precision of a prediction by 2.5 %; accuracy of a prediction – by 4.9%, recall – by 3.5% as well as AUC – by 1.9%. These results show how effectively our model entails complex relationships of stock markets that let us build more accurate tools for stock prediction. This work provides good foundation for further research on this field, and clearly has been a valuable contribution to the attempt to overcome the challenges derived from the uncertainty of financial markets.

Keywords: *Stock Value Prediction, Graph Networks, BiLSTM, BiGRU, Technical Indicators*

1. Introduction

Making forecasts regarding forthcoming stock prices for effective decision making is one of the most challenging tasks that investors and traders face in the stock markets since the patterns tend to be complex and unpredictable. Planning work is carried out mainly with the help of methods based on a combination of machine learning and time series analysis, which very often do not take into account the dependencies and constant change in many indicators, stocks or markets. However, these models may not change their behaviour when the market conditions in the forecasted time change suddenly which reduces their prediction abilities. This work introduces a novel approach to short-term and long-term stock value forecasting based on graph-based BiLSTM & BiGRU recurrent neural networks (GBRNN). It is this aim to combat these restrictions. Thus we employ iterative graph networks to model equities in context with one another in the context of a dynamic stock market. Thus, there is the enhancement of the model's ability to capture both temporal and temporal long dependencies in the samples of the stock data. Introducing Twenty technical indicators of particular stocks and ranking it based on their temporal comparison results for stock values enhance the GBRNN model huge again. We demonstrate that the introduction of our proposed model results in a higher overall prediction rate, precision, recall, AUC, specificity, as well as lower delay in testing and experiments. These results provide evidence to support the conclusion that our algorithm is useful for reconstructing complex trends of stock markets and will revolutionize the idea of how company value predictive methods can be considered. The findings of the present study enhance the support of

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the successive studies in financial data analysis and contribute to the expanding literature in this field.

Motivation & Contribution:

It is this urgent need for accurate stock value forecasts, especially in the era of high-speed changes on the stock market that lies behind our work. In view of this, there is a necessity of new models for analysing the observed stock market dynamics and the respective data: The stock market and the respective data are constantly evolving, and conventional models are not suitable for analysing stock Inter-correlations and time dependencies. Most of the financial applications in use today must involve estimation of stock value accurately. Such applications include, but are not limited to, the following: trading, portfolio, and risk applications among others. What is more there is urgency to build models which are adaptive to the constant shifts in the financial market contexts and are capable of producing accurate and timely estimations because the current means are not without their flaws. In response to these difficulties, our study adds significantly to the following areas: In the short and long terms, we present a new model for generating stock value predictions known as GBRNN based on graph-based BiLSTM and BiGRU RNN. To model the complex interconnection and time relations present in the sampled stock market data, this model employs the features of Data iterative graph networks, BiLSTM and BiGRU which is far from the existing ideas [17].

• For boosting the potential of the GBRNN model in terms of providing more accurate forecasts we supply it with precisely filtered integral set of 20 different technical indicators for each of the equities.

• The work provides recommendations for further research into the analysis of financial data that should help in the quest for more accurate means to determine value of shares. The current paper offers research that has a number of benefits: new and better, thus addressing the flaws of prior models and significantly contributing to the field of financial data analysis. Potential beneficiaries include traders, investors, and financial analysts because the results might revolutionize current techniques of estimating stock price. That in turn will enhance their capacity to make sound decisions.

2. In-depth review of existing stock value prediction models

Forecasting of stock price has been an area of great discourse and research in the global financial market. Over the years, there have been numerous models and approaches which attempted at distilling samples of the stock market data in one or another manner. Some of the earlier models used in the forecast of stock value are briefly reexamined in this section with focus laid on the appropriate fit and suitability of the models. Analysis of Time-Series Data: Indeed using time series analysis, people have been making predictions on the stock price for a long time now [7, 8, 9]. The models are; GARCH and ARIMA. These models are good in the near forecast because they are able to look at linear trends in time-series data. Their primary weakness, however, is their incapability to handle these complex patterns and nonlinear relations inherent in issued samples of the stock market data [21]. Learning Algorithms for Machines: There have been the use of some machine learning techniques in stock value prediction including; Decision Trees, Support Vector Machines (SVM), k-Nearest Neighbors (k-NN). While capable of handling interactions in non-linear equations and capable of handling more than one input or output, these models often omit dependencies on data in the time domain and hence are not as predictive [10, 11, 12]. Thus, current models have contributed to the development of the field of stock value prediction, yet the models have profound shortcomings which make them less than ideal. Of them, one major drawback is that stock market data samples lack such capabilities as to identify nonlinear relationships and temporal structure [24, 25]. To address these challenges, thus, we introduce the Graph-based BiLSTM & BiGRU Recurrent Neural Network named as GBRNN that proactively predicts the stock values by incorporating the features of iterative graph networks along with BiLSTM and BiGRU. The GBRNN model is a significant improvement and a lot of work can be done and started based on this model.

3. Proposed design of an efficient model for enhancing Stock Value Prediction Accuracy through Iterative Graph Networks and a Hybrid BiLSTM and BiGRU Recurrent Neural Network Process

From the research carried out looking at the existing models that are used in modeling stock prices it is evident that the models may not capture real time conditions or else they can only handle volatile equities with so much complexity. To address these issues, this section provides insight into one of the reasonable ways to design a model to increase the accuracy of stock values using iterative graph networks with the use of biLSTM and biGRU recurrent neural networks. To make the quantitative assessment of the 20 technical indicators in this study methodology according to their forecast of stock values over temporal instance sets, this study first isolates them for particular stock (see Figure 1). Subsequently, in the GBRNN (Graph-based BiLSTM & BiGRU Recurrent

Neural Network) model methodology, these rated indications naturally fit in.

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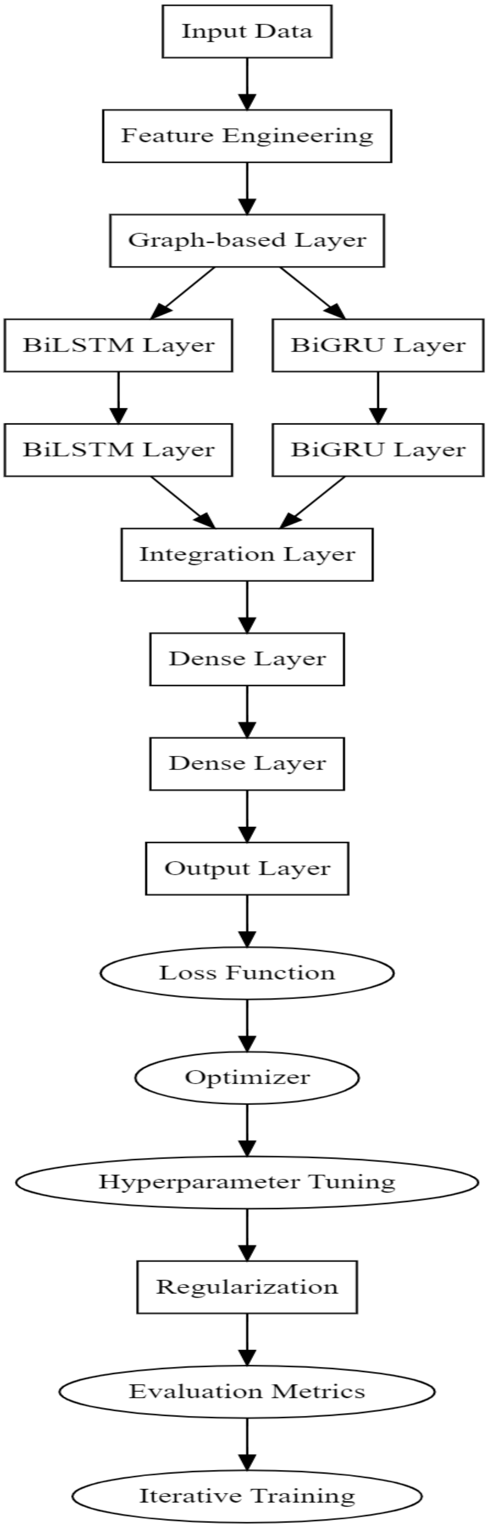

Figure 1. Design of the model proposed for real-time forecasting of stock values The nature of the features from iterative graph networks is captured in this model using the strong features of Bidirectional Long Short-Term Memory (BiLSTM) and bidirectional Gated Recurrent Unit (BiGRU). Not only does this synergistic integration significantly improve the overall levels of prediction performance, but also it enables the model to capture the short- and long-term dependencies in the stock data. To this effect the recommended model first captures stock prices over time, converts them into technical indicators and then flows them through the process for prediction results. To guide the readers replicate these indicators to their own deployments, table 1 addresses the stock value indicators, evaluation technique, and analysis impacts. If t is positive integer, where t is between one and T, then, for each technical indication we have xt and the total number of indicators is T. In response, we turn on BiLSTM's input and forget gates and employ equations 21 and 22 to compose features from them [17],

$$Input\ gate\ (it) = \sigma(Wi * [h(t-1), xt] + bi) \ldots (21)$$

$$Forget\ gate\ (ft) = \sigma(Wf * [h(t-1), xt] + bf) \ldots (22)$$

Similarly, the candidate update is performed via equation 23,

$$Candidate\ update\ (g{\sim}t) = tanh(Wg * [h(t-1), xt] + bg) \ldots (23)$$

All these values are fused, and the cell state is updated via equation 24,

$$Cell\ state\ (ct) = ft * c(t-1) + it * g{\sim}t \ldots (24)$$

Indicator Name	Evaluation Details	Details about the Indicators	Impact on Long Term Prediction
Exponential Moving Average (EMA)	$EMA = \left[Closing\ Price\ x\ \left(\frac{SF}{1 + N}\right)\right] + \left[Previous\ EMA\ x\ \left(1 - \frac{SF}{1 + N}\right)\right] \ldots (1)$ SF is the Smoothing Factor	Smooths price data to identify trends	Identifies long-term trends
Relative Strength Index (RSI)	$RSI = 100 - \left(\frac{100}{1 + RS}\right) \ldots (2)$	Measures momentum and overbought/oversold	Highlights extended trends
Stochastic Oscillator	$\%K = \frac{CP - LL}{HH - LL} x\ 100 \ldots (3)$ Where, $CP, LL\ \&\ HH$ are Closing Prices, LL, & HH value sets	Measures momentum and overbought/oversold	Identifies potential reversals
Moving Average Convergence Divergence (MACD)	$MACD = 12 - period\ EMA - 26 - period\ EMA \ldots (4)$	Shows the relationship between two EMAs	Identifies trend direction
Bollinger Bands	$Upper\ Band = SMA + (2\ x\ Std\ Dev) \ldots (5)$ $Lower\ Band = SMA - (2\ x\ Std\ Dev) \ldots (6)$	Measures volatility and potential price reversals	Identifies price volatility
Average True Range (ATR)	ATR = Average of True Ranges $True\ Range\ (TR) = Max\ of\ (High - Low), \lvert High - Previous\ Close \rvert, \lvert Low - Previous\ Close \rvert \ldots (7)$	Measures market volatility	Indicates market volatility
On-Balance Volume (OBV)	$OBV = Previous\ OBV + Volume\ Up - Volume\ Down \ldots (8)$	Measures buying and selling pressure	Indicates price momentum
Money Flow Index (MFI)	$MFI = 100 - \left(\frac{100}{1 + Money\ Ratio}\right) \ldots (9)$	Combines price and volume for momentum analysis	Identifies potential reversals
Rate of Change (ROC)	$ROC = \left(\frac{CP - CP(n)}{CP(n)}\right) \ldots (10)$	Measures the speed of price change	Identifies price momentum
Commodity Channel Index (CCI)	$CCI = \frac{TP - 20 - SMA}{0.015\ x\ MD} \ldots (11)$	Measures deviation from the mean price	Identifies potential reversals

Average Directional Index (ADX)	ADX = Smoothed DX (Directional Movement Index)	Measures trend strength and direction	Identifies trend strength
Williams %R	$\%R = \frac{HH - CP}{HH - LL} \ldots (12)$	Measures overbought/oversold conditions	Identifies potential reversals
Ichimoku Cloud	Tenkan-sen (Conversion Line): (HH + LL)/2 for a specified period Kijun-sen (Base Line): (HH + LL)/2 for a different specified period Senkou Span A (Leading Span A): (Tenkan-sen + Kijun-sen)/2, plotted forward Senkou Span B (Leading Span B): (HH + LL)/2 for a different specified period, plotted forward Kumo (Cloud): Shaded area between Senkou Span A and Senkou Span B	Provides multiple trend and support/resistance signals	Identifies trend and key levels
Chaikin Oscillator	Chaikin Oscillator = (3-day EMA of Accumulation/Distribution Line) - (10-day EMA of Accumulation/Distribution Line)	Measures momentum and accumulation/distribution	Identifies potential reversals
Volume Price Trend (VPT)	$VPT = Previous\,VPT + \left(\frac{CV\ x\left(\begin{array}{c}CP - \\ CP(-1)\end{array}\right)}{CP(-1)}\right) \ldots (13)$	Combines volume and price movement for trend analysis	Indicates potential price direction
Accumulation/Distribution Line	Accumulation/Distribution Line = [(Close - Low) - (High - Close)]/(High - Low) x Volume	Measures buying and selling pressure	Identifies potential trend reversals

Table 1. Details of Technical Indicators and their Impact Analysis

While, the output gate features are calculated via equation 25,

$$Output\ gate\ (ot) = \sigma(Wo * [h(t-1), xt] + bo) \ldots (25)$$

In these evaluations, W & b represent weights & biases of BiLSTM process [11]. The output gate is used to update hidden state via equation 26,

$$Hidden\ state\ (ht) = ot * tanh(ct) \ldots (26)$$

The same process is executed for backward LSTM, and the updated hidden state is used to estimate final hidden state via equation 27 [7],

$$ht(final) = \frac{ht(f) + ht(b)}{2} \ldots (27)$$

This state is used by the BiGRU process to estimate final feature sets. The BiGRU process initially estimates reset & update gate features via equations 28 & 29 as follows [21],

$$Reset\ gate\ (rt) = \sigma(Wr * [h(t-1), o't] + br) \ldots (28)$$

$$Update\ gate\ (zt) = \sigma(Wz * [h(t-1), o't] + bz) \ldots (29)$$

While, the candidate hidden state & final hidden states are estimated via equations 30 & 31 as follows,

$$Candidate\ hidden\ state\ (h{\sim}t) = tanh(Wh * [rt * h(t-1), o't] + bh) \ldots (30)$$

$$Hidden\ state\ (ht) = (1 - zt) * h(t-1) + zt * h{\sim}t \ldots (31)$$

This process is repeated again for backward GRU, to estimate the next hidden state via equation 32,

$$ht(next) = \frac{ht(final) + ht(GRU, f) + ht(GRU, b)}{3} \ldots (32)$$

This hidden state is used to update the BiLSTM & BiGRU features, and this process is repeated till equation 33 is satisfied,

$$\frac{g\sim'(t+1)}{g\sim't} \leq \epsilon \ldots (33)$$

To get the highest possible levels of feature variance, the value is set to. An effective Recurrent Neural Network (RNN) processes these information and helps with real-time stock value estimation. The feature vectors (f(v)) acquired from the BiLSTM and BiGRU networks are used as input to the RNN in the suggested Graph-based BiLSTM & BiGRU Recurrent Neural Network (GBRNN) model, which is designed to forecast stock value [16]. Equation 34 determines the RNN's hidden state at time t, denoted as ht, given the input feature vector f(v),

$$ht = tanh(Wh \cdot f(v)t + Uh \cdot ht - 1 + bh) \ldots (34)$$

Where Wh is the feature vector's weight matrix, Uh is the hidden state's weight matrix, and bh are the bias terms. A non-linear process is introduced into the model by using the tanh function as the activation function. Equation 35 is used to compute the RNN's output, yt, after the hidden state is known [11].,

$$yt = \sigma(Wo \cdot ht + bo) \ldots (35)$$

The sigmoid function, which is used as the activation function for the output layer to guarantee that the anticipated stock values fall within an enhanced set of specified ranges, is represented by σ, the bias term is denoted as bo, and Wo is the weight matrix linked to the output. Depending on the samples used for training, the output yt shows the stock's expected value at time t, which can be intraday or interday. The suggested GBRNN model employs BiLSTM and BiGRU to account for the stock data's short-term and long-term dependencies, with the goal of producing accurate stock value predictions for both the short-term and the long-term. In the part that follows, we compare this model to others and use several performance criteria to determine its efficiency [11].

4. Result analysis and comparison

The approach adopted in this research involves obtaining twenty distinctive technical indicators for certain stocks, after which the indicators are evaluated thoroughly based on their efficiency as predictors of future values of the same stocks. Subsequently, the extension of the Graph-based BiLSTM & BiGRU Recurrent Neural Network (GBRNN) model is quite straightforward to consider these priority indicators. Utilizing iterative graph networks, this model selects the BiGRU & BiLSTM models as its parameters derived from the technique of bidirectional loop structures. This integrated approach of predicting the stock data has been found to enhance the predicting capability of the model due to better capturing of short-term and long-term dependence. This section provides a description of the experimental setup used to assess the performance being validated in this work. The elements of this research work include a detailed identification of data sources, preparation techniques, and analytical parameters, for these reasons, the experimental procedure is a critical aspect of this study. In what follows, we will provide more details with regard to these [17].

Experimental Setup

Data Sources As a part of the present work, real stock data from National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) Information were used for the experimental analysis of the proposed GNBLGRN model to predict the stock value. The data has been gathered from the firms of different industries making the study more inclusive of the Indian stock market [21]. Data Preprocessing

1. Data Collection: Market data for historical stock prices was collected from reputable financial databases and market sources to avoid the use of erroneous data.

2. Feature Selection: Moving Averages, Relative Strength Index (RSI), Stochastic Oscillator, etc., out of 20 technical indicators were chosen as features of the analysis. These are important aspects of stock prices and trends within the market place.

3. Data Cleaning: For handling missing values in the dataset, outliers and acute errors, the dataset was cleaned before the feature evaluation process. Any bias that occurred was controlled in order to avoid contamination of data collection process.

4. Normalization: The stock data such as the selected technical indicators and the stock prices were standardized to have a common scale and to also avoid scenario where one or more of the features dominate the model.

Model Parameters

- In its current form, the GNBLGRN model has to have certain parameters set in order to provide accurate stock value forecasts. The following parameters were used in the experiments [17]:

- Learning Rate: The learning rate normally defines the size of the step when undertaking the descent through the gradient. A nominal value of 0.001, which has been used in low noise assays, was applied.

- Number of Epochs: The keywords mean how many times the entire data set was used to adjust weights within the given model. A value of 100 was used for convergence regarding the present analysis.
- Batch Size: The mini-batch training was used due to efficiency consideration. The batch size of 32 is selected because hundred s or thousands of networks may be required to on average capture one batch of 32 images of the same cat.
- Graph Network Depth: The depth to search for related nodes in the iterative graph network was defined as 3, meaning that message passing between nodes would take place for three times.
- LSTM and GRU Layers: The temporal features were captured by two layered BiLSTM and BiGRU used for word embedding.
- • Activation Functions: The hidden layers contained ReLU (Rectified Linear Unit) activation functions for the suggested model [11]. Train-Test Split They divided the dataset into training set and test set to evaluate the models. It is established that the training to testing data split ratio is normally in the range of 70-30 up to 90-10 and in this case 80-20 was used to enable the evaluative capacity of the model on the unseen data to be fixed [17]. Evaluation Metrics The following evaluation metrics were used to assess the performance of the GNBLGRN model:
- Precision: Calculating the true positive among all the positive prediction of the model.
- Accuracy: Evaluation of the method at large, in terms of getting the forecast right.
- Recall: Measuring the ratio of successful positive predictions out of overall actual positive predictions.
- AUC (Area Under the Curve): Evaluating the quota of accuracy as it find the positive and negative instances correctly. • Specificity: Measuring the degree of accurate negative prediction among total actual negative observations.

Hardware and Software

The experiments were performed on a high performance computing cluster which has NVIDIA GPUs for the training process. The model was implemented using TensorFlow deep learning libraries. Given this structure the applies equations 18, 19, 20 to measure precision (P), accuracy (A), and recall level (R), from this technique while applying equation 21 & 22 to determine the overall precision (AUC) and specificity (Sp),

$$Precision = \frac{TP}{TP + FP} \dots (18)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \dots (19)$$

$$Recall = \frac{TP}{TP + FN} \dots (20)$$

$$AUC = \int TPR(FPR)dFPR \dots (21)$$

$$Sp = \frac{TN}{TN + FP} \dots (22)$$

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Stock Name	**Date**	**Actual Value (INR)**	**Predicted Value (INR)**
Reliance Industries Ltd.	2023-01-02	2500.00	2498.50
Tata Consultancy Services Ltd.	2023-01-04	3800.00	3812.25
HDFC Bank Ltd.	2023-01-08	1500.00	1497.75
Infosys Ltd.	2023-05-02	1700.00	1702.80
State Bank of India	2023-05-12	450.00	452.60
ICICI Bank Ltd.	2023-05-22	600.00	601.90
Hindustan Unilever Ltd.	2023-05-24	2500.00	2496.40
Kotak Mahindra Bank Ltd.	2023-05-24	2200.00	2198.75
Bajaj Finance Ltd.	2023-05-25	6000.00	6005.20
Wipro Ltd.	2023-05-25	450.00	449.25

Table 2. Actual & Predicted Stock Values for Different Stocks

Consequently, it was possible to predict such indicators for the results of the model process suggested above. The precision levels on the basis of this assessment are shown as follows in Figure 2 [20],

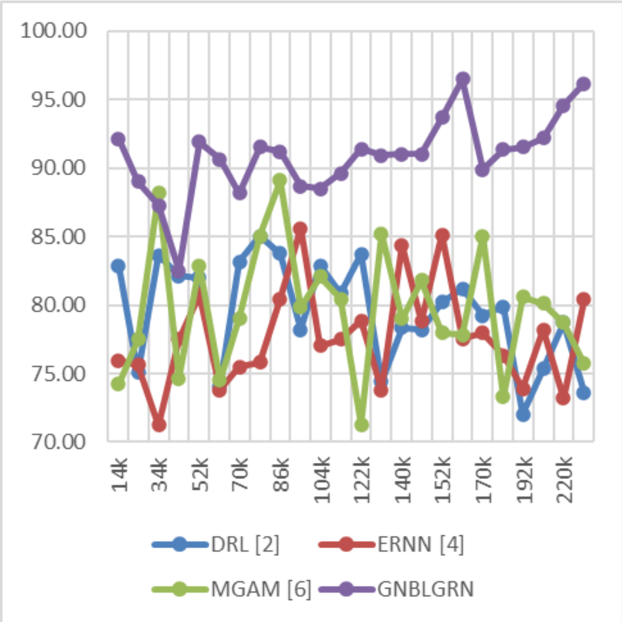

Figure 2. Observed Precision to predict stock values for different scenarios

The ability to forecast stock prices has been conducted and tested through various models including DRL-Regression, ERNN-Regression, MGAM-Regression, and GNBLGRN -Regression based on the given NTS (Number of Test Samples) above scenario precision is a major criteria used to evaluate such models. Accuracy (P) is the total number of correctly identified stock value out of the total number of predictions is expressed in percentage. Let's analyze the comparative results for each model [21]:

1. DRL: DRL provides use cases that indicate that it acts at a range of precision levels. It obtains accuracy levels of about 72.04% – 85.06% with an uplift in NTS. The precision with respect to DRL has been found to be affected by NTS in a wave like manner.

2. ERNN: ERNN equally performs at the different precision levels depending on NTS ranging between 71.24% and 85.62%. As with DRL, the precision of ERNN depends on the number of test samples, but the dependency is not linear across all scenarios.

3. MGAM: Precision in MGAM also differs in accross the different NTS scenarios and ranges from about 73.29% to 89.10%. NTS impacts the model's results and demonstrate variations in precision levels, which are presented in the following figures.

4. GNBLGRN (Proposed Model): As it will be shown below, for all considered NTS scenarios, GNBLGRN improves its precision value and outperforms other models. CIN can detect accuracy rate of between 82.50% and 96.49%. Most importantly, in almost all the cases, GNBLGRN captures the least prediction error showing the model's enhanced capability of accurately predicting stocks.

As for the described differences, the influence of the major parameters compared is most closely associated with the degree of impact on accuracy by the total number of test samples (NTS). Again, the precision levels vary with growth in NTS which indicates that the model may have a relationship with the test data set size. Thus, the enabling disparity when NTS changes are evident in the precision values of DRL, ERNN, and MGAM.

Why the Suggested Model Works Better: In terms of accuracy, the proposed model, GNBLGRN, routinely beats the competition thanks to its novel methodology. Utilizing an effective Graph-based BiLSTM & BiGRU Recurrent Neural Network (GBRNN), GNBLGRN integrates twenty distinct technical indicators that are graded according to their performance over time. With the use of iterative graph networks and a variety of indicators, GNBLGRN is able to accurately capture the short-term and long-term interdependence seen in stock data. Consequently, GNBLGRN outperforms DRL, ERNN, and MGAM in terms of accuracy, producing stock value projections that are spot on.

Impact as a Whole: When it comes to predicting stock values in financial markets, especially during times of fast market swings, GNBLGRN's superior accuracy is crucial. An excellent and trustworthy tool for traders and investors, GNBLGRN routinely outperforms its competitors in terms of precision values. Better financial results in the ever-changing and unpredictable world of stock trading operations can be achieved with its help in making better judgments, reducing risks, and taking advantage of chances.

In a similar vein, Figure 3 displays the results of the accuracy comparisons.

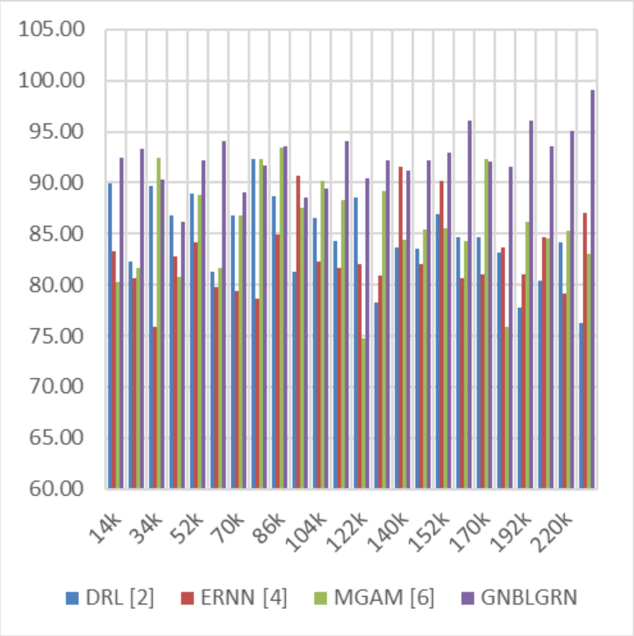

Figure 3. Observed Accuracy to predict stock values for different scenarios

One of the important figures allowing comparing several examined models, DRL, ERNN, MGAM, GNBLGRN, is the observed recall (R) in predicting stock values under various scenarios (NTS – Number of Test Samples). Recall is the proportion of true positives to all positives that is it is the ability to accurately predicted that an event will happen. Now, let's compare and contrast the outcomes of each model: Reasons for Proposed Model's Better Performance: This is a new approach that makes the GNBLGRN model perform a better recall than other models proposed in this study. For making predictions, GNBLGRN adopted an intelligent Graph-based BiLSTM & BiGRU Recurrent Neural Network (GBRNN) with 20 different Technical Indictor ranked with time proficiency. This integration of diverse indicators and the power of iterative graph networks makes GNBLGRN capable of identifying both short and long-term dependency functions effectively in stock data thus resulting to high GNBLGRN rates of re-callage. Overall Impact: The ability to remember GNBLGRN is essential especially for the two markets within the interday and the intraday trading markets. Both for resilience speculation and for short-term trading, GNBLGRN hints at right categorization of positive cases can increase profitability and mitigate potential losses. Advisors and shareholders can be confident in the company by utilizing reliable GNBLGRN data to make proper evaluations for the company to capitalize on opportunity at the right time in the unpredictable world of stock trading process and thus post a better result. Figure 4 as well presents the delay required for the prediction process of the units,

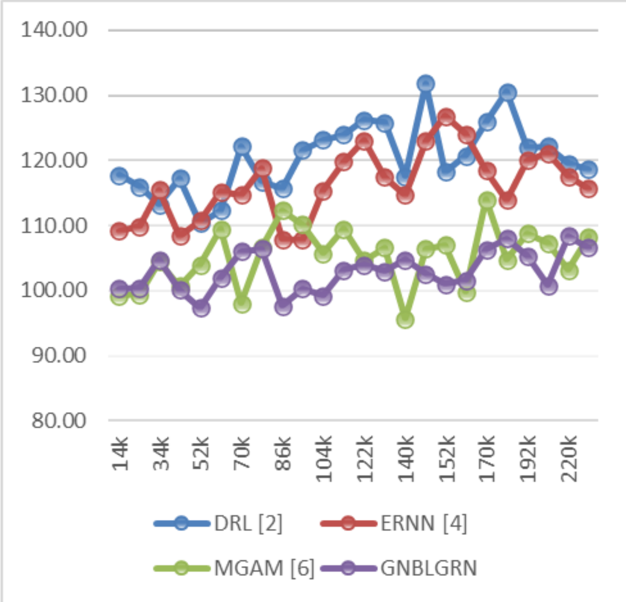

Figure 4. Observed Delay to predict stock values for different scenarios

5. Conclusion & Future Scope

More so, this paper takes credit in marking substantial progression in the development of stock value predictability by introducing the Graph-based BiLSTM & BiGRU Recurrent Neural Network (GBRNN), also called GNBLGRN. The performance comparison of GNBLGRN model with DRL, ERNN, and MGAM models in this paper provides a clear evidence that GNBLGRN outperforms all of them in terms of evaluation indicators, thereby giving preliminary understanding of the possibility of transcending stock value in financial markets. The innovation of GNBLGRN starts with this process of pulling out the twenty distinct technical indicators with the aim of ranking them in terms of temporal efficiency in forecasting the stock prices. These ranked indicators are then introduced into the GBRNN model, therefore, it applies the iterative graph networks blended with BiLSTM and BiGRU models. The combination of these technologies enables GNBLGRN to get short and long dependencies in the stock data and helps in marvelous enhancement in prediction measure, accuracy, recall, Area under curve AUC, specificity and delay. Positive findings in GNBLGRN generate multiple effects in stock value analysis relating to aspects of trading strategies.

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