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Research Article

Enhanced Stock Market Prediction with Bigdata Analytics over the Cloud Data Using LSTM and Gated Recurrent Neural Network (LSTM - GRNN)

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Abstract:

Stock market prediction is an essential field in finance, where proper prediction of stock prices will fetch reasonable amounts of money and improve the performance of various investment strategies. Nevertheless, there will always be weaknesses in using conventional predictors because of the nonlinear patterns of financial data. This study explores a cloud-based framework for stock market prediction using LSTM-GRNN, to capture time-series dependencies and patterns in sequential data. In the first data preprocessing stage, we scaled our data using Min-Max normalization techniques to avoid stability issues and minimize bias. The second stage employs the ALO algorithm to recognize the best features and reduce noise to improve the prediction precision of results derived from high dimensions. Last, the classification is done using the LSTM-GRNN model, which integrates LSTM and GRNN to consider short- and long-term dependencies of stock price movements. Moreover, suppose these models are deployed in a cloud environment. In that case, they can incur quick computations and be relatively integrated into the real-time data feed, making the system implementable for financial analysis and decision-making. This work suggests ways through which complex RNN architecture can be integrated with cloud resources to improve the performance of the stock market prediction models, pointing out the direction for future work in financial prediction.

1. Introduction

The stock market is a crucial element of the financial markets since it allows people to buy and sell stocks of corporations that have gone public. As an open system, the stock market represents a relatively unstable environment and depends on economic processes, political instability, and others [1]. Every investor and analyst have looked for suitable models to forecast stock prices to achieve high returns and little risk. New and more excellent AI and machine learning techniques have been introduced in the model to increase the forecast of stock prices [2]. Statistical and econometric models for forecasting the stock market have proven weak because of the non-linear patterns in financial series data. These models are primarily inadequate because they fail to grasp long-term dependencies and a shift in the market [3-4]. Stock data also has high volatility and many noises; pure historical stock price prediction might not fit well in market fluctuation [5-6]. This paper proposes a cloud-based model that utilizes Long Short-Term Memory and Gated Recurrent Neural Networks (LSTM- GRNN) for stock price prediction to overcome these limitations. This prediction model likewise has the advantage of being developed on a cloud-based platform, which could enhance scalable computation, on-demand resource provision, and capability to treat large sets of data in real-time, which is crucial in financial applications [7]. In their present formulation, LSTM has the memory cell as a means of storing information from previous observations that are likely to be relevant to future outcomes and GRNN gating mechanisms that allow the discarding of information that will be irrelevant [8,9,10]. This was done to enhance the accuracy of prediction as the proposed methods in modeling have differential strengths in capturing intricate and obscure patterns in stock prices. Recent research has revealed that the LSTM-GRNN models are effective in financial prediction. The proposed model advances this research by adding optimality to the structure, improving the predictive performance of stock market data [11,12]. The outcome is a robust cloud environment that can reliably deliver actual stock predictions to investors and financial analysts.

1.1 Contribution of the Research

- The proposed method is easier to compare this or that stock or the same stock at two different points in time.
- It is essential for models that depend on feature scales, such as neural networks, where feature scaling will enhance the model's capability to converge and perform better.
- The ALO method is easy for researchers to search for feature space and arrive at the most appropriate features useful in stock market prediction.
- The proposed method is one of the most effective over predicting and analysis of time-series characteristic issues of stock market prediction.
- Fit the training set using an LSTM-GRNN to achieve a minimum loss (MSE), and it estimates future stock prices.

2. Literature Survey

The author illustrated how decision fusion may be used for stock market prediction by integrating forecasts with different types of data, using new methodologies as base learners, and fusing sentiment analysis with decision fusion techniques. Furthermore, rather than employing a single model, the optimal prediction is sometimes made by combining forecasts from several models [13]. Thus, Deep Learning (DL) models used for technical analysis-based stock market predictions were studied. Four primary perspectives served as the foundation for the discussions: risk management, trading tactics, profitability metrics, and prediction approaches [14]. However, it is essential to validate the model using profitability metrics and model performance because the objective is to generate financial market estimates. To ascertain how social media and financial news information affect the precision of stock market forecasts for the ensuing ten days, the author [15] uses algorithms on these data. Prediction quality and performance are enhanced by examining feature selection and spam tweet reduction in data sets. A new integrated Long-Short-Term Memory (LSTM) method is utilized in the unique article to increase predicting performance in complex stock markets. In a similar vein [16], the suggested approach concurrently improves stock price forecasting's accuracy and relevance. The author [17] provided a detailed survey on the AI approaches to stock market prediction, including recent innovations such as sentiment analysis and reinforcement learning. The review emphasizes deep learning models in the case of market activity forecasting and high accuracy in short-term predictions. However, they point out drawbacks, such as the models depending on the market's noise and requiring large amounts of data, which can slow computationally. Convolutional Neural Networks with LSTM (CNN-LSTM) addressed the problem. The hybrid model was successful in capturing the temporal and spatial characteristics of market data and provided an improved level of predictability. However, the authors also described the challenges of training time and cloud resources that may restrict actual time use [18]. The study suggested a new homogeneous ensemble classifier for stock market prediction dubbed Genetic Algorithm-Support Vector Machine (GASVM), which is based on an enhanced SVM kernel parameter optimization and feature selection mechanism [19]. Making the most money from precise forecasts of market trends is a difficult task. The novel and effective Time Series Recurrent Neural Network (TRNN) algorithm proposed in this study to analyse trade volumes for stock price prediction is a major advancement. Sliding windows are also used to process time series data [20]. Both the Attention Mechanism Variant LSTM (AMV-LSTM) framework and the related backpropagation technique are used. The AMV-LSTM's parameters are updated using the Adam gradient descent technique. However, because stock price fluctuations over time are nonlinear and extremely unpredictable, AVM-LSTM has poor stability and is prone to overfitting, which leads to low prediction accuracy [21]. The effects of integrating LSTM models into conventional trading techniques are investigated by the author [22]. Whether tactics improved with LSTM technology outperform conventional methods alone is the main focus of the inquiry. However, the vanishing gradient issue affects LSTM. Precise stock price forecasting can lower investing risks and boost profits. LSTM hyperparameters are optimized by the Sparrow Search Algorithm (SSA). As a result, applying statistical techniques to characterize nonlinear financial data is difficult [23]. As recommended by the author [24], Padding-based Fourier Transform Denoising (P-FTD) eliminates the noise waveform in the frequency domain of financial time series data and fixes the problem of data divergence at both ends when restoring to the original time series. The anticipated value also lags behind the size and direction of the historical real data values, a phenomenon known as a time lag. When traders and investors are making decisions about their stock market investments, financial news disclosures offer useful information. Stock market fluctuations can be predicted using an ensemble Recurrent Neural Network (RNN) technique that combines LSTM, Gated Recurrent Unit (GRU), and SimpleRNN. Because of the intricacy and ambiguity of the natural language employed in financial news, it is unable to interpret its substance [25]. Different equities are affected by different elements because of their diverse sector types and geographic locations. Subsequently, it is crucial to identify a multi-factor combination that works well for a given company in order to forecast its price. An improved LSTM-NN technique was used to fix the problem. But because market data is time-sensitive, the LSTM-NN is not the best approach for stock prediction [26]. The author [27] has studied an extended reinforcement learning scheme specific to managing stock portfolios. This method performed exceptionally well in optimizing gain since trading scenarios could be adjusted on the fly. Nevertheless, it was mentioned that high computational costs and the problem of setting hyperparameters are the main disadvantages, especially when it comes to applying it to general cloud computing infrastructures. The innovative application of an LSTM with attention techniques for stock market abnormality prediction. The intended attention layers of the model direct attention to relevant data features, resulting in improved prediction accuracy. However, it has been discovered that the training of these models may require tremendous cloud resources, which present profound scale and real-time issues in dynamic market settings [28]. The stock market is too unpredictable because of the stock's volatile character. One of the biggest obstacles to making very accurate predictions about the future stock price is applying all extracted criteria at once. Artificial Neural Network (ANN) is one of the most recent prediction methods used for the stock market. However, because to its poor accuracy, the ANN model proved too challenging to utilize for stock market prediction [29]. Correspondingly, the recommended composition explores the practical application of the soothsaying device and concerns regarding the tact of the fundamental principles provided. Additionally, a system literacy version of the composition is provided for predicting the share lifestyles in an aggressive request. Since it is typically supplied utilising the dataset's everyday economic file, relying solely on one dataset for soothsaying will not be adequate and could produce an inaccurate outcome [30]. Stock prices are difficult to predict because they are erratic and often changing. To measure the variables influencing the stock price and the influence of technology on the dynamic business environment, a sustainable framework for stock price prediction is put forth. Technical analysis is difficult and more complicated since technical analysts heavily rely on statistical data and graphic patterns [31]. The volatility of the stock market makes it very difficult to forecast the direction of asset movements with any degree of accuracy. Offered a fresh approach to enhancing machine learning efficacy by employing an adaptive technique to choose relevant training data. The uneven dataset, however, caused the employed method's prediction time to be excessively slow [32]. Creating accurate models of the equities market enables investors to make better choices. A special two-stage framework was used to achieve the goal; it consists of a mean-variance method and a mix of "perceptron" and "passive-aggressive algorithm." However, because of the strong correlation between stock prices, batch processing approaches make stock market analysis more difficult [33]. Although the stock market's volatility, utilising it is both practical and prudent artificial intelligence to generate well-informed predictions prior to making an investment. One of the shortcomings of the suggested approach to stock market prediction is that it doesn't offer any understanding of the advantages and disadvantages of using cutting-edge technologies for this purpose [34]. The task of stock market prediction is extremely difficult and has drawn significant attention from scholars in a variety of disciplines. A Gaussian Naïve Bayes and Linear Discriminant Analysis (GNB-LDA) approach was used to address the problem. Nevertheless, the stock market was not adequately addressed by the GNB-LDA [35].

3. Proposed Method

In this section we introduced cloud-based framework LSTM-GRNN method to consider short- and long-term dependencies of stock price movements. To predict the stock market movements, we perform three stages: preprocessing, feature selection, and classification. In figure 1 illustrate the various stages of the proposed method For this, we use Min-Max normalization, which, as explained before, is immune to inputs and very sensitive to them but has no fundamental stability problem and does not have a bias. Also, models that use feature scales are like neural networks, where adding feature scales will improve the ability of the model to converge. The ALO algorithm is used in this context to select the best features and eliminate noise. ALO is used similarly to enhance the precision of the outcomes that emerge from various dimensions. Due to removing many features, ALO is a more efficient model for training since training requires a lot of computational resources, which are expensive in a cloud-based model. The LSTM-GRNN adds the ability to the model to handle and remember dependencies, thus giving the model a lucky chance at handling complex temporal relations within stock data. Compared to other models, LSTM-GRNN is more complicated in structure, which will make the model retain information from short-term and long-term periods, so it has higher accuracy in time series forecasting. This is especially helpful in applications running on the cloud because predictive accuracy is critical.

3.1 Stock Market Prediction Dataset

To illustrate the proposed method's work, we use a stock market prediction data set taken from Kaggle to classify in search of an exciting stock. This dataset can be used to build deep learning models to predict a stock price given an index. Also, it can show the list of patients who are potential candidates for developing this disease during treatment planning. Each dataset we used for predicting a stock price (investing) tries to estimate the price for the next day and only for the stock of interest (figure 2). Most attempt to select an appropriate stock out of the index, be it Standard and Poor’s 500, Nasdaq, etc. They need only one company, the best, and don’t want to fail, that is, perform poorly. Companies are presented as rows, and within each company, the columns are divided by age based on the youngest and oldest companies on the date of comparison. The first column denotes the companies. The following includes the age, market, date these shares were entered in the format of year, month, day, hour, and minute, share volume, the traditional prices of the share such as the closing price, opening price, high price, and many more, some prices and volume statistics- the target price. The target is mainly 1 when the rate of close price rises at least 5 percent in five days (open market days). The target is 0 in any other case.

3.2 Min-Max Normalization method

One technique that can be used in data preprocessing, particularly for time series data like stock prices, is min-max normalization. This method standardizes the data range to a smaller scope, often [0,1] in most cases for DL methods to manage input data at different scales easily. The Min-Max normalization technique scales each data point, i, in the data to a new value i’, within a target range of [0, 1] or [−1, 1]. The following equation illustrates the min-max normalization equation that was used:

$$i' = \frac{i - i_{min}}{i_{max} - i_{min}} \tag{1}$$

Assume that i is the initial value, i_{min} is the dataset's minimal value, i_{max} is its highest value, and i' is the transaction-normalized value. The range of the normalised values is 0 to 1. In the dataset, 0 represents the smallest value and 1 represents the greatest value. The presence of outliers that technically pertain to the survey should be considered because they may distort calculations made under the maximization of the mode and minimization of the range. Let us imagine that we have stock prices for a period in which the aim is to standardize them to enhance the chances of identifying relative trends. For example, if the minimum stock price in a dataset is $150 and the maximum stock price is $200, a cost of $300 will be normalized using equation 2 as follows.

$$i' = \frac{200 - 150}{300 - 200} = \frac{50}{100} = 0.5 \tag{2}$$

This normalized value makes it easier to compare this or that stock or the same stock at two different points in time. Min-Max normalization is essential for models that depend on feature scales, such as neural networks, where feature scaling will enhance the model's capability to converge and perform better.

3.3 Antlion Optimization method

In this section, we select the appropriate features from the preprocessed dataset with the help of Antlion Optimization (ALO). The ALO algorithm is an optimization technique driven by nature inspired by the hunting characteristics of antlions. It is widely used in various fields to solve optimization problems, such as choosing features to stock market prediction. Therefore, the feature ranking scheme of the ALO algorithm enables the selection of the most informative attributes/ features from a preprocessed data set, optimizing for higher recognition accuracy and low computational cost. Also, significant to note that in the ALO algorithm, ants move randomly as if searching for optimal solutions through the exploration and exploitation phases. The position of an ant after s steps in one dimension can be represented in equation 1,

$$I_s = [o, c(2 \times (q > 0.5) - 1)] \quad (3)$$

Let assume, I as position of ants, c as cumulative sum of values, and q as random number generated in each s. In equation 4 we normalized the I,

$$I_{norm} = \frac{(I - I_{min}) \times (U_{max} - U_{min})}{I_{max} - I_{min}} + U_{min} \quad (4)$$

Let assume, I_{norm} as normalized position of the ant, U_{max}, U_{min} as the upper and lower bound of search space, and the I_{max} and I_{min} as the maximum and minimum I reached in random walk. Because random walks may go beyond search space, the position of each ant must be constrained to the search space of each dimension. This ensures that all solutions are valid. By following the equations, we perform the antlion's pit trapping in equation 5,

$$U_{min} = U_{min} + D \;\&\; U_{max} = U_{max} - D \quad (5)$$

Let assume, D as contraction constant, it is used to decreases over time, gradually tightening the search space and leading to exploitation. Lacking short-range attraction pheromones, ants are "trapped" by antlions by shifting the boundaries, bringing them nearer to the antlions. This mechanism allows one to understand what parts of the region are promising in order to explore them further. In equation 6 we select and evaluate the fitness of I,

$$F = f(p) + \lambda \times (n) \quad (6)$$

Let assume, p as prediction accuracy, λ as regularization parameter, and n as the number of features. The equation 6 controlling the trade-off between accuracy and feature count. The fitness of each I is evaluated based on a F. In feature selection for stock market prediction, this F often balances prediction accuracy and feature subset size to select the most relevant features. In equation 6 we perform the elitism mechanism to retaining best solution,

$$I_E = b(I_r, I_z) \quad (7)$$

Let assume, b as best, r as current solution, and z as new solution. ALO includes E, which stores the best antlion (solution) identified in the search and compares it to generated solutions. This makes it easy to avoid losing the best solution as the iterations are conducted. The algorithm continues indefinitely, until the termination condition is reached in the future, it can be the number of iterations or the convergence limit. Finally, the features corresponding to the elite solution are chosen for stock market prediction. Equations in this work combine into the ALO algorithm, making it easy for researchers to search for feature space and arrive at the most appropriate features useful in stock market prediction. Decision makers also find that it enhances the capability of crucial predictive models since it eliminates the noise while only concentrating on the most suggestive characteristics in the data set. As shown in Figure 3, the ALO method can generate random numbers using a flowchart based on the ALO method, evaluate the maximum and minimum random walks, and select the optimal features to provide the best solution.

3.4 Long Short-Term Memory with Gated Recurrent Neural Network (LSTM-GRNN) method

LSTM-GRNN is designed to accommodate sequence data that suffer from vanishing gradient problems associated with traditional RNNs. LSTMs are one of the most effective over predicting and analysis of time-series characteristic issues of stock market prediction. In the following section, fundamental equations and definitions, as well as the classification of the used datasets according to LSTM-GRNN, are provided. In LSTM, each cell has a set of customized units and gates that regulate the circulation of information. In equation 8 we perform the forget gate (f),

$$f_p = \sigma\left(U_f \cdot \left[g_{p-1}, a_p\right] + b_f\right) \quad (8)$$

Let assume, p as time, U as weight, g as hidden state, g_{p-1} as hidden state through the previous cell, a_p as current input, b_f as the bias of forget gate, and σ as the activation function. The information from the previous cell state that should be forgotten is determined by the f. We perform the input gate (i) through the equation 9,

$$i_p = \sigma\left(U_i \cdot \left[g_{p-1}, a_p\right] + b_i\right) \quad (9)$$

$$\tilde{C}_p = tanh\left(U_C \cdot \left[g_{p-1}, a_p\right] + b_C\right) \quad (10)$$

Here, $\tilde{C}_p$ is known for the candidate cell state. The i determines what fresh data should be kept in the C. In equation 11 we update the cell state,

$$C_p = f_p * C_{p-1} + i_p * \tilde{C}_p \qquad (11)$$

The C_p is updated by combining the previous cell state and the new candidate information. After update the cell we perform the output layer through equation 12,

$$o_p = \sigma\left(U_o.\left[g_{p-1}, a_p\right] + b_o\right) \qquad (12)$$

$$g_p = o_p * tanh\left(C_p\right) \qquad (13)$$

Equation 12 determines how much of the cell state it needs to output. Equation 13 means that a combination of the output gate and cell state is used to calculate the new hidden state. The GRNN combines the f and i into a single update gate. This makes the usage less complex and the computation much less intense while retaining sequence modelling capability. We update the gate through equation 14,

$$k_p = \sigma\left(U_p.\left[g_{p-1}, a_p\right] + b_k\right) \qquad (14)$$

Here, k_p is known for the vector of the updation gate. This equation controls the extent to which the previous hidden state is carried forward. In the equation 15 we reset the gate,

$$r_p = \sigma\left(U_r.\left[g_{p-1}, a_p\right] + b_r\right) \qquad (15)$$

This equation decides how much past information to forget. Then we perform candidate activation function through equation 16,

$$\tilde{g}_p = tanh\left(U.\left[r_p.g_{p-1}, a_p\right] + b\right) \qquad (16)$$

This equation creates a candidate for the new hidden state. Then we update the hidden state through equation 17,

$$g_p = k_p.g_{p-1} + \left(1 - k_p\right).\tilde{g}_p \qquad (17)$$

This equation 17 integrates the previous hidden state and the candidate hidden state depending on the update gate. In stock market prediction, the type of data needed is a data set such as the Stock market prediction dataset. This dataset comprises time series data of stock prices, which is the most relevant for learning the model based on LSTM-GRNN to train to see temporal dependencies and chronology. In normalizing or scaling the dataset and creating a sequence, the previous ten days' stock price is taken as a feature, and the next day's price is given as output. Use an LSTM-GRNN to fit the training set to achieve a Mean Square Error (MSE), and it estimates the future stock prices. To solve the long-term memory problems related to the vanishing gradient problem in RNNs, a network model known as LSTM was developed. The LSTM-GRNN model efficiently manages the massive amount of input data stored at each time step by using gating methods to control the information flow. The input gate, output gate, and forget gate combine to produce three control gates, which comprise the central component of the LSTM-GRNN model, as shown in Figure 4.

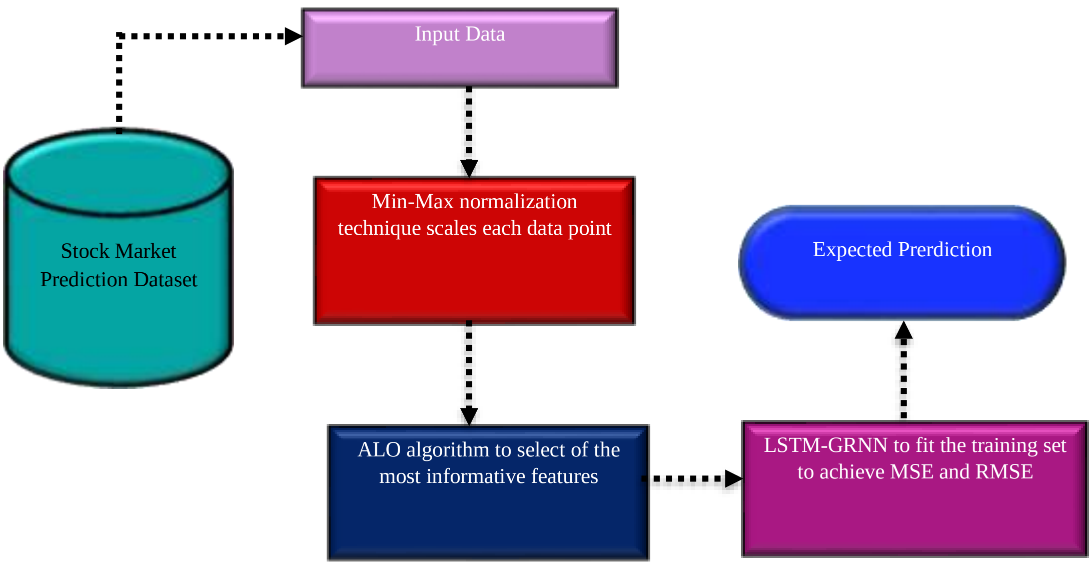

***Figure 1.** Architecture Diagram of the proposed method*

52	16-03-2022	15.55	16.24	15.2	15.55	15.55	250980	ASLE	52.18862	60.9947	50.06465	58.20826	47.37756	56.09584	0.031634	21279.7	0.031634	21279.7	0.031634	21279.7	0.118875	-0.11887	0.042452	0.004787
53	17-03-2022	15.55	16.24	15.55	16.82	16.82	213380	ASLE	56.39374	57.20945	53.06105	55.60154	49.55688	54.17682	0.085337	24668.78	0.085337	24668.78	0.085337	24668.78	0.114566	-0.11457	0.244921	0.397069
54	18-03-2022	16.88	16.91	15.925	16.48	16.48	1108880	ASLE	68.07591	83.43758	55.76783	78.9681	51.56036	74.4283	0.162546	97355.07	0.162546	97355.07	0.162546	97355.07	0.120789	-0.12071	0.378699	0.724041
55	21-03-2022	16.64	16.84	16.16	16.39	16.39	204580	ASLE	59.83099	50.36758	55.31942	56.82883	51.15474	51.18331	0.214092	82089.88	0.214092	82089.88	0.214092	82089.88	0.13263	-0.13263	0.208389	0.657926
56	22-03-2022	16.43	16.749	15.84	16.03	16.03	208780	ASLE	54.93591	50.28626	52.5755	56.91346	49.56324	51.25546	0.223693	69525.44	0.223693	69525.44	0.223693	69525.44	0.144224	-0.14422	-0.08454	0.268051
57	23-03-2022	15.95	15.95	15.57	15.61	15.61	150880	ASLE	50.7451	48.83777	49.90944	49.88555	47.87451	50.21154	0.197149	54328.29	0.197149	54328.29	0.197149	54328.29	0.150947	-0.15095	-0.30155	-0.23258
58	24-03-2022	15.63	16.37	15.63	16.37	16.37	89080	ASLE	57.21462	48.82356	54.36858	47.98257	51.0246	48.77931	0.232453	35353.51	0.232453	35353.51	0.232453	35353.51	0.161279	-0.16128	0.06716	-0.08276
59	25-03-2022	16.21	16.39	16.06	16.29	16.29	54400	ASLE	56.3572	48.45715	53.82895	47.67888	50.68689	48.52722	0.251143	18933.78	0.251143	18933.78	0.251143	18933.78	0.172651	-0.17265	-0.04506	0.18598
60	28-03-2022	16.25	16.569	15.525	15.86	15.86	93680	ASLE	51.87979	47.63592	50.99584	48.58918	48.91018	49.24585	0.228954	8951.128	0.228954	8951.128	0.228954	8951.128	0.179785	-0.17976	-0.30785	-0.17083
61	29-03-2022	15.92	16.17	15.75	15.92	15.92	46980	ASLE	52.44463	46.13189	51.36719	47.56206	49.16387	48.424	0.213782	-2662.33	0.213782	-2662.33	0.213782	-2662.33	0.184047	-0.18405	-0.26784	-0.39296
62	30-03-2022	15.95	16.07	15.61	15.64	15.64	61080	ASLE	49.53728	46.80425	49.53846	47.90838	48.02821	48.68783	0.177169	-10634.5	0.177169	-10634.5	0.177169	-10634.5	0.18318	-0.18318	-0.4012	-0.48164
63	31-03-2022	15.39	15.745	15.39	15.72	15.72	70180	ASLE	50.37936	47.12471	50.06753	48.13865	48.37588	48.88001	0.152859	-16082.8	0.152859	-16082.8	0.152859	-16082.8	0.179362	-0.17936	-0.31882	-0.53394
64	01-04-2022	15.74	16.29	15.74	16.25	16.25	125780	ASLE	55.63442	49.13076	51.43655	49.55776	50.60942	49.90864	0.174042	-15638.4	0.174042	-15638.4	0.174042	-15638.4	0.178693	-0.17869	-0.03716	-0.17565
65	04-04-2022	16.31	16.5	16.12	16.3	16.3	68600	ASLE	56.10431	47.16194	51.74325	48.14833	50.81428	48.85885	0.192612	-19698.7	0.192612	-19698.7	0.192612	-19698.7	0.180445	-0.18044	-0.05439	0.087244
66	05-04-2022	16.26	16.49	15.57	15.62	15.62	65380	ASLE	48.80334	47.0452	49.15633	48.09683	48.04862	48.79832	0.151058	-22916.5	0.151058	-22916.5	0.151058	-22916.5	0.176752	-0.17675	-0.43351	-0.30598
67	06-04-2022	15.5	15.78	15.319	15.55	15.55	64190	ASLE	47.89786	48.99988	48.71053	48.03483	47.77548	48.7759	0.111228	-25271.2	0.111228	-25271.2	0.111228	-25271.2	0.168527	-0.16853	-0.41282	-0.66981
68	07-04-2022	15.53	16	15.53	15.95	15.95	57380	ASLE	52.1589	48.72655	51.33744	47.85218	49.451	48.64685	0.110494	-27367.1	0.110494	-27367.1	0.110494	-27367.1	0.161246	-0.16125	-0.15839	-0.40152
69	08-04-2022	15.87	15.89	15.48	15.58	15.58	44580	ASLE	47.78377	48.18480	48.61413	47.49784	47.80788	48.4003	0.075321	-29713.1	0.075321	-29713.1	0.075321	-29713.1	0.150471	-0.15047	-0.3678	-0.35854
70	11-04-2022	15.46	15.78	15.405	15.52	15.52	72180	ASLE	47.66144	47.58856	48.35026	48.35677	47.78986	48.9689	0.046112	-29020.5	0.046112	-29020.5	0.046112	-29020.5	0.137789	-0.13779	-0.31482	-0.52715
71	12-04-2022	15.7	15.97	15.33	15.72	15.72	52380	ASLE	49.95912	46.65322	49.92189	47.77275	48.61507	48.57785	0.03859	-29729.7	0.03859	-29729.7	0.03859	-29729.7	0.125089	-0.12501	-0.16318	-0.13681
72	13-04-2022	15.495	15.945	15.495	15.77	15.77	52280	ASLE	50.54072	48.64826	50.28617	47.78989	48.82652	48.57504	0.03621	-29936.6	0.03621	-29936.6	0.03621	-29936.6	0.113888	-0.11389	-0.11839	-0.15395
73	14-04-2022	15.9	15.91	15.57	15.75	15.75	57180	ASLE	50.29021	46.94448	50.12226	47.93853	48.74464	48.68086	0.032378	-29375.6	0.032378	-29375.6	0.032378	-29375.6	0.10368	-0.10368	-0.11704	-0.11993
74	18-04-2022	15.6	16.13	15.6	16.88	16.88	70380	ASLE	53.73015	47.78129	52.12126	48.40652	49.94389	48.96949	0.051252	-27551.8	0.051252	-27551.8	0.051252	-27551.8	0.097116	-0.09712	0.031657	0.019932
75	19-04-2022	16	16.76	16	16.73	16.73	55280	ASLE	60.96549	46.87512	56.64687	47.8935	52.76268	48.6581	0.12112	-27009.6	0.12112	-27009.6	0.12112	-27009.6	0.10012	-0.10012	0.312318	0.456359
76	20-04-2022	16.71	16.94	16.35	16.43	16.43	142280	ASLE	56.88121	52.44277	54.35292	51.0096	51.49447	58.54644	0.150615	-29356.7	0.150615	-29356.7	0.150615	-29356.7	0.10644	-0.10644	0.081039	0.515819
77	21-04-2022	16.65	16.787	15.95	16.03	16.03	52580	ASLE	51.91289	47.00126	51.4596	47.9311	49.86381	48.65681	0.140182	-20276.8	0.140182	-20276.8	0.140182	-20276.8	0.110963	-0.11066	-0.17048	0.015173
78	22-04-2022	15.99	16.093	15.11	15.15	15.15	85980	ASLE	43.04957	49.10795	45.89455	49.12287	48.55431	49.37539	0.080385	-18188.7	0.080385	-18188.7	0.080385	-18188.7	0.104372	-0.10437	-0.62085	-0.69358
79	25-04-2022	15.04	15.34	14.5	15.12	15.12	68280	ASLE	42.78277	48.02486	45.88815	48.59957	48.44708	49.00411	-0.00521	-17612.4	-0.00521	-17612.4	-0.00521	-17612.4	0.090663	-0.09066	-0.51259	-1.04001

Figure 2. *Sample Image of Stock Market Prediction Dataset*

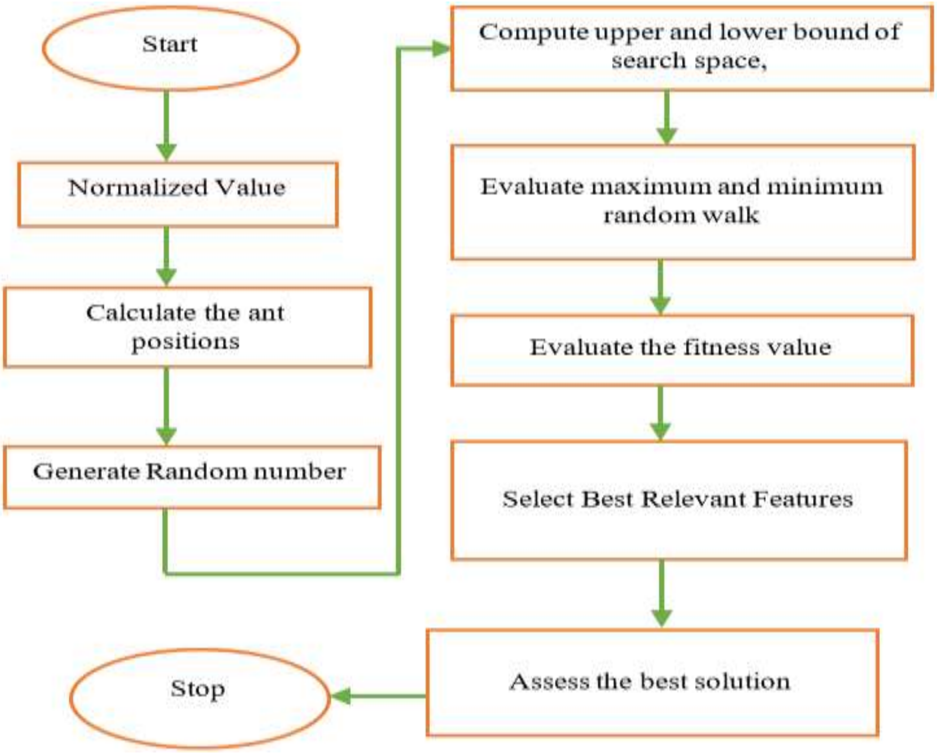

Figure 3. *The ALO Method Based Flowchart Diagram*

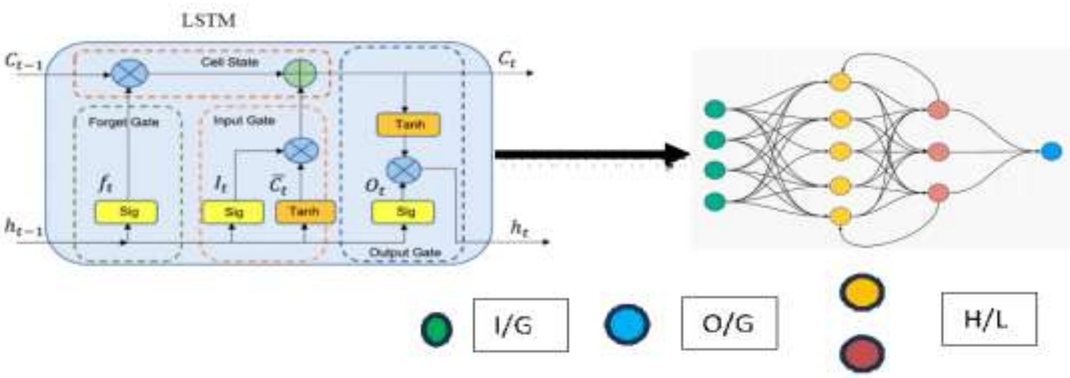

Figure 4. *The Proposed LSTM-GRNN Technique based Architecture Diagram*

3. Result and Discussion

The evaluation metrics in this section can assess the value of the stock data classification method in the business context. The suggested LSTM-GRNN approach can be used to examine the statistical evaluation of stock market data prediction. Additionally, the suggested approach can be contrasted with alternative approaches to assess the properties of the stock market prediction dataset. Furthermore, stock market prediction data can be enhanced through analysis using various evaluation criteria, including, accuracy, F1-score, precision, Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Recall, F-Measure and False Rate.

Table 1. *Simulation Parameter*

Parameter	Value
Dataset Name	Stock market prediction
Number of Dataset	7,782
Used Tool	Jupyter
Used Language	Python
No. of Training	6,478
No. of Testing	1,304

Table 1 shows that stock prediction can be evaluated using Python programming to generate and analyze Jupyter notebooks, utilizing simulation parameters for comparative analysis.

$$\text{Precision}=\frac{\mathrm{P^T}}{\mathrm{P^T+P^F}}\times 100$$

$$\text{Recall}=\frac{P^T}{P^T+N^F}$$

$$\text{False Score}=2\times\frac{\text{Pre}*\text{Rec}}{\text{Pre+Rec}}$$

$$\text{Accuracy}=100\mathrm{N^F}\,\frac{\mathrm{P^T+N^T}}{\mathrm{P^T+N^T+P^F+N^F}}\times 100$$

$\text{MSE}=\frac{1}{n}\sum_{x=1}^{n}(j_x-\hat{j}_x)^2$ Let assume, n as the number of observations, j_x is the actual value, and $\hat{j}_x$ as the predicted value.

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{x=1}^{n}(j_x-\hat{j}_x)^2}$$

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{N}|j_x-\hat{j}_x|$$

Both MSE and RMSE measure the model's prediction error, with RMSE making it easier to interpret errors in the original scale.

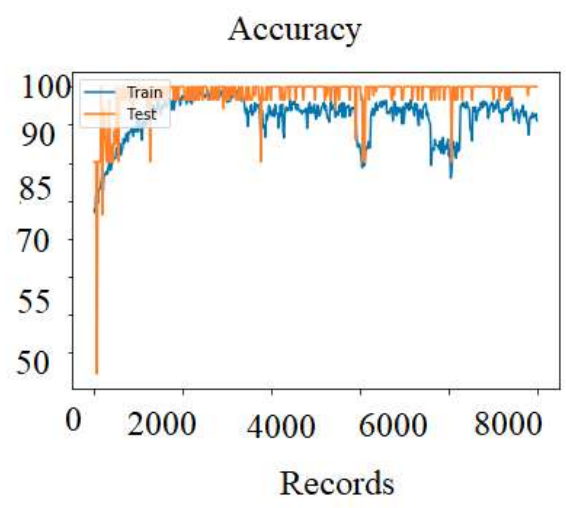

Figure 5. *Stock Market Prediction Based on Training and Testing Accuracy*

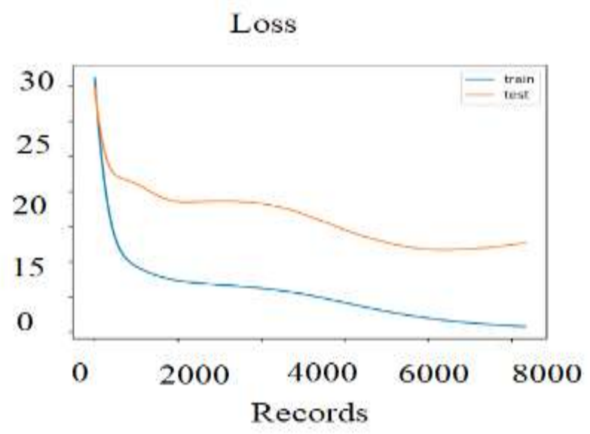

Figure 6. *Stock Market Prediction Based on Training and Testing Loss*

The proposed LSTM-GRNN framework's performance using the stock market predicting dataset is evaluated and discussed. The accuracy and loss of the proposed model and training method are also analysed to determine the stock market's performance rating. Figures 5 and 6 show that the training and testing accuracy and loss in stock market prediction are 96.7% and 11.8%, respectively.

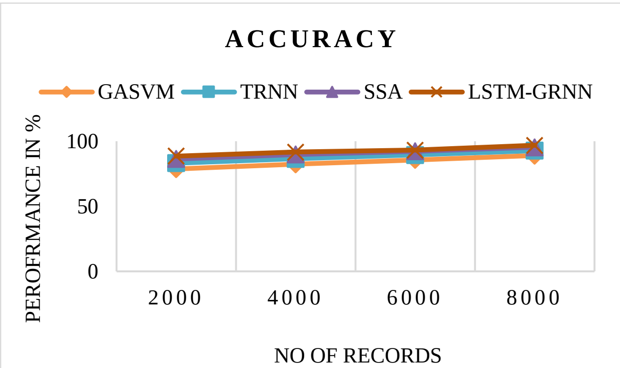

Figure 7. *Analysis of Accuracy*

Figure 7 shows that using features extracted from a stock market prediction dataset, accurate analyses can be given to investors after the extraction of appropriate time series by using selected feature subsets. The proposed LSTM-GRNN model can select stock market data features and enhance accuracy up to 96.7%. Compared to previous methods, the accuracy shows significant improvements: By applying the newly proposed GASVM, which yields 89%, TRNN is improved to 92.8%, and, more significantly, the SSA reaches 95.4%. High accuracy indicates that a model can predict many outcomes, therefore being a reliable forecaster. Accurate predictions of stock price trends have the following benefits: increased chances of traders making the right decisions to reduce losses because they can differentiate between up and down trends.

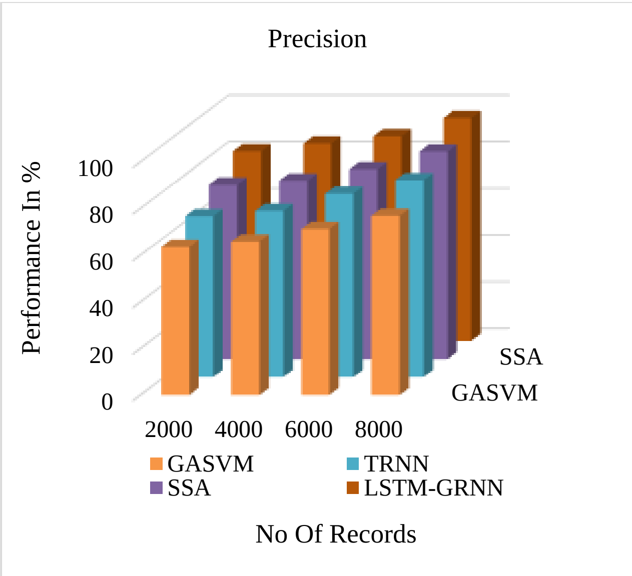

Figure 8. *Analysis of Precision*

Figure 8 shows that when performing precision analysis on the subsets of features selected from stock market prediction datasets to classify the stock prediction. It shows that when utilizing the proposed LSTM-GRNN method, the precision rate of analysis prediction improved to 95.63%. Further, if this method is compared and contrasted with the previous methods, including the existing process, the observation was that the precision rates enhanced to 76.94%, 84.361%, and 88.93%, respectively. High precision implies that if the model gives a signal that there is a change in price in either direction, the prediction is most likely accurate. Less false alarms also imply less wrong buy/sell signals, this is very crucial in stock market since constant false signals would only increase unnecessary transaction costs.

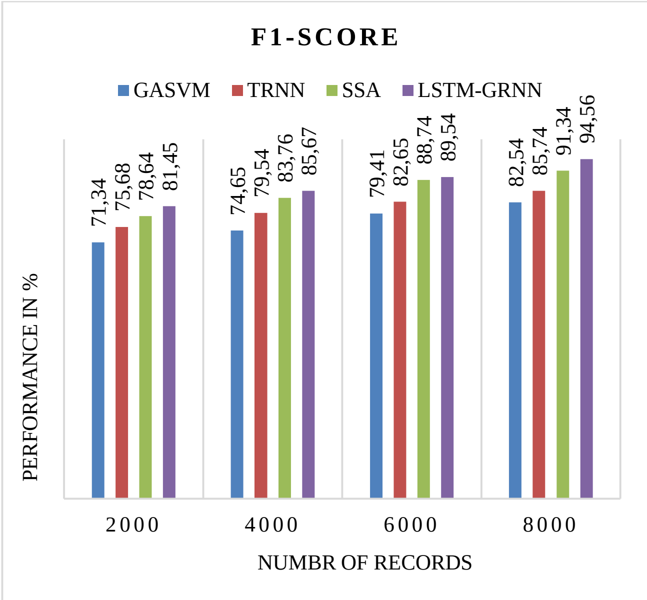

Figure 9. *Analysis of F1-Score*

Figure 9 shows that F1-Score Analysis can predict feature subsets in the stock market prediction dataset. Compared to previous approaches, the recognized accuracy is high, 82.54, 85.74, and 91.34. The methods presented here indicate the possibility of increasing the corresponding F1-Score predictions of stock market prediction data. Furthermore, applying the suggested LSTM-GRNN method for stock market prediction in F1-Score analysis led to more enhancement, the proposed method gained 94.56 % accuracy. The F1 score works in proportion to precision and recall since a model in which false positives and negatives are equally detrimental is ideal here. The F1 score is the average of recall and precision, which makes it worthwhile in models where both False Positive and False Negative are prejudicial. A high F1 score maintains a good measure that is free of too many false positive or false negative situations and, as a result, is suitable for integrated markets.

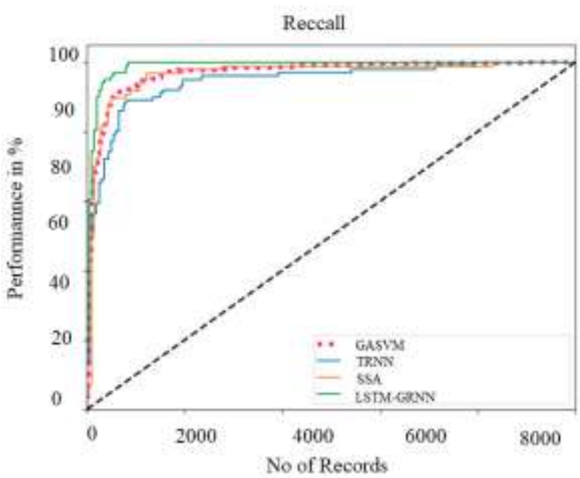

Figure 10. *Analysis of Recall*

As shown in Figure 10, the stock market performance ratio can be predicted by forecasting according to the proposed algorithms. Furthermore, the recall rate when using the proposed LSTM-GRNN method has been analysed to be 95.8%. Then, the ratio is described as 82%, 87%, and 91% when the proposed method is compared with the previous GASVM, TRNN, and SSA methods for stock market prediction.

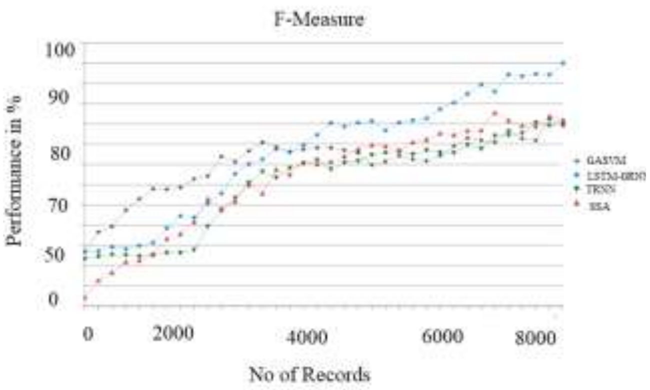

Figure 11. *Analysis of F-Measure*

As shown in Figure 11, the stock market's performance ratio can be predicted by forecasting according to the proposed algorithm. Also, using the proposed LSTM-GRNN method, the F-measure ratio was analysed to be 95.29%. Comparing the proposed method with conventional stock market forecasting methods such as GASVM, TRNN, and SSA, the ratios are considered to be 85%, 89%, and 92.8%.

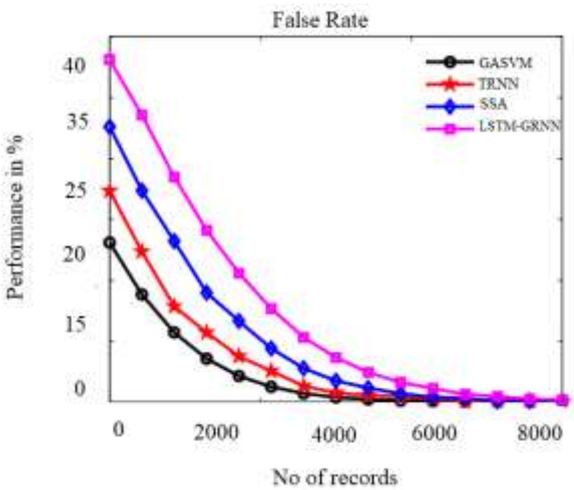

Figure 12. *Analysis of False Rate*

Compared to earlier techniques, the suggested algorithm can forecast the stock market performance estimation false rate, as shown in Figure 12. Furthermore, the false rate was 10.9% using the suggested LSTM-GRNN approach. The false ratios are evaluated to be 19%, 17%, and 15% when comparing the proposed method with traditional stock market forecasting techniques such as GASVM, TRNN, and SSA.

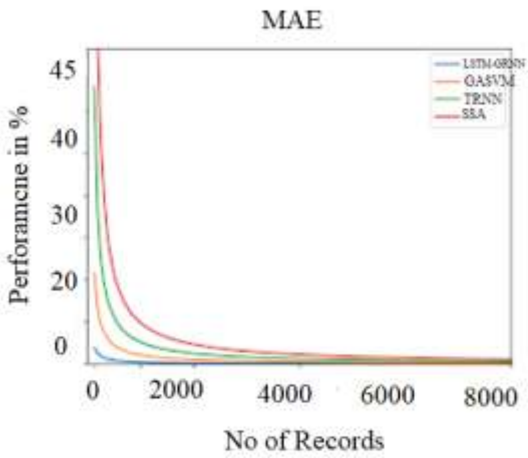

Figure 13. *Analysis of MAE*

As shown in Figure 13, the proposed algorithm can predict the stock market's MAE ratio. The analysis of the MAE performance conducted with the LSTM-GRNN method provides a ratio of 9.05%. In comparison, previous stock market prediction methods such as GASVM, TRNN, and SSA reported MAE ratios of 18%, 17%, and 14.8%, respectively.

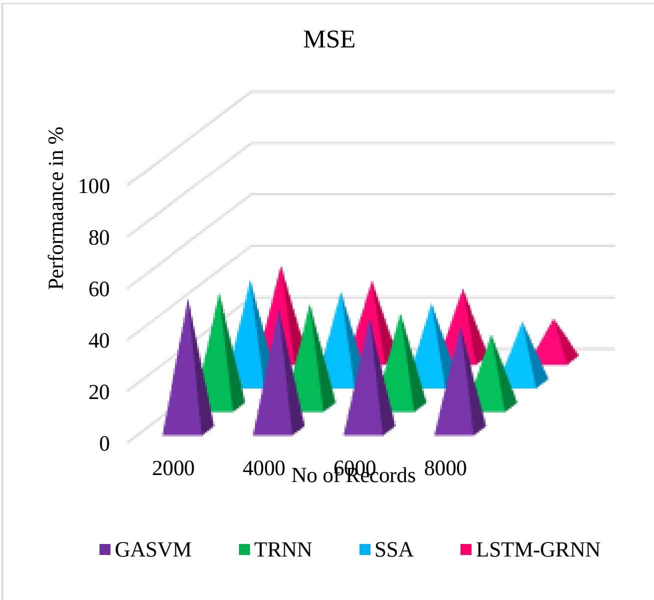

Figure 14. *Analysis of MSE*

As shown in Figure 14, predicting different features on the stock market prediction dataset involves finding the mean of square error of a part of the selected features to get better prediction results. As with the reheat parameters, the LSTM-GRNN method outperforms established techniques like GASVM, TRNN, and SSA with lower accuracy percentages of 40.9%, 28.41%, and 24.31%, respectively. Similarly, when accurately predicting the fault score analysis of a model, the use of the proposed LSATM-GRNN method results in a decrease in the emission classification accuracy of a model by 16.32%. MSE reflects the distances between estimates and fundamental values, which are significant in case of high error. Hence, a lower MSE of stock price predictions indicates higher reliability and accuracy of the values, giving less possibility of prediction errors that may result in massive losses.

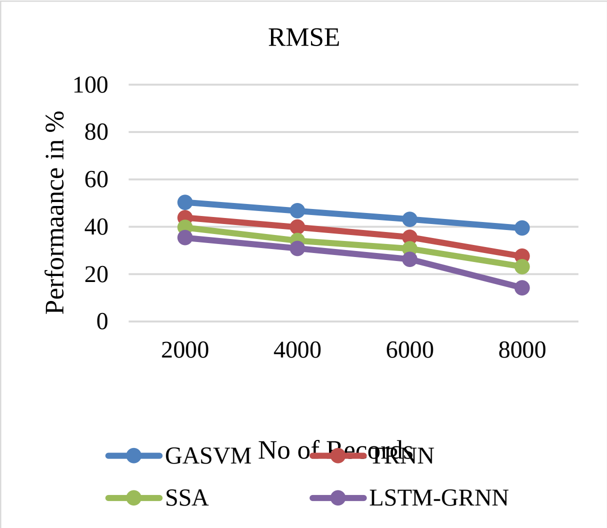

Figure 15. *Analysis of RMSE*

When testing features on the stock market prediction dataset, estimating the RMSE of the selected features is essential, as shown in Figure 15. Compared to GASVM, TRNN, and SSA on accuracy, the proposed LSTM-GRNN method represents 39.45% for the GSAVM, 27.56% for the TRNN, and 23.21% for the SSA. Hence, applying the proposed LSATM-GRNN for accurate fault score analysis prediction decreases the emission classification accuracy by 14.23%. RMSE is measured in the same unit as the model's dependent variable, and therefore, it is easy to interpret it in terms of price accuracy. Low RMSE ensures that predicted stock prices are nearly actual, thus a small chance of extreme variation. This gives the traders confidence in the price forecasted, especially when it is made for the short-term horizon, where the accuracy of the forecast is of utmost importance.

5. Conclusion

In this paper, we classified the stock market prediction dataset using the LSTM-GRNN method with a high accuracy of 96.7% and low MSE and RMSE of 16.32% and 14.23%, respectively. We employ Min-Max normalization, which has no fundamental stability problem and is very sensitive to inputs but does not have a bias. Also, models that rely on feature scales, such as neural networks, where introducing feature scales will boost the model's performance in terms of convergence. Identifying the best features and filtering noise is performed using the ALO algorithm while enhancing the precision of outcomes emerging from different dimensions. It becomes simpler to fail at identifying the best solution, better still, as the iterations are being made. There is always the possibility that the algorithm is repeated until the termination condition is met in the future, which may be the number of iterations or convergence limit LSTM-GRNN is applied to capture short- and long-term dependency on stock price moves as the independent variables in normalizing or scaling the dataset and forming a sequence, the previous 10-day movements in stock price are used, while the subsequent day's price is the dependent variable. The experiment results prove that the given model is effective, which, in turn, proves that the strategies considered in this work are more accurate and stable in comparison with typical methods of stock market prediction.

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