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Optimal Game Theory Model for Stock Price Prediction

V. S. Triveni[1], T. Deepthi[2] and M. P. Molimol[3]

[1]Professor, Department of Mathematics, Geethanjali College of Engineering and Technology, Hyderabad, email: vstriveni@gmail.com,

[2]Associate Professor, Department of Mathematics, Geethanjali College of Engineering and Technology, Hyderabad, email: deepthitogercheti@gmail.com

[3]Assistant Professor, Department of Mathematics, Geethanjali College of Engineering and Technology, Hyderabad, email: mmolimol@gmail.com

Corresponding author mail id: deepthitogercheti@gmail.com

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Abstract

The prediction of stock price movement direction is significant in financial circles and academic. Stock price contains complex, incomplete, and fuzzy information which makes it an extremely difficult task to predict its development trend. Predicting and analysing financial data is a nonlinear, time-dependent problem. The existing deep learning models showed much variance and showed overfitting in the model. Thus, the model was not able to generalize well to unseen future data. The existing Long Short-Term Memory (LSTM) model would do well on the training data but was not able to predict the future data. Therefore, it is important to remove redundant and irrelevant attributes from the Shanghai dataset before evaluating algorithms. The objective is to navigate through the search space and locate the best or a good enough combination that improves performance over selecting all attributes. Therefore, Game theory is an approach for decision-making based on several players of various conflicts of interest and mutually interdependent situations. Co-operation and interaction are the important processes in the Game theory and this is considered a rational method to solve conflict based on the feature interaction. The results obtained by the proposed Game theory model showed an accuracy of 92.54 % better when compared with the existing GAN-ERMSE obtained 61.45% of accuracy.

Key words: Decision-making, Irrelevant Attributes, Game theory, Shanghai, Stock Price Prediction,

1. Introduction

The Stock price prediction using machine learning models discovers the future values of a company stock and also helps for other financial assets traded with an exchange [1]. The entire idea is to predict the stock prices for gaining a significant profit [2]. The main factors considered for the prediction includes physical factors, physical factors, rational and irrational behaviour etc., All of these factors are combined for making the share prices volatile and dynamic which has made the model to predict the stock prices difficult to obtain higher accuracy [3]. The financial system is in a range of stability that is capable to facilitate the performance of an economy and dissipating financial imbalances that arise endogenously significantly results adverse and unanticipated events [4]. The stock market is an institution which connects potential buyers and sellers for companies' stocks [5]. A business is considered to be financially stable if is effective resources, making smart investments, profiting, and increases the wealth. Therefore, the business is required to be successful for improving the performances [6].

The game theory is utilized on occasions understands to interact among the decisionmakers. The Nash famous equilibrium is a steady model which states the model showed an interaction among distinct players where there is no player who can do better to choose different actions when players does not change [7-9]. The data trustworthiness and efficiency are considered to select the features, and the model assigns the disagreement measure to the features to eliminate the irrelevant features in the feature selection [10]. The contributions of the present research work are as follows:

- To utilize Game Theory for analysing the data collected from the stock market that makes the best decisions in the model and understands the scenario to produce a stable stock market.
- To analyse the stock market behaviour that provide a thorough analysing of a stock market behaviour among Shanghai Index.
- The forecasting method is used for ceasing in the stock market reached an effective hypothesis that carried out financial forecasting methods thereby making the conventional method successful.

The structure of the research paper is as follows: the section 2 is the literature review of the existing researches, section 3 is the proposed method, section 4 is the results and discussions provided for the proposed method. The section 5 is the conclusion for the present research work.

2. Literature Review

The existing methods based on stock price prediction are reviewed in this section.

Jiake Li [11] developed a Convolution Neural Network (CNN) to extract in-depth emotional information Market Stock Index Prediction Based on Network Security. Traditional stock forecasting models use forecasting models based on stock time series analysis, but time series models cannot consider the influence of investor sentiment on stock market changes. In order to use investor sentiment information to make more accurate stock market forecasts, this paper establishes a stock index forecast and network security model based on time series and deep learning. At the data source level, other information sources, such as basic features, are introduced to further improve the predictive performance of the model. In the future, we will further carry out relevant research in order to provide a reference and suggestion for the development of the financial market.

Yanfeng Jiang et al [12] developed Back Propagation neural network prediction model and the optimized particle swarm optimization-neural networks (PSO-BP). The experimental results show that the prediction effect of the PSO-BP neural network is higher than that of the BP neural network prediction model obtained by the two prediction models in the prediction process of the Shanghai Composite Index; the error rate of the BP neural network prediction model. After comparing and analysing the results of the forecast error value, it is concluded that the PSO-BP neural network forecast model has a more accurate forecast of stock prices and smaller errors, and the forecast of future trends is also consistent with actual trends. The value predicted by the BP neural network algorithm has a large error with the actual value, and the predicted trend does not match the actual value.

Farahani and Hajiagha [13] integrated artificial neural network and metaheuristic algorithms for forecasting stock price. The main goal of this article is to predict stock price indices using artificial neural network (ANN) and train it with some new metaheuristic algorithms such as social spider optimization (SSO) and bat algorithm (BA). Then, we used genetic algorithms (GA) as a heuristic algorithm for feature selection and choosing the best and most related indicators. We used some loss functions such as mean absolute error (MAE) as error evaluation criteria. However, in GA, there is no guarantee that the best and most related technical indicators have been selected and required to overcome the local optima trap.

Dr. M. Durairaj and B. H. Krishna Mohan [14] developed a Convolutional Neural Network (CNN) to financial time series prediction. The modelled time series is input to CNN to obtain initial predictions. The error series obtained from CNN predictions is fit by PR to get error predictions. The error predictions and initial predictions from CNN are added to obtain the final predictions of the hybrid model. The effectiveness of the proposed hybrid Chaos-CNN PR is tested by using three types of foreign exchange rates of financial time series for stock market indices based on the Shanghai Composite Index datasets. It is also possible to extend the proposed Hybrid to various financial and non-financial time series that can improve the classification results.

Ashish Kumar et al [15] developed Generative Adversarial Network (GAN) and Enhanced Root Mean Square Error (ERMSE) based on deep learning model for Stock Price Movement Prediction. It was proposed a generic model consisting of Phase-space Reconstruction (PSR) method for reconstructing price series and Generative Adversarial Network (GAN) which is a combination of two neural networks which are Long Short-Term Memory (LSTM) as Generative model and Convolutional Neural Network (CNN) as Discriminative model for adversarial training to forecast the stock market. Although a range of techniques is available to predict the stock index close price, but they have so far failed to provide enough accuracy and processing time

3. Proposed work

The present research work follows the below mentioned steps

3.1 Dataset

Simulation Environment and Data. Compared with individual stocks, the volatility of stock indexes is generally smaller because stock indexes are composed of many stocks in different industries and can better reflect the overall economic momentum and overall conditions. Therefore, the most representative Shanghai Stock Exchange Index (Shanghai Stock Exchange Index, code 000001 CNN to extract in-depth emotional information) and Shenzhen Stock Exchange Index (Shenzhen Component Index, code 399001) are selected as the research objects. Select historical stock data with a time span from January 1, 2015, to December 31, 2019. +e data includes 7 attributes: date, closing price, opening price, highest price, lowest price, rising or falling price, and volume. All data are downloaded from the Tushar financial big data platform. According to the time span, three different experimental data sets are set up. +e data of 1,219 trading days in 5 years Start Random initialization particles (including weight, acceleration coefficient, and initial position) Evaluate each particle, find the function adaption value, the most historical position Meet the end condition? Update particle speed and position according to formula Evaluate the fitness value of particles Evaluate the historical best position of power Update the global according to the optimal position End Figure 2: Index prediction process based on deep learning [16]. 4 Security and Communication Networks from 2015 to 2019 is the first group, the data of 731 trading days in 3 years from 2017 to 2019 is the second group, and the data of 244 trading days in 2019 is the first group—three groups. Use deep learning models to train these three data sets and predict the closing prices of the two stock indexes.

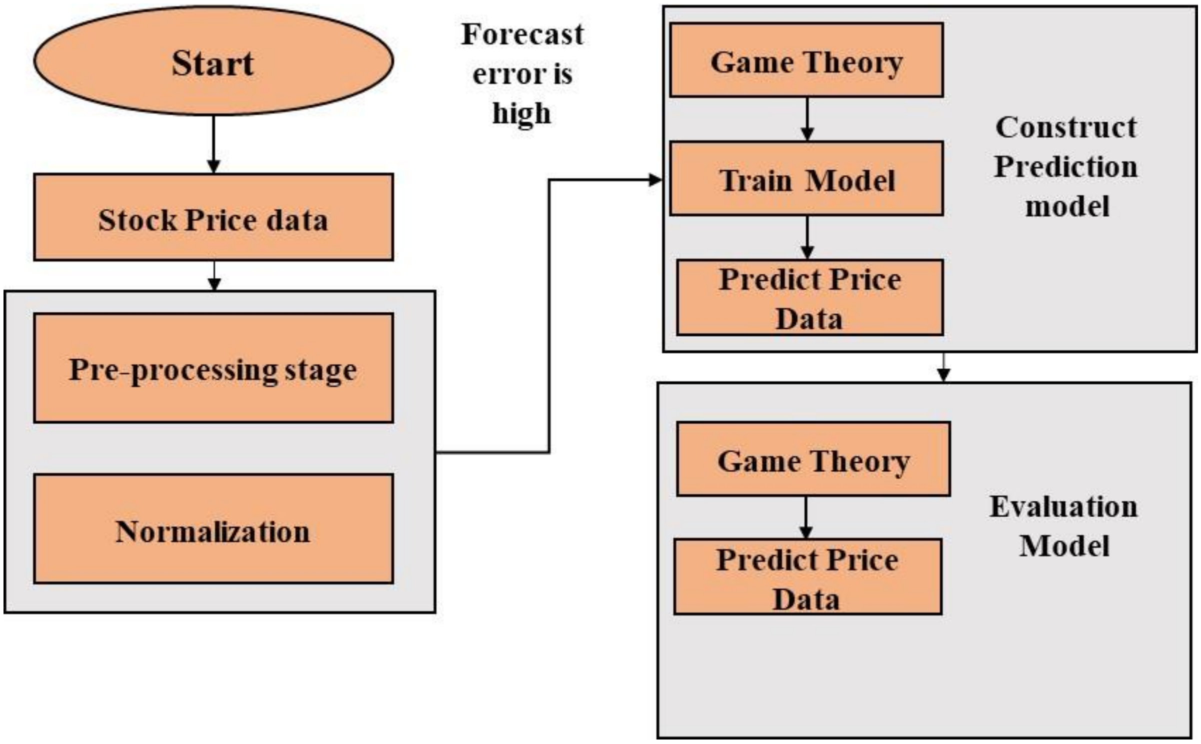

Figure 1 : Block diagram of the proposed research work

3.2 Feature Selection based on game theory-based approach

The game theory-based approach is applied in this model and two action status is present for each game player. First, every i^{th} CM needs to perform drop (D) i.e., dropping packets of malicious action or no drop (ND) i.e., not dropping packets. The CM is performed with D action to save batter power in the network. Second, CH performs no Beacon (NB) or Beacon (B) action status. The benevolent CM is provided with permission and denoted as action B i.e., does not drop packets to send the observed data. The sleep mode of CM is also activated based on the B permission and battery lifetime is saved to take packet transmission rest or to get power recovery while recharging is available. If D is applied in i^{th} CM, then NB action is performed in the model.

3.2. 1 Dynamic Bargain Game Method

Game theory is an approach for decision-making based on several players of various conflicts of interest and mutually interdependent situations. Co-operation and interaction are the important processes in the Game theory and this is considered a rational method to solve conflict based on the feature interaction. The game theory tool is used to obtain the negotiation process transformed from intersection resolution. The scenario of typical game theory is described as follows.

The players: The players are regarded as entities to influence the game outcome and the players are denoted as $G = \{V_1, V_2, V_3\}$.

The strategies: Game strategy set is a player sequence of action that consists of completing plan. This strategy is used to decide the action is necessary for the particular step and the set of strategies is denoted as $S = \{Accelerate, Uniform, Decelerate\}$. The strategy denotes the state of feature like increases in speed, maintain same level and dropping speed.

The payoff: Players are applied with the payoff to benefit the players with its strategy at the end of the game. Each player has payoffs set of $P_m = \{S_1, S_2, S_3\}, m = 1, 2, 3$.

In this part, the acceleration element is classified into three categories and strategy is varied in the range of $[a_{min}, a_{max}]$ that is different from the deceleration and acceleration of fixed value in a static game.

3.2.2 Payoff Design

This method focuses on three important aspects (three players) of the network such as efficiency, safety and interaction. Safe intersection and more efficiency between the features is considered as objective in this method. The conflict of place and time is predicted based on the neighbour's shared states and unsignalized intersection is followed in this method. The co-operation method is applied to increases the network traffic in the shared states and velocity changes influence the efficiency. Control strategies in the feature aspects are limited to the node's execution capacity (transmission rate).

The payoff is sorted into two levels based on different aspects by considering the safety and efficiency intersection level. The execution capability is considered at the feature level and the payoff is given as follows in equations (1 & 2).

$$f_{p,m}^i = \alpha_{p,m} T_m^i + \beta_{p,m} \Delta T_{m,n}^i - \gamma_{p,m} \Delta v_m^i + \delta_{p,m} \Delta \alpha_{\mathrm{m}}^{\mathrm{i}}, \quad (1)$$

$$m, n \in \{1,2,3, m \neq n\}, i \in N \quad (2)$$

Where pair of nodes, feature ID, priority are denoted as mn, m, p subscript and the i^{th} iteration is denoted in superscript. Each feature weight elements are denoted as $\alpha_{p,m}$, $\beta_{p,m}$, $\gamma_{p,m}$, and $\delta_{p,m}$, respectively. Matrix $T_m^i = \left[T_1^i, T_2^i, T_3^i\right]^T$ and $\Delta T_{mn}^i = \left[\Delta T_{12}^i, \Delta T_{13}^i, \Delta T_{23}^i\right]^T$ denotes the weights corresponding of $\alpha_{p,m} = [\alpha_{p,m1}, \alpha_{p,m2}, \alpha_{p,m3}]$ and $\beta_{p,m} = [\beta_{p,m12}, \beta_{p,m13}, \beta_{p,m23}]$, respectively. Matrix transpose operation is denoted using superscript "T" and weights are satisfy using the following condition in equation (3).

$$W.\alpha_{p,m}^T + W.\beta_{p,mn}^T + \gamma_{p,m} + \delta_{p,m} = 1 \quad (3)$$

Where $W = [1, 1, 1]$, various weights combinations are denoted based on the interaction degree and various driving characteristics.

The payoff of each level in each related element is given as follows.

Intersection Level in payoff: The intersection level in the payoff focuses on the features that are described as safe and efficiency.

The negotiation game of crossing efficiency is the key aspect. The TTC is applied for each feature with parameters of p_m, v_m, and a_m, as given in equation (4).

$$\begin{cases} T_m^i = \sqrt{\left(\frac{v_m^i}{a_m^i}\right)^2 + \left(\frac{2p_m^i}{a_m^i}\right)} - \left(\frac{v_m^i}{a_m^i}\right), m = 1,2,3, i \in N, \\ v_{min} \leq v_m^i \leq v_{max} \end{cases} \quad (4)$$

The constraint is set for the minimum and maximum velocity, network traffic rules is applied in the method. The acceleration, velocity, and collision point position are denoted as p_m^i, v_m^i, and a_m^i in certain iteration loop, respectively.

Cooperative intersections basic principle is safe travel of data. Each feature safety pair is denoted as Time Difference to Collision (TDTC), as given in equation (5).

$$\Delta T_{mn}^i = \left|T_m^i - T_n^i\right|, m, n \in \{1,2,3, n \neq m\}, i \in N \quad (5)$$

Each feature safety is defined as the TDTC in a certain loop that indicates each feature with the appropriate time to transfer the data. Equation (5) denotes the two nodes' time difference to consecutively pass the data with ensuring safety. The interaction crossing efficiency is denoted in equation (6).

Equation (6) is defined based on the third term in equation (1).

$$\Delta v_m^i = v_m^{i+1} - v_m^i, m = 1,2,3, i \in N \quad (6)$$

The velocity change and initial velocity affect the network traffic efficiency. The feature speed up is improved based on positive value and feature slowdown is denoted in negative value. Network traffic efficiency is improved based on the negative sign.

Feature Payoff: The acceleration and deceleration of features affect the efficiency and safety of the nodes. The acceleration and deceleration change is denoted in equation (7).

$$\Delta a_m^i = \left|a_m^i - a_m^{i-1}\right|, m = 1,2,3, i \in N \quad (7)$$

Normalization: Different parts with different dimensions are considered based on a zero-mean normalization is adopted in equation (8).

$$y^* = \frac{y - \mu_y}{\sigma_y} \quad (8)$$

Where original input and normalized input are denoted as y, y^*, μ_y denotes the y expectation and σ_y is a standard deviation of y.

3.2.2. Pareto-Optimal Set

A satisfactory solution of Pareto-optimal solution is introduced in this method. Each feature is not ensured with the best payoff by minimizing global payoff. The genetic algorithm is applied to select minimum global payoff for Pareto-optimal solution search. The optimal solution is regarded as a fitness function, as given in equation (9).

$$F_p^i = \omega_{p,1}^i . f_{p,1}^i + \omega_{p,2}^i . f_{p,2}^i + \omega_{p,3}^i . f_{p,3}^i \quad (9)$$

Where payoff functions $f_{p,1}^i$, $f_{p,2}^i$, and $f_{p,3}^i$ are considered in i^{th} generation are provided in equation (1) that is measured using strategy set $\{a_1^i, a_2^i, a_3^i\}$. The coefficient weight are denoted as $\omega_{p,1}^i, \omega_{p,2}^i$, and $\omega_{p,3}^i$. Each generation i is constantly applied in $a_{min} = -2\, m/s^2$, $a_{max} = 2\, m/s2$. The global optimal strategy set is applied after the genetic algorithm standard procedure.

3.2.3. Bargaining Game

A bargaining game is applied to improve the mutual interaction between the features using disagreement point $d(k)$ and decision space Υ, which is defined as $\{(\Upsilon, d(k))\}$.

The general game is used to formulate the bargaining and to search Pareto-optimal set in a general game, and each feature weighted global payoff is minimized to formulate the game problem. The game problem is defined in equation (10).

$$\min_{u(k)} \sum_{m=1}^{M} \omega_m \phi_m(u(k)) \quad (10)$$

$$\text{S.t. } u_m(k) \in u_m, m = 1,2,3$$

Where each feature weight coefficient payoff is $M = 3$ and ω_m.

Fitness function is applied for disagreement point to develop bargaining game based on cooperative game theory. The disagreement point $d_m(k)$ at time step k is denoted as $d_m(k) = \varphi_m(u^p(k))$ and $u^p(k)$ are obtained to solve the following problem, as in equation (11).

$$\min_{u_m(k)} \max_{u_{-m}(k)} \phi_m(u(k)) \quad (11)$$

$$\text{S.t. } u_m(k) \in u_m, m = 1,2,3$$

$$u_{-m}(k) \in u_{-m}, m = 1,2,3$$

Where feature m strategy set is denoted as $u_{-m}(k)$ and worst-case feature is denoted as G and the best benefit is denoted as $d_m(k)$ that is used to measure the worst case.

The disagreement point of the bargaining game based on the Nash solution is given in equation (12).

$$\max_{u(k)} \prod_{m=1}^{M} \left[d_m(k) - \phi_m\big(u(k)\big)\right]^{\omega_m} \quad (12)$$

$$\text{S.t. } d_m(k) > \phi_m\big(u(k)\big), m = 1,2,3$$

$$u_m(k) \in u_m, m = 1,2,3$$

The maximization problem is rewritten equivalently as in equation (13).

$$\max_{u(k)} \sum_{m=1}^{M} \omega_m \log\,[d_m(k) - \phi_m(u(k))] \quad (13)$$

$$\text{S.t. } d_m(k) > \phi_m\big(u(k)\big), m = 1,2,3$$

$$u_m(k) \in u_m, m = 1,2,3$$

The problem (13) is solved in a distributed manner using the feasible-cooperation method. If the greedy method is applied in a strategy that focuses on the local payoff to having more benefit in the cooperation manner and greedy strategy is applied in the current iteration.

4. Results and Discussion

To explore whether it is possible to learn useful information from first day's price series before predicting the up and down compared to the market price on last day, an extensive value is tabulated on the financial datasets and compare the proposed method with several baseline methods. In this resultant section, the proposed system is simulated by using python 3, Intel i5 processor, and 4 GB RAM. The proposed system uses the Stock Market datasets for evaluating the results.

4.1 Experimental Data

Each financial time series features where the experimental results showed that close variables are the research object. For each stock price series, the true label for each day's up and down is marked according to the following rule is shown in the equation (7).

$$y_i = \begin{Bmatrix} 1\ X_i \le X_{i+1} \\ 0\ X_i > X_{i+1} \end{Bmatrix} \quad (7)$$

Where $y_i$denotes the up or down, X_i is Closed value of each stock on i^{th} day and X_{i+1} is Closed value of each stock on $i+1^{th}$ day. The confusion matrix evaluated for classification predictions are shown in table 2.

Table 2. Confusion matrix of classification results

True Value	**Forecast Result**	
	Positive	Negative
Positive	True Positive	False Negative
Negative	False Positive	True Negative

4.2 Evaluation

Generally, the prediction of the trend of stock price can be regarded as a two-category problem. Therefore, the prediction results fall into one of four cases based on the consistency of their real class labels and the predicted labels as True Positive, False Positive, True Negative, Or False Negative. These measures are denoted as TP, FP, TN, and FN the number of corresponding samples, respectively, the confusion matrix for the classification result has the following form. The standard performance measures are Accuracy, Recall, Precision, F1 score to evaluate the performance of individual stock prediction. These scores are calculated as follows:

Accuracy: The accuracy is defined as the degree of closeness of a calculated or measure value to its original value. Accuracy is the most important performance measure as it is simply a ratio of properly predicted observation to the total number of observations. The expression for accuracy is given in Eq. (8).

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{8}$$

Precision: The precision is a measure of closeness of two or more measurements of each other. Precision is the ratio of True Positive to the sum of the False Negative and True Positive. The expression for precision is given in Eq. (9).

$$Precision = \frac{\mathrm{TP}}{TP+FP} \tag{9}$$

Recall: The recall is the ability of the classifier to determine all the positive samples. The worst value is 0 and best value is 1. Recall can be defined as the ratio of true positive to the sum of True Positive and False Negative, which represented in Eq. (10).

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

F1 score: F1 Score is the weighted average of Recall and Precision. Therefore, the F1 score takes both False Negatives and False Positives into account. The expression for F1 score is derived in Eq. (11).

$$F1\ Score = \frac{2TP}{2TP+FP+FN} \tag{11}$$

Where TP is the number of samples in which the positive class sample is predicted to be a positive class, and TN is the number of samples in which the negative class sample is predicted to be a negative class, the denominator is the number of all test sample.

True Positive: True positive is a result where the model correctly predicts the positive class.

True Negative: True negative is a result where the model correctly predicts the negative class.

False Positive: False positive is a result where the model incorrectly predicts the positive class.

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False Negative: False negative is a result where the model incorrectly predicts the negative class.

4.3 Quantitative Analysis

By extracting trend features from the reconstructed sequence, the developed method improved the accuracy of the prediction results on almost all the datasets. From Table 1 and Table 2, LSTM is a competitive baseline considering higher Recall and Precision scores on some datasets. However, LSTM is essentially time consuming than LSTM-RNN in the training period due to the intrinsic vanishing gradient problem. It is also shown in both Table 1 and Table 2 that, traditional time series analysis method and signal processing method like Wavelet method was inferior to machine learning-based methods LSTM which are 4% - 6% less in prediction accuracy and more less than deep learning model. This reveals the limitations of traditional financial time series prediction methods on nonlinear times series modelling. Overall, the proposed LSTM-RNN model is superior to the baseline methods. With respect to Accuracy and Recall traditional signal processing methods, the proposed LSTM-RNN attained 7% to 8% higher values respectively. Although F1-scores do not achieve the best performance on all datasets, they are close to the best results. Table 1 shows the comparison results for the existing and the proposed method for the performance measures accuracy and recall. Similarly, table 2 shows the comparison of the existing and the proposed method comparison values like precision and F1 score.

Table 3. Comparison of the existing and the proposed method for the performance measures Accuracy (Acc) and Recall (Rec)

Data		**S&P 500**		**APPL**		**GOOGL**		**IBM**		**Shanghai**	
Metrics		**Acc**	**Rec**	**Acc**	**Rec**	**Acc**	**Rec**	**Acc**	**Rec**	**Acc**	**Rec**
METHODS	Wavelet	48.77	49.52	51.83	54.48	51.80	53.49	51.18	52.26	69.58	69.99
	LSTM	55.88	71.91	54.34	77.08	56.25	84.21	62.85	63.34	75.96	79.87
	Game theory	61.33	74.56	58.9	78.97	58.65	86.43	68.76	65.76	92.54	92.78

Table 4. Comparison of the existing and the proposed method for the performance measures Precision (Pre) and F1 score (F1).

Data		**S&P 500**		**APPL**		**GOOGL**		**IBM**		**Shanghai**	
Metrics		**Pre**	**F1**	**Pre**	**F1**	**Pre**	**F1**	**Pre**	**F1**	**Pre**	**F1**
ETHODS	Wavelet	52.41	50.92	53.55	54.01	49.46	51.39	53.09	52.67	69.87	68.78
	LSTM	56.14	63.05	54.41	63.79	59.25	69.56	68.80	58.60	72.48	79.57
	Game theory	61.56	65.64	61.32	66.63	65.41	73.43	72.2	59.76	92.78	92.76

Fig. 2 and Fig. 3 shows the comparison of graphs for the proposed method and the existing methods. The values obtained from LSTM and Wavelet techniques evaluated are compared with the proposed Optimum Game theory model, with various financial markets. The developed models used a greater number of features that caused gradient vanishing and data redundancy. The accuracy is decreased as more feature causes more computing cost. The proposed model overcomes such limitation and achieves best prediction accuracy when compared with the existing models. The results showed that game theory model handle financial time series data better than traditional time series prediction method.

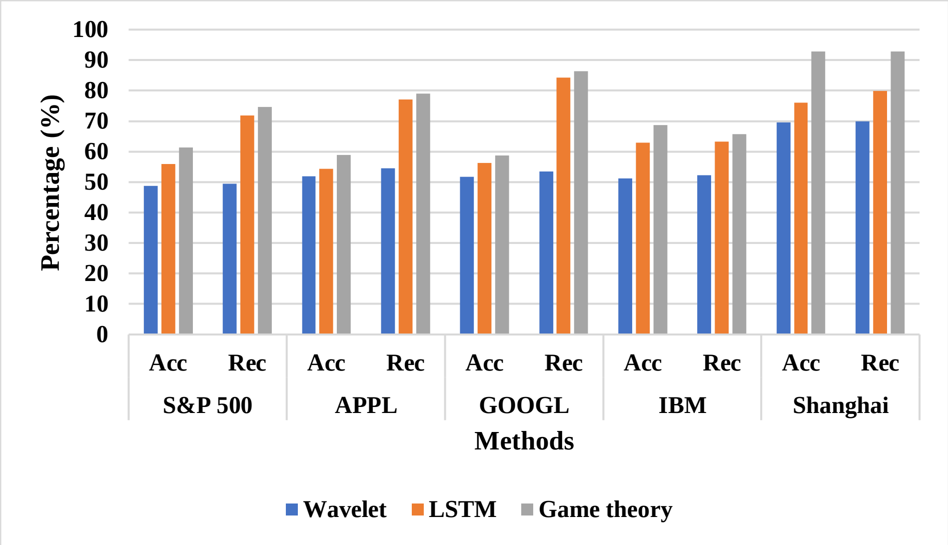

Figure 2: Results obtained in terms of accuracy and recall

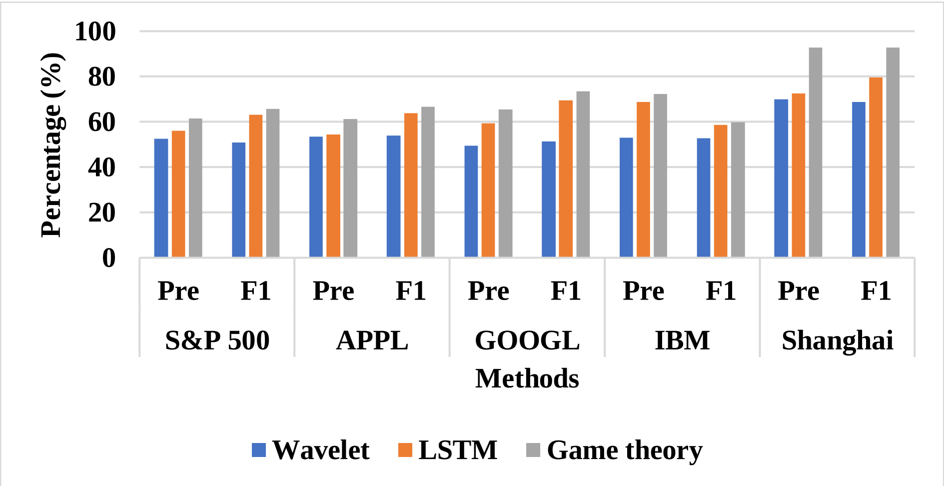

Figure 3: Results obtained in terms of accuracy and recall

4.3 Comparative Analysis

The developed CNN model used the data source level, other information sources, such as basic features, are introduced for further improving the predictive performance of the model that obtained accuracy of 53% and error rate of 9.80. Similarly, the developed BP-PSO predicted by the BP neural network algorithm has a large error of 6.37 with the actual value, and the predicted trend does not match the actual value. However, in GA, there is no guarantee that the best and most related technical indicators have been selected and required to overcome the local optima trap showed 0.602 of error value. The existing Hybrid to various financial and non-financial time series required to improve the classification results in terms of error value as 1.1094. Although a range of techniques is available to predict the stock index close price, but they have so far failed that showed 61.45% required better accuracy.

Table 3: Comparative analysis

Methodology	Accuracy (%)	Error rate
CNN [11]	53	9.8070
BP-PSO [12]	-	6.37
Social Spider Optimization and Bat Algorithm [13]	-	0.602
Hybrid Chaos-CNN-PR [14]	-	1.1094
GAN-ERMSE [15]	61.45	0.0585
Proposed Game Theory	92.54	0.048

The present research work utilized proposed game theory obtained accuracy of 92.54% and error rate 0.048.

5. Conclusion

Game theory is an approach for decision-making based on several players of various conflicts of interest and mutually interdependent situations. Co-operation and interaction are the important processes in the Game theory and this is considered a rational method to solve conflict based on the feature interaction. The forecasting method is used for ceasing in the stock market reached an effective hypothesis that carried out financial forecasting methods thereby making the conventional method successful. The Proposed Game Theory obtained an accuracy of 92.54% and 0.048 obtained better when compared with the existing GAN-ERMSE obtained 61.45% of accuracy.

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