

# Targeted Sentiments and Hierarchical Events based Learning Model for Stock Market Forecasting from Multi-Source Data

C. Bhuvaneshwari, R.Beena

**Abstract:** Stock market price movement forecast from multi-source data has gained massive interest in recent years. Studies were focussed on extracting the events and sentiments from different source data and employ them in learning the stock price movement patterns. This approach provided accurate and highly reliable forecasting as it involves multiple stock price indicators. However, some aspects of sentiment analysis and event extraction increase the training time and computation complexity in big data stock analysis. To overcome these issues, the hierarchical event extraction and the target dependent sentiment analysis are performed in this paper to improve the learning rate stock price movement patterns. In this paper, the events are hierarchically extracted from news articles using Deep Restricted Boltzmann Machine (DRBM). The target based sentiments from the tweets are detected using Improved Extreme Learning machine (IELM) whose parameters are optimally selected using Spotted Hyena Optimizer (SHO). The stock indicators obtained from these two processes are used in the learning process performed using Tolerant Flexible Multi-Agent Deep Reinforcement Learning (TFMA-DRL) model for analysing the stock patterns and forecasting the future stock trends. The forecasting results obtained by using the TFMA-DRL model by combining the stock indicators of targeted sentiments and hierarchical events are trustworthy and reliable. Evaluations are performed using three datasets collected for 12 months period from three sources of Twitter, Market News and Stock exchange. Results highlighted that the proposed stock forecasting model achieved 90% accuracy with minimum training time.

**Keywords:** Stock market forecasting, stock prediction, target dependent sentiment analysis, event extraction, Deep Restricted Boltzmann Machine, Improved Extreme Learning machine, Spotted Hyena Optimizer, Tolerance based Flexible Multi-Agent Deep Reinforcement Learning.

## I. INTRODUCTION

Many companies and business organizations indulge in the design and development of many products and services that are essentially required around the world. The market performance of an organization is depended on many factors and can be visualized using through the market indices. Stock market is one of the important catalogues to determine the market performance of company or entity [1]. When the stock index of an entity is not performing better, it can be interpreted that their product is low on sales or the value of the product has decreased. Similarly, when the stock indexes composed by many companies are poor, it denotes that the

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economy is not good and might be not completely productive [2]. Hence the stock market analysis and forecasting approaches have gained more exposure in the history. Prediction of future stock price movements from the past and present knowledge is vital in reviving the hopes of investors and providing stable environment for the business organizations [3]. It allows the traders and stock investors in deciding their course of action in the day-to-day stock markets. The markets are influenced by many factors like the financial news, government policy changes, global investment variations, trade reports, social events and economic conflicts [4]. These factors constitute the indicators for the stock price movements and hence the extraction of such indicators will be vital in deciding the authenticity of the stock forecasting models.

Statistical models and data mining methods are some of the traditional stock analysis methods that provided simple but effective forecasting based on the price variation patterns [5]. The disadvantage in such methods is that they rely on the statistics and does not reflect the external factors. In recent years, the use of machine learning [6] and deep learning algorithms [7] for the stock market forecasting has resulted in higher accuracy and reduced time and computation complexity. However, the major challenge in stock market forecasting is the lack of ability to handle data from multiple sources. Most research studies have developed forecasting models that analyze the single-source data to extract the stock indicators. The indicators may be stock indexes or stock prices from news articles. The business community has been constantly looking for techniques that can extract multiple indicators to determine the stock prediction. The forecasting based on multiple indicators includes the extraction of multiple external factors each obtained from a set of multiple source data. Hence the research on future stock trends forecasting has gradually shifted towards the use of multi-source data to extract and learn from multiple indicators [8].

The main constraint in stock forecasting using multi-source data is the efficient fusing of the sentiment and event indicators by the learning algorithm. Tolerance based Multi-Agent Deep Reinforcement Learning (TMA-DRL) [9] has been previously applied for this purpose. However, the mutually correlated indicators can be further improved when the target dependent sentiments and hierarchical events are used. Hence in this paper, the target based sentiments are extracted using IELM optimized by SHO [10] while the hierarchical events are extracted by DRBM.

As the indicators have evolved, the learning model is enhanced by introducing the flexibility policy. Thus the proposed TFMA-DRL is developed for improving the cohesion between the stock indexes and the indicators to provide high accuracy in stock future trend analysis. The experiments are conducted over the tweets, news and stock price datasets collected from the respective sources for a period of 12 months. The rest of this article is structured as: Section 2 provides a discussion on latest related studies. Section 3 describes the stock indicators extraction from the tweets and news data and demonstrates the suggested TFMA-DRL learning model for stock forecasting. Section 4 provides the evaluation outcomes while section 5 makes a summary of this study and recommends future research options.

## II. RELATED WORKS

Stock market prediction has a long established history of research analysis. The recent studied have largely focussed on applying the deep learning algorithms for stock market forecasting as the deep models significantly reduce the training time. Another major advantage of using the deep learning models is their ability to extract additional information from the residual data through extensive deep analysis. Singh and Srivastava [11] employed deep neural networks (DNN) with the principle component analysis to accurately predict the Google stock price movements. Yu and Yan [12] also used DNN for stock forecasting based on the long short-term memory networks (LSTM) to provide highly accurate prediction. However, these models have high mean square error and higher complexity. Fischer and Krauss [13] used the deep learning model of LSTM stock market prediction with high accuracy and reduced time. Jiang et al. [14] introduced improved stacking framework using ensemble models and deep learning for stock forecasting with high accuracy. Xu et al. [15] also used a deep learning model of convolution neural network (CNN) for stock forecasting. Kelotra and Pandey [16] introduced optimized deep-convolution LSTM for stock estimation. Moews et al. [17] introduced lagged correlation-based deep learning for future stock price analysis. Song et al. [18] also used deep learning model for stock estimation based on the relationship between the features and input vectors. All these approaches provided higher accuracy of prediction but the major limitation is that they considered only single economic indicator for estimation.

From the above studies, the main inference is that the reliability of a prediction model is ensured only when multiple indicators are used. The use of multiple source data to extract multiple indicators and fuse them to improve stock prediction has been effectively performed by Zhang et al. [8]. Based on this strategy, Zhang et al. [19] used coupled hidden Markov model to predict stock prices from news data and stock prices. Zhang et al. [20] used three data of tweets, news data and stock price index datasets as multi-sources to predict the future stock prices using multiple instance learning. These approaches improved the prediction accuracy significantly and also increased the convergence rate. However, these studies suffered the problem of nonlinearity when fusing the data which has slightly reduced the optimal performance. Xu et al. [21] introduced mixed data sampling based support vector regression for predicting the stock prices from

multi-source data. Although highly accurate, this approach extracts the sentiments only from macro-blogs which cover only smaller audience unlike the micro-blogs.

Deep learning models have also been successfully employed for the stock price forecasting from multi-source data analysis. Li et al. [22] designed a multimodal LSTM algorithm for extracting the events from news to enhance the stock price estimation. Devi and Mohan [23] developed stock price estimation model using LSTM with Cellular Automata. This approach enhanced the prediction accuracy by 2.67% but this approach lacks the tool for extracting additional information on specialized features. Maqsood et al. [24] designed a stock price estimation model using deep learning based on local and global event sentiments. This approach has greater scope for analysing very larger data without the computational complexity and provided high prediction accuracy but slow convergence rate. From the methods in literatures, some important aspects are learned. The first and foremost aspect is that the inclusion of multi-source data might be challenging but has high potential for prediction improvement. Similarly, the use of general sentiments and events can be ambiguous in some sets of stock price data. Hence this study has been structured to include indicators from multi-source data with target dependent sentiments and hierarchical events serving as the unique indicators to improve the prediction accuracy. For achieving this objective in this study, the IELM and DRBM algorithms are presented along with tolerance and flexibility policies based Multi-Agent Deep Reinforcement Learning model.

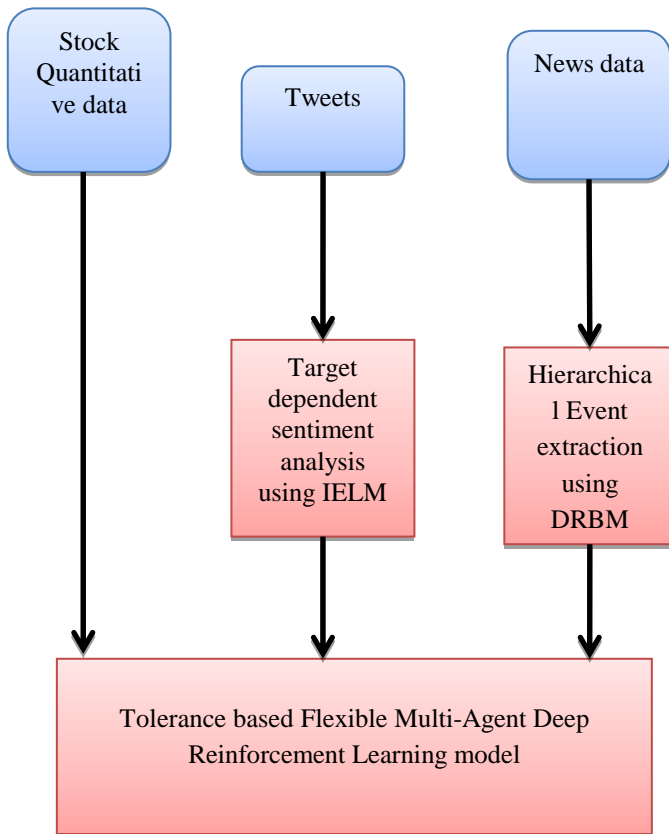
## III. METHODOLOGY

Forecasting of the future trends in stock prices can be accurately provided when the targeted opinions and hierarchical events are extracted. The main reason is that they can accelerate the deep learning model through their more meaningful and relational aspects based indicators. Fig. 1 shows the working model of the proposed framework for stock forecasting. The stock data and the other two input data are denoted as vectors for  $n$  number days beginning from  $n=1$  day. The sequential organized data of news articles, tweets and stock indices are represented as multi-source group data  $G$ . this representation ensures the day-to-day analysis of the stock data based on the sentiment and event indicators.

### A. Data Collection and Pre-processing

Tweets, news articles and stock index prices are collected from online sources for a period of 12 months from October 1, 2018 to September 30, 2019. The duration is fixed based on the financial quarter years in India of which the fourth quarter year starts from October 1. It is predetermined such duration is due to the effect of final quarter reports in the first quarter economy in the country.

**Stock price data:** Stock price indexes were gathered from BSE and NSE online sites for each day of the specified 12 months duration. The BSE 500 and NSE 500 price indices were selected for evaluation because they represent the top 500 companies listed in stock markets. The data encompasses the initial, final, high and low prices of stocks, traded dividends and revenue percentage of top 500 companies listed in NSE and BSE.



**Fig.1. TFMA-DRL with target sentiments and hierarchical events based stock forecasting framework**

**News data:** The market and economics news headlines and news preamble were gathered from standard business news website <https://www.moneycontrol.com>. Originally 47,652 news articles from October 1, 2018 to September 30, 2019 were obtained. The news with non-English sentences omitted and the final dataset was prepared containing 10,026 news articles.

**Tweets:** Tweets were crawled using the Twitter developer tool based on 50 stock price related keywords. Originally 176248 tweets were gathered and initial filtering removed the non-English tweets to form the final dataset with 66,542 tweets.

Pre-processing of all three source data was performed to remove the noise and resolve the missing value problem. Data cleaning and missing value resolution are performed for stock price data. The removal of other language data and the generalized data cleaning is done on the news data while the tweet pre-processing techniques namely removing url, punctuation and special symbol removal and case normalization, stop words removal, lemmatization and part-of-speech (PoS) tagging were performed for the tweets. For each of the trading days, the targeted sentiments from tweets and the hierarchical news events were extracted and the corresponding stock prices are learned by the deep learning model. For each dataset, the data from the first 11 months are used for training and the last month data is used for testing.

### B. Hierarchical news event extraction

The input news data is fed into the DRBM to extract the hierarchically related events. The main benefit of using hierarchical events is that they provide inter-linked events through which the influencing factors can be correlated.

When one of the event occurs, the possibility of the other event happening can be assumed based on the hierarchical ordering. The DRBM is formed by merging the deep Boltzmann machine (DBM) and restricted deep Boltzmann machine (RBM) [25]. The DBM model has enhanced representation power than the RBM due to the additional connections between the hidden layer nodes. However, the RBM has better feature analysis through data dependent term based approximation. Combining RBM and DBM can enrich the event extraction based on the additional ordering of DBM and accurate extraction of RBM. The DRBM is a multi-layer neural network where each of the layers is RBM that directly transmits the values to the next hidden layer units. The syntactic structures were extracted using HanLP text parser model. The tree based sentence structures defining the object and subjects of the sentences and the core words are linked together to represent the event details. The input layer is plotted with the coded m-dimensional vector for computing the n-dimensional vector of the hidden layer. The state of hidden layer nodes of RBM is denoted as  $h$  and that of DBM are represented as  $v$  which are combined as  $m$ . The  $m^{(l)}$  represent the state of l-th layer and in DRBM  $m^{(i+1)}$  is the unified layers of the RBM's  $h^{(i)}$  and DBM's  $v^{(i+1)}$ .  $m^{(0)}$  represent the input layer of the whole network. The energy is defined on each layer unlike the DBM as each layer denoted the individual RBM. The energy for l-th layer is given as

$$E(m^{(l)}, m^{(l+1)}; \theta^{(l)}) = -b^{(l)\top} m^{(l)} - c^{(l)\top} m^{(l+1)} - m^{(l)\top} MW^{(l)} m^{(l+1)} \quad (1)$$

Here  $MW$  denoting the mutual weights,  $b$  represent the visible units' biases and  $c$  represent the hidden units' biases. The upward and downward data passing is given as in RBM model

$$p(m_j^{(l+1)} = 1 | m^{(l)}) = \sigma(\sum_i m_i^{(l)} MW_{ij}^{(l)} + c_j^{(l)}) \quad (2)$$

$$p(m_i^{(l+1)} = 1 | m^{(l+1)}) = \sigma(\sum_j m_j^{(l)} MW_{ij}^{(l)} + b_i^{(l)}) \quad (3)$$

$p(m_j^{(l+1)} = 1 | m^{(l)})$  and  $p(m_i^{(l+1)} = 1 | m^{(l+1)})$  are the upward and downward data passing models for the l-th layer with j-th feature. Based on this model, the output obtained from the DRBM given to the sentence2vec model for training. It provides the sentence vectors to be used as fine features for learning using TFMA-DRL.

### C. Targeted sentiments extraction

First the targets are extracted using the stock price increasing or decreasing keywords. These keywords are assigned as specialized target to extract the targeted sentiments. The input data  $x$  is mapped to the hidden layer  $H$  using the mapping function  $H = a(Wx + b)$  where  $W$  denote the input weight matrix,  $a(\cdot)$  denote the activation function and  $b$  represent the bias vector. The hidden layer is plotted into the remodelled input vector  $\hat{x} = a(W'H + b')$  using the modified metrics  $W'$  and  $b'$ . The training process of the ELM parameters is performed by minimizing the remodelling errors

between the actual input and encoded outcomes. The parameters of IELM are derived similar to the traditional ELM [26]. For the N training data samples with input X and output O with varying dimensions, the estimated function can be learned through the computation of the output weights. The training stage consists of two processes: the random mapping and least squares constraints solving. The random mapping process is to build the hidden layer with random neurons which are mapped using sigmoid function.

$$H(x) = \{1 + \exp[-(W^T x + b)]\}^{-1} \quad (4)$$

In this hidden layer, the output vector is modelled as  $H(x) = R^{N \times \xi}$ , where r is the dimension of variables and  $\xi$  denote the number of hidden nodes. The output can be modelled as

$$\hat{o}_n = H(x_n)\gamma, \quad n = 1, 2, \dots, N \quad (5)$$

Here  $\gamma$  is the output weight of the hidden layer. It can be achieved by reducing the cost function  $\Gamma_{IELM}$

$$\min_{\gamma \in R^{H \times r}} \Gamma_{IELM} = \|O - \hat{O}\|^2 = \|O - H\gamma\|^2 \quad (6)$$

The output weight can be modelled using least squares constraints solving to obtain the modified weights

$$W'\gamma = H^\dagger O \quad (7)$$

Where  $H^\dagger$  denote the Moore–Penrose generalized inverse of H.

The training process of the IELM is performed which uses the samples  $(X, Y)$  and employs the fully connected multi-layered network structure. The constraints of the IELM are determined by the training process ensured by hunting behaviour optimization SHO [10] based parameter optimization and then the classification can be performed directly. The process of applying the SHO to the ELM is briefly provided in Algorithm 1.

**Algorithm 1: SHO based IELM for targeted sentiments extraction**

**Input:** ELM parameters, N= Tweets, F= Total features, f= feature subsets

**Output:** Targeted tweet sentiments

**Begin**

Set the variables of initial population, iterations, number of classes

Fetch the targeted keywords

**While** iterations =1

**For**  $h = 1$  hidden layer

Construct the network using Eq. (4)

Assign parameters (Weights, bias and number of hidden layers nodes) as spotted hyena subsets

Cluster search space

Estimate the fitness value (Accuracy of ELM)

Compare with other hyena

**If** fitness of (i+1)-th hyena > fitness of i-th hyena

Assign  $i \leftarrow i + 1$

**Else**

Check next hyena

**End if**

Rank the hyena based on descending fitness

Update the solutions

Return best solution (Weights, bias and number of hidden layers nodes)

**End for**

Train the network using training data

Determine the output weights using Eq. (7)

Perform ELM classification based on targets

Return targeted sentiments

Iteration = iteration + 1

**End while**

**End**

**D. Tolerant Flexible Multi-Agent Deep Reinforcement Learning (TFMA-DRL) model**

The proposed TFMA-DRL model is formulated using the tolerance policy [27] and adaptive/flexibility policy [28] to the generalized multi-agent DRL. Fig.2 shows the application of tolerance and flexibility policies to the deep Q-networks to form the TFMA-DRL.

Let  $\theta$  be the function estimate constraint of Q-networks,  $a_t$  is the action from action set A and  $s_t$  is the state of function built on bootstrapping the instant consequences of the restructured Q-function. The instant consequence  $r_{t+1}$  attained in instant state  $s_{t+1}$  from the next state consequence is given by the Q-function for the bootstrap target  $v_t^Q$  adding the instant consequence next state. The tolerance policy is applied to the multiple agents to avoid the comparative overgeneralization as in [9]. The tolerance also improves the probability of convergence to obtain global optimal solution for the agents.

The tolerance amount is assessed at time t within a indicated tuple  $(s_{t-1}, a_{t-1}, r_t, s_t, tol(s_t, a_t)_t)$  using the temperature value Temp and the associated hash-key  $\phi(s)$  for the state-action pair  $(s, a)$ .

$$tol(s, t) = 1 - e^{-K * Temp(\phi(s), a)} \quad (8)$$

Here  $(\phi(s), a)$  is represented to the temperature value by a dictionary and the hash-keys are assessed. The temperature decay value is also estimated as in [9] and integrated to learn the model.

Similarly, the flexibility policy is applied by the action-state model of Q-network. First the multiple policies of the network is learned. Given a scenario  $z \in Z$ , the gradient of the policy  $\mu_i^z$  corresponding to the parameter  $\theta_i^z$  is given by

$$\nabla_{\theta_i^z} J(\mu_i^z) = \mathbb{E}_{x, a \sim \mathcal{D}^z} [\nabla_{\theta_i^z} \mu_i^z(a_i | q_i) \nabla_{a_i} Q_i^{\mu, z}(x, a_1, \dots, a_N)] \quad (9)$$

Here  $\mathcal{D}^z$  denotes the experience replay buffer of tuples. The centralized action-value function  $Q_i^{\mu, z}$  is updated as

$$\mathbb{E}_{x, a, r, x'} [(Q_i^{\mu, z}(x, a_1, \dots, a_N) - y)^2] \quad (10)$$

$$y = r_i + \gamma Q_i^{\mu', z}(x', a'_1, \dots, a'_N) \quad (11)$$

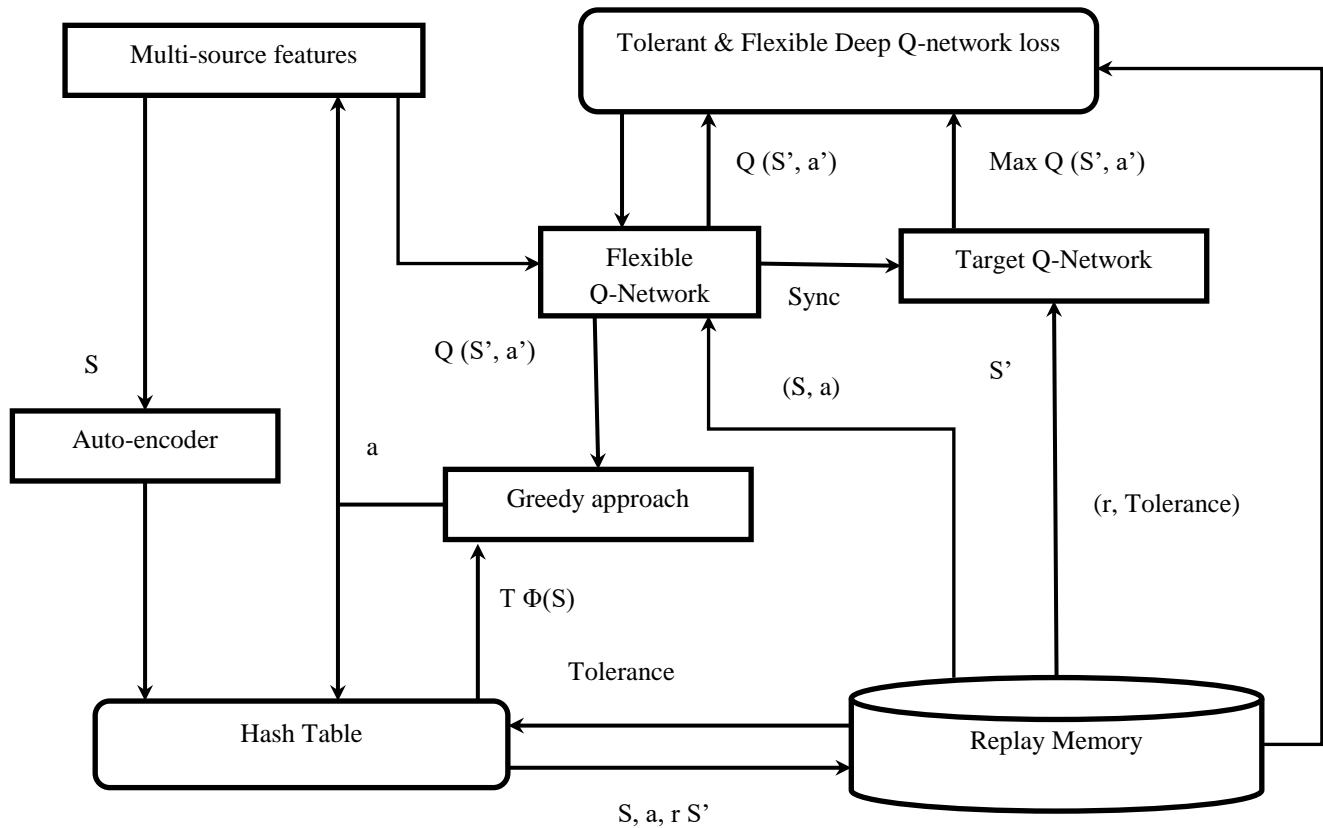


Fig.2. Architecture of TFMA-DRL

$\tau_i$  is the adjustment factor value,  $\gamma$  is the output weight of the hidden layers and  $\mu'$  denotes the set of target policies with delay  $\theta'$ . The policies are trained with the DRL and the one which gives perfect solution to the data samples is flexibly selected. The cross entropy loss function is minimized to update the network parameters flexibly

$$\nabla_{\mu_i} J(\phi_i) = \mathbb{E}_{(h_i, \mu_i)} \left[ \sum_{t=1}^T \sum_{\mu_i'} -y^{\mu_i'} \log(p_i^t(\mu_i')) \right] \quad (12)$$

Here  $y^{\mu_i'} = \begin{cases} 1, & \mu_i' = \mu_i \\ 0, & \mu_i' \neq \mu_i \end{cases}$  and  $p_i^t = \phi_i(q_i^t, h_i^{t-1})$ .  $p_i^t$  is the policy distribution,  $t$  is the time step,  $\phi_i$  is the predictor parameter, and  $(q_i^t, h_i^{t-1})$  is the function based on input observations  $q_i^t$  and last-step history  $h_i^{t-1}$ . This procedure lasts until the required training results are obtained and then the network structure is finalized. Algorithm 2 summarizes the procedures in TFMA-DRL.

**Algorithm 2: TFMA-DRL model for stock price forecasting**

**Input:** Quantitative, hieratical events and targeted sentiment features, learning rate  $\alpha$  and  $\beta$ , number of agents, weight  $\theta$ , Maximum iterations, Initial  $Temp$ ,  $t$   
 $t \leftarrow 0$   
 Set all agents  
**For** iteration  $iter = 0, iter\_max$  **do**  
 Rearrange gradients  $\nabla_{\theta_t}$  and  $\nabla_{\theta_i^z}$   
 Coordinate weights  
 Get sample tuple from ERM for all agents  
**Repeat**

**For** each agent  
 Evaluate the loss function, data training ratio  
 Sample action  $a_t$  at state  $S_t$   
 Plot each state-action pair to system agents  
 Form relationship map  
**End for**  
 Take action  $a_{t+1}$  for all agents  
 Estimate tolerance amount for each state  
 Apply flexibility policy  
 Select best policy with  $\mathbb{E}_{x, a, r, x'}$   
 Model outcomes  $r$   
 $t \leftarrow t + 1$   
**Until** end state for all agents  
 Update weights for all agents  
 Return gradients and loss  
**End**

**IV. RESULTS AND DISCUSSIONS**

The investigation has been carried out on the proposed TFMA-DRL model based stock forecasting using the three source data such as Tweets, news articles and stock index prices, in MATLAB tool. The performance of the TFMA-DRL is compared with that of the TMA-DRL [9] in terms of accuracy, precision, recall, F1- score and execution time and the results are tabulated. Table.1 shows the forecasting results obtained for the proposed TFMA-DRL and the TMA-DRL.

Table- I: TFMA-DRL vs. TMA-DRL

Metrics	TMA-DRL	TFMA-DRL
Accuracy (%)	79.778	90.00
Precision (%)	80.04	98.9
Recall (%)	80.60	90.00
F1-score (%)	89.50	94.7368
Time (seconds)	151.95	135.0085

From table 1, it can be seen that the performance of the proposed TFMA-DRL is better than the TMA-DRL model for efficient stock price forecasting.

Apart from the TMA-DRL model, the proposed model is compared with other existing algorithms namely SVM, ANN, ELM and MIL [20]. SVM and ANN are the commonly employed baseline methods while Elm is considered more in recent researches for stock prediction. The MIL is the latest approach performing stock forecasting from multi-source data.

Fig.3 displays the accuracy evaluation of the suggested TFMA-DRL model against the prevailing stock prediction models. From the comparison, it is apparent that the suggested TFMA-DRL has higher accuracy than the existing models. TFMA-DRL has accuracy of 90% and it is 10.22% greater than TMA-DRL, 17.45% higher than MIL, 21.45% larger than ELM, 27.72% more than ANN and 30.55% higher than SVM.

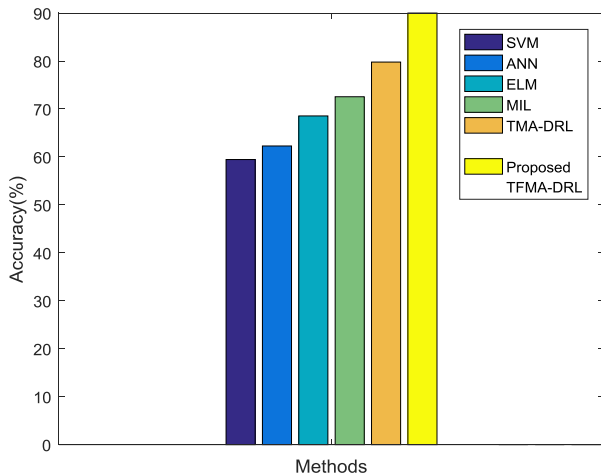


Fig.3. Accuracy Comparison

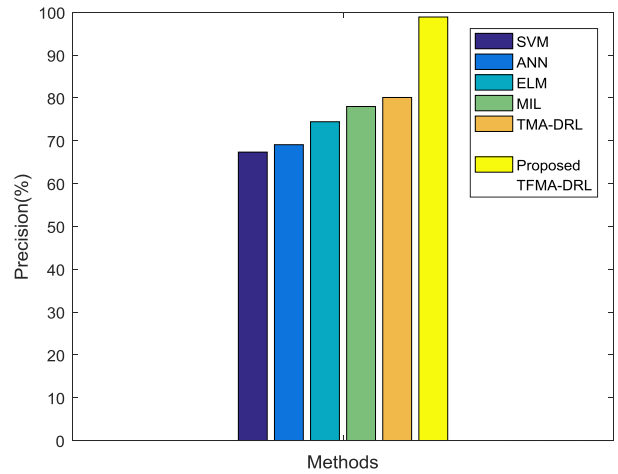


Fig.4. Precision Comparison

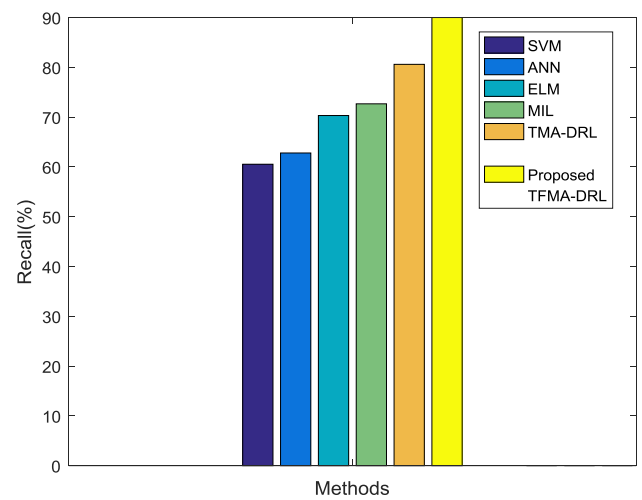


Fig.5. Recall Comparison

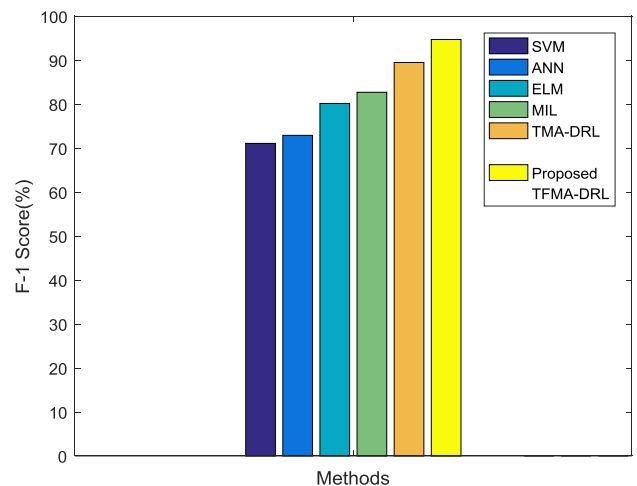


Fig.6. F1-score Comparison

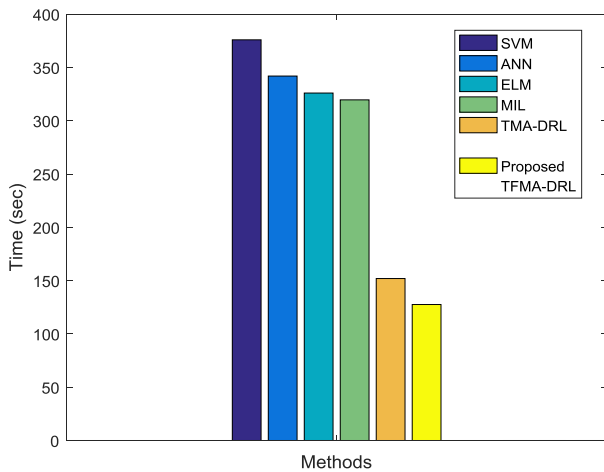


Fig.7. Time Comparison

Fig.4 shows the precision evaluation of the suggested TFMA-DRL against the existing models. TFMA-DRL has high precision of 98.9% which is 18.8% greater than TMA-DRL, 20.9% higher than MIL, 24.5% larger than ELM, 29.4% more than ANN and 31.6% higher than SVM.

Fig. 5 shows the recall evaluation of the suggested TFMA-DRL against the prevailing models. The results show that the TFMA-DRL has high recall than other models. TFMA-DRL has recall of 90% and it is 9.4% greater than TMA-DRL, 17.3% higher than MIL, 19.81% larger than ELM, 27.2% more than ANN and 29.46% higher than SVM.

Fig. 6 illustrates the f1-score evaluation of the suggested TFMA-DRL based stock forecasting model against the existing models. The plot results show that the TFMA-DRL has high f1-score than other IDS models. TFMA-DRL has f1-score of 94.7368% which is 5.2% greater than TMA-DRL, 12% higher than MIL, 14.52% larger than ELM, 21.8% more than ANN and 23.6% higher than SVM.

Fig.7 illustrates the processing time evaluation for the suggested TFMA-DRL model against the prevailing models. The main evaluation of this research study is to decrease the time complexity. From the figure, it is proved that the time complexity of the suggested TFMA-DRL is very less. TFMA-DRL consumes 135.0085 seconds for the whole stock price forecasting process which is significantly less than the other compared models. The main reason for this enhancement is the use of superior design approach of TFMA-DRL using the deep learning architecture with tolerance and flexibility policies.

## V. CONCLUSION

Future stock market price trends forecasting is a vital research area that has significant scope in business planning and nation's economy building process. This paper suggested the used of hierarchical events and targeted sentiments extracted from the news articles and tweets, respectively to learn the stock price variations. DRBM and IELM with SHO were used for the event extraction and sentiment analysis. These stock indicators are fed to the learning model of TFMA-DRL to predict the stock price movements more accurately and within less time. The integration of tolerance and flexibility policies to the deep reinforcement learning has results in increased accuracy of 90% for stock price

forecasting. This approach has also reduced the time complexity considerably with minimum training time. In future, the other policies like cooperation in deep reinforcement learning will be investigated. In addition, the possibility to include additional indicators from other sources like research articles will also be analysed to improve the accuracy further without increasing the complexity.

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