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Prediction and Analysis of International Trade Data Based on Deep Learning

Abstract: **-** There are several interrelated factors at play behind the scenes that contribute to unpredictable changes in stock prices. Global economic statistics, shifts in unemployment rate, monetary policies of influential nations, immigration laws, natural catastrophes, public health issues, number of other factors might all be contributing factors. Everybody involved in stock market wants to increase earnings, lower risks due to careful analysis of market. The main difficulty is compiling the diverse data, placing it in a single basket, and building a trustworthy model to produce precise forecasts. In this manuscript Prediction and Analysis of International Trade Data Based on Deep Learning (PA-ITD-DTG-MG-CRN) is proposed for Prediction and Analysis of ITD. The data for proposed PA-ITD-DTG-MG-CRN method collected from Import Genius Trade Dataset and the input data is pre-processed using a Multi-Window Savitzky-Golay filter (MWSGF) for Tokenization, removing stop words and text vectorization for prediction and analysis. The Dual Temporal Gated Multi-Graph Convolution Recurrent Network (DTG-MGCN) is expected and analyzes data related to International trade, classifying it into groups such as financial data, KYC data, global trade data, bank data. Therefore, that the DTG-MGCN does not include explicit optimization procedures to guarantee precise forecasting and analysis of data related to International trade data and the Giraffe Kicking Optimization Algorithm (GKOA) is used for enhance the performance of the DTG-MGCN by optimizing its parameters, thereby increasing its accuracy in prediction, analyzes of the International trade data. The effectiveness of the proposed PA-ITD-DTG-MG-CRN method is analyzed with performance metrics likes accuracy, precision, sensitivity, specificity, FI-score, computational time, error rate. Proposed PA-ITD-DTG-MG-CRN method achieves 31.89%, 25.45% and 19.32% higher accuracy, 32.12%, 23.49%, 30.94% higher precision and 26.87%, 34.65%, 23.94% lower error rate when analyzed with existing methods such as Prediction Method of International Trade Risk Depend on Stochastic Time-Series Neural Network (PM-ITR-STSN), novel ensemble deep learning method for stock prediction depend on stock prices and news (NEDL-SP-SPN) and predicting stock market index utilizing LSTM (PDT-STI-LSTM) respectively.

Keywords: Bank Data, Dual Temporal Gated Multi-Graph Convolution Recurrent Network, Financial Data, Giraffe Kicking Optimization Algorithm, Global trade Data, Import Genius Trade Dataset, International Trade Data, KYC Data, Multi-Window Savitzky-Golay filter.

I. INTRODUCTION

International trade data analysis and prediction is a difficult undertaking that requires the use of sophisticated techniques, such as statistical modeling and advanced machine learning. These methods are used by experts and researchers in this field to enhance decision-making processes, spot possible trends, and provide deep insights into trade patterns. Predictive modeling is one method that makes use of previous data to forecast future trading patterns [1-3]. Trade volume forecasting is made possible by utilize of ML methods likes NNs, regression models, time series analysis. These models also help in evaluating the effects of different economic variables on the dynamics of International commerce as well as identifying significant elements influencing trade patterns [4-6]. In addition, the examination of foreign trade data goes beyond simple forecasting and investigates hidden trends and connections [7-9]. Finding groups of nations with comparable trade patterns, spotting anomalies, and figuring out the relationships between various economic indicators are all made possible by employing strategies like data visualization, exploratory data analysis, and clustering algorithms [10-12]. The use of natural language processing (NLP) techniques has become more popular recently as a means of gaining insightful information from textual data related to International trade. Researchers may get a sophisticated knowledge of the different aspects impacting the dynamics of International commerce by using sentiment analysis and topic modeling on sources including news stories, policy papers, and economic reports [13-15]. To sum up, utilizing cutting-edge analytical methods greatly improves our understanding of International trade [16-18]. It is simpler for stakeholders to create policies that promote cooperation and

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economic progress, adjust to changes in the market, and make well-informed judgments [19, 20]. As technology progresses, it will be possible to combine machine learning, data analytics, and natural language processing in a way that is even more dynamic and informative for the world of International trade.

This paper's problem statement focuses on the inherent difficulties in analyzing and forecasting data related to International commerce. Because of this task's intricacy, advanced machine learning and statistical modeling are just two of the sophisticated approaches that must be applied in order to give thorough insights into trade patterns.

The complex dynamics of projecting future trading patterns still require attention even with the use of predictive modeling, which combines techniques like neural networks, regression models, and time series analysis. Furthermore, more effort has to be put into uncovering hidden patterns and linkages in International trade data, especially when it comes to spotting abnormalities and comprehending the links between different economic indicators. Furthermore, even if the use of natural language processing (NLP) techniques has grown in popularity recently, there is still a need to improve these approaches in order to get a more nuanced knowledge of the variables influencing the dynamics of International commerce. By addressing these issues, the area of International trade analysis and forecast will advance and make it possible to formulate better policies, make better decisions, and adjust to changing market conditions.

Major contribution of this paper a follows;

- Prediction and Analysis of International Trade Data Based on Optimized Dual Temporal Gated Multi-Graph Convolutional Recurrent Network (PA-ITD-DTG-MG-CRN) is proposed.
- Here, the data is collected from Import Genius Trade Dataset.
- The dataset sourced from Import Genius Trade Dataset was employed in conducting Tokenization, removing stop words and text vectorization in pre-processing using the Multi-Window Savitzky-Golay filter (MWSGF).
- In International trade data prediction, the Dual Temporal Gated Multi-Graph Convolution Recurrent Network (DTG-MGCN) emerges as a prominent technique. DTG-MGCN’s primary function lies in effectively classifying the International trade data categories into financial data,KYC data,global trade data, bank data. It accomplishes this by leveraging the pre-processed data from the MWSGF.
- To further enhance the performance, DTG-MGCN utilizes the Giraffe Kicking Optimization Algorithm (GKOA) to fine tune and optimize its predictive accuracy.

Remaining portion of this work structured as below: section 2: literature survey, section 3: describes proposed methodology, section 4: illustrates outcomes with discussion, section 5: conclusion.

II. LITERATURE REVIEW

In 2022, Xu and Dong [21], have presented PM of ITR depend on Stochastic Time-Series Neural Network. In this research, a risk prediction model using BP and ARIMA neural networks is designed and proposed. The model is capable of making accurate predictions across several time series and successfully mitigating risk. With the aid of BP neural network method, ARIMA, method presented optimizes structure of design method and offers high accuracy, error control for various time series. Goal of creating a time series prediction method was to increase model's prediction accuracy; also, it is a useful method for making the prediction model more feasible. The inter-sequence analysis approach has several potential applications and can significantly increase efficiency and reduce costs when used to financial risk prediction.

In 2022, Li and Pan [22], have suggested NEDL method for SP depend on stock prices with news. This research presents revolutionary DL technique for stock movement prediction in future. The model combines two RNNs with fully connected neural network using blended ensemble learning. Utilize S&P 500 Index as a test case for this study. Utilizing same dataset, studies demonstrate that blended ensemble DL model works significantly better than the best current prediction model, lowering the MSE from reduction, raising precision, recall, F1-score, movement direction accuracy. The aim was to elucidate this design philosophy, demonstrate that, in comparison to other conventional approaches, ensemble DL technologies really forecast future stock price patterns more accurately, help investors make better investment decisions.

In 2022, Bhandari and et.al [23], have suggested predicting stock market index utilizing LSTM. The research predicts closing price of S&P 500 index next day using specific NN architecture called LSTM. To capture behaviour of stock market in larger sense, well-balanced combination of nine predictors was carefully created within the purview of technical indicators, macroeconomic data, fundamental market data. The selected input variables were utilized to create single-layer, multilayer LSTM methods, their performances are evaluated using the conventional metrics of correlation coefficient, MAPE, RMSE. In comparison to multilayer LSTM models, experimental findings demonstrate that single layer LSTM method attains better fit, higher prediction accuracy.

In 2022, Talagala and et.al [24], have presented feature-depend forecast method performance prediction. A time series forecast model performance prediction meta-learning approach is presented in this research. The model models forecast error based on time series characteristics by using Bayesian multivariate surface regression in the method. Which forecasting model or combination is used in the end is determined by the smallest anticipated error. Feature-based time series simulation, or GRATIS, is used to enrich the reference dataset to enhance representativeness of training data. With a lower computational cost and more interpretability than previous methods, the framework performs comparably when tested on M4 competition data. It offers information on several aspects of forecasting performance, including model selection and meta-learner methods.

In 2023, Wu et.al [25], have presented, A graph-depend CNN-LSTM stock price prediction process with leading indicators. This paper suggests a novel framework structure that combines LSTM-CNN to provide a stock price prediction that was more accurate. The name of this new technique is stock sequence array convolutional LSTM, rather fittingly. It creates sequence array from historical data, its leading indicators (futures, options), utilizes it as CNN framework's input image, extracts specific feature vectors from the convolutional, pooling layers, and uses those vectors as the LSTM's input vector. Ten stocks from Taiwan and the United States are used as the experimental data. When directly compared to earlier techniques, the suggested algorithm in this article produces greater prediction performance.

In 2022, Chhajer and et.al [26], have suggested, applications of ANNs, SVM, and LSTM for stock market prediction. An overview of ML, AI as tools for predictive analytics in stock market is provided by this paper. In addition to discussing the benefits and drawbacks of utilizing ML to anticipate stock market movements, it sheds light on potential advantages and disadvantages of using cutting-edge technology in this field. This study delves further into the ways that three machine learning technologies—LSTM, support vector machines, and ANNs—are utilized in the prediction of stock markets.

In 2022, Banik and et.al [27], have presented, LSTM depend decision support system for swing trading in stock market. In order to help swing traders with their analysis and prediction of future stock prices, LSTM enforced Decision Support System is built in this paper. In addition to other technical indicators like MFI, relative RSI, stock price's support, resistance, five Fibonacci retracement levels, company's and NIFTY industry average stock price's MACD and SIGNAL LINE analysis, Decision Support System creates report that includes expected values of company stock for next 30 days. The investment selections made by the trader might be enhanced by investment success score found in report.

III. PROPOSED METHODOLOGY

In this section, a Prediction and Analysis of International Trade Data Based on Optimized DTG-MGCN is discussed. In proposed methodology section dataset, network and optimization are described. The inter-sequence analysis approach has several potential applications and can significantly increase efficiency and reduce costs when used to the prediction of International trade data. The proposed PA-ITD-DTG-MG-CRN prediction model aims to increase the model's prediction accuracy and is a useful method of increasing the model's practicability. Block diagram of proposed PA-ITD-DTG-MG-CRN is given below in figure 1,

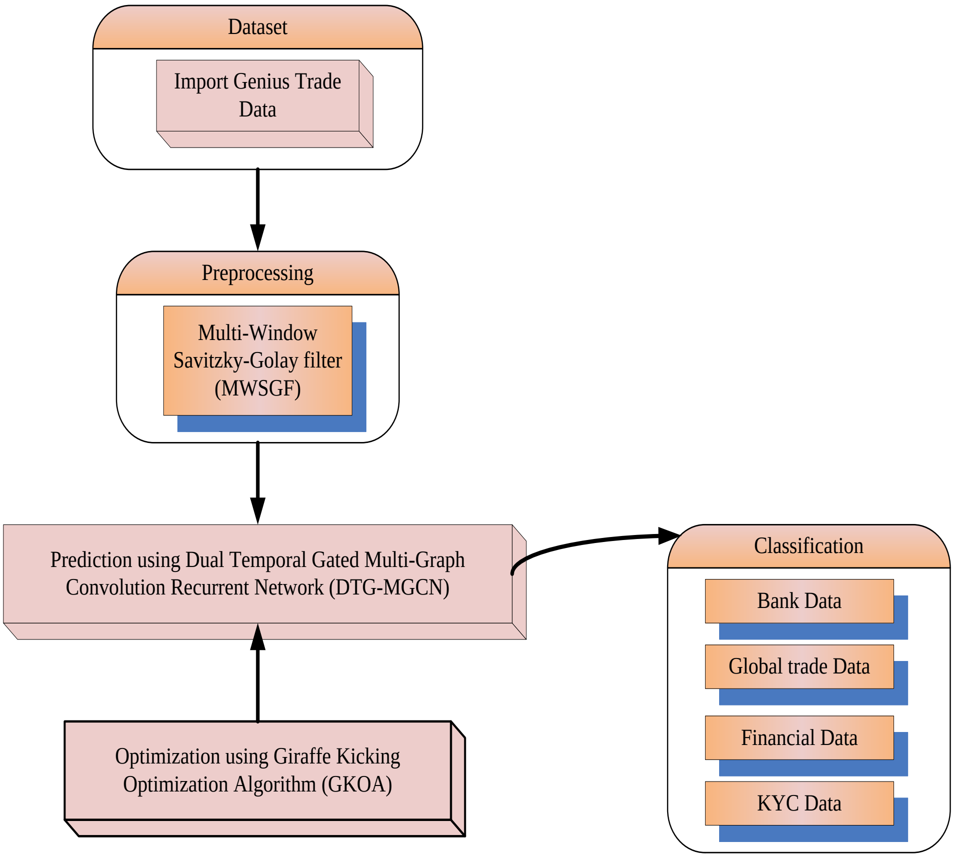

Figure 1: Block diagram of proposed PA-ITD-DTG-MG-CRN

A. Data Acquisition

In this section the Import Genius Trade Dataset [28] is discussed. Import Genius is a top supplier of market intelligence tools and import/export data, enabling companies to make wise choices in the context of International commerce. Import Genius Dataset's extensive database and cutting-edge analytics tools help businesses reduce risks, find new business possibilities, and obtain a thorough understanding of International trade activity. Additionally, these data go beyond simple raw data and offer sophisticated analytics tools that enable firms to glean insightful information from the data and convert it into actionable knowledge. This information aids in determining a company's history of International commerce, including the nations and businesses with whom it has transacted, the goods it has imported or exported, and the volume of goods it has handled. Governments, banks, investment firms, and other financial institutions have utilized this data for risk profiles, background checks on companies through KYC, and investigations into company's trade volume, product strategy or risk tolerance for possible investment possibilities.

B. Pre-processing using Multi-Window Savitzky-Golay filter

In this section, MWSGF [29] is discussed. The MWSGF gathered the data from Import Genius Trade Dataset for pre-processing. In pre-processing the collected data used by MWSGF for Tokenization, removing stop words and text vectorization for prediction and analysis. The SG filter is convolution that simplifies least-squares fitting and is used to smooth and calculate the derivatives of a series of successive values. Convolution may be thought of as weighted moving average filter where the weights are specified by degree-specific polynomial. From the raw values, a set of apparent resistivity data points may be analyzed. Assume this method have a degree polynomial and a symmetric window of size. Thus it is given the equation (1),

$$Q(j) = \sum_{l=0}^{o} b_l j^l \tag{1}$$

Here, $Q(j)$ represent the polynomial at the central point, o represent the polynomial degree, j denotes the iterations and b_l denotes the kth weight coefficient. The residual function that is minimized in each window is as follows: equation (2),

$$\delta_o = \sum_{j=-N}^{N}(Q(j)-y[j])^2 = \sum_{j=-N}^{N}\left(\sum_{l=0}^{o} b_l j^l - y[j]\right)^2 \quad (2)$$

Here, $Q(j)$ represent the polynomial at the central point, δ_o represent the residual function, $y[j]$ represent the data point, o represent the polynomial degree, j denotes the iterations, N denotes half width of window, b_l denotes the kth weight coefficient. In order to calculate filter output, window slides point by point. Input data points are convolved in windows by fixed impulse response in this procedure. As a result, the filter output may be expressed in equation (3),

$$z(l) = \sum_{j=-N}^{N} \omega_j y[l-j] = \sum_{j=-N}^{N} \omega_{l-1} y[j] \quad (3)$$

Here, ω_j denotes the fixed impulse, j denotes the iterations, N denotes the half width of the window and $y[j]$ represent the data point. This approach differentiates the residual function with respect to the vector to obtain the weight coefficients vector and of the polynomial. It then sets the derivatives to zero; it is shown in equations (4),

$$\sum_{l=0}^{o}\left(\sum_{j=-N}^{N} j^{k+l} b_l\right) = \sum_{j=-N}^{N} j^k y[j], \; k = 0,1,,.....,o \quad (4)$$

Here, o represent the polynomial degree, j denotes the iterations and b_l denotes the kth weight coefficient, N denotes half width of window, $y[j]$ represent the data point. Determine the vector of the data point. Equation (4) may be expressed as a matrix, as illustrated in equation (5),

$$(B^U B)b = B^U y \quad (5)$$

Here, B^U represent the matrix, b denotes the weight coefficient and y denotes the data point. Matrix is shown in equation (6),

$$B^U = \begin{bmatrix} (-N)^0 & \cdots & (-1)^0 & 1 & 1^0 & \cdots & N^0 \\ (-N)^1 & \cdots & (-1)^1 & 0 & 1^1 & \cdots & N^1 \\ (-N)^2 & \cdots & (-1)^2 & 0 & 1^2 & \cdots & N^2 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ (-N)^o & \cdots & (-1)^o & 0 & 1^o & \cdots & N^o \end{bmatrix} \quad (6)$$

Here, B^U represent the matrix, N denotes half width of window, o represents polynomial degree. After that, the weight coefficient vector may be obtained using equation (7),

$$b = (B^U B)^{-1} B^U y = B * y \quad (7)$$

Here, B^U represent the matrix, b denotes the weight coefficient and y denotes the data point. The matrix is independent of input data points in window and only depends on size of the window, degree of polynomial. Therefore, the polynomial coefficients of all the windows are the same. Two important SG filter parameters are window size and polynomial degree, as was previously indicated. Generally, it is preferable to maximize window size though keeping polynomial degree. Using this strategy, MWSGF pre-processes the acquired data for tokenization, eliminating stop words, and vectorizing the text for analysis and prediction.

C. Prediction using Dual Temporal Gated Multi-Graph Convolutional Recurrent Network

In this section DTG-MGCN [30] is discussed. DTG-MGCN is using the pre-processed data from MWSGF for predict and analyze the International trade data. The DTG-MGCN extracts the graph vertexes and correlations are represents graph edges that are mathematically indicated by adjacency matrices. The correlation between network vertices is represented by the adjacency matrix. It is the basis for aggregating geographical information and key to operating graph convolution. The neighbour-hood graph, which represents the physical distance between locations, the functional similarity graph, which represents functional similarity between locations depend on POI data, landscape similarity graph are the three types of correlations that are taken into consideration in this work and converted into the corresponding graph. The Euclidean distance between any two locations' centers in a neighbourhood graph indicates how close they are to one another spatially. Equation (8) defines a criterion that determines if they are adjacent.

$$B_{O,jk} = \begin{cases} 1, & dis(wj, wk) \le M \\ 0, & otherwise \end{cases} \tag{8}$$

Here, $B_{O,jk}$ represent the neighbourhood graph, w_j and w_k are denotes the places and M represent the graph laplacian. Each item in the vector represents number of points that belong to associated category and the vector's size is equal to functional categories. In a similar vein, this compute landscape similarity graph utilizing static street view photos, as indicated by equation (9),

$$B_{M,j,k} = sim\left(T_{w_j}, T_{w_k}\right) \in [0,1] \tag{9}$$

Here, $B_{M,j,k}$ represent the landscape similarity graph and T_{w_j}, T_{w_k} denotes street view feature vectors of place w_j, place w_k respectively. It uses the created graph and multi-graph convolution to simulate spatial link seen in equation (10),

$$Y_{m+1} = \bigcup_{B \in \overline{B}} \left(\sigma f\left(B; \theta_j\right) Y_m X_m\right) \tag{10}$$

Here, Y_m and Y_{m+1} are represent feature vectors of places in layer m and $m+1$, σ represent activation function, $\overline{B}$ represents set of graph and $f(B;\theta j)$ denotes the aggregation matrix based on graph. While the linear results in ST-MGCN are aggregated prior to the activation function, the convolution results from several graphs are combined in this study after activation function. This adjustment better maintains integrity of various correlation graphs. To represent temporal interdependence between historical observations in prior timestamps, periodic timestamps, in temporal correlation modeling, use dual temporal gated branches. After that, integrate the encoded findings. Equation (11) illustrates how graph convolution operation by max degree and related graph laplacian matrix are used to produce the information aggregation.

$$\widehat{Y}^{(u)} = \left[Y^{(u)}, G_H^{L'}\left(Y^{(u)}\right)\right] \quad u = 1,2,\ldots U \tag{11}$$

Here, $Y^{(u)}$ denotes the t-th observation, $G_H^{L'}$ represent the graph convolution operation, L' denotes the max degree and U represent the temporal observation. Second, the summary of every temporal observation is generated by applying global average pooling over all areas. Each timestamp's contextual data is further aggregated by it. As seen in equation (12),

$$a^{(u)} = G_{pool}\left(\widehat{Y}^{(u)}\right) = \frac{1}{|W|} \sum_{u=1}^{|W|} \widehat{Y}_{j,:}^{(u)} \quad u = 1,2,..U \tag{12}$$

Here, a represent the vector, $\widehat{Y}_{j,:}^{(u)}$ denotes the t-th observation, U represent the temporal observation and G_{pool} represent the global average pooling. Equation (13), which applies an attention action to the summed vector,

$$t = \sigma\left(X_2 \delta\left(X_1 a\right)\right) \tag{13}$$

Here, X_1 and X_2 are denotes the trainable weights, δ represent the ReLU, σ denotes the sigmoid function and t denotes the reweighting factor. Lastly, in equation (14) the reweighting factor is applied to the original historical input.

$$\overline{Y}^{(u)} = Y^{(u)} \circ t^{(u)} \tag{14}$$

Here, $Y^{(u)}$ denotes the t-th observation, t denotes the reweighting factor and $\circ$ denotes the dot product. The gated sequence in various timestamps of an area is encoded into a single vector using a common RNN layer with weight across all regions after contextual gating. Equation (15) therefore expresses the production of a single vector using LSTM.

$$I^{H}_{j,:} = LSTM\left(\bar{Y}^{(u)}_{j,:}, \bar{Y}^{(u+1)}_{j,:}, \bar{Y}^{(u+2)}_{j,:}, \ldots, \bar{Y}^{(U-1)}_{j,:}, \bar{Y}^{(U)}_{j,:}; X_3\right) \tag{15}$$

Here, $I^{H}_{j,:}$ represent the single vector, $\hat{Y}^{(u)}_{j,:}$ signifies t-th observation, U represents temporal observation, $LSTM$ denotes data continuity in temporal dimension and X_3 denotes the weight.It appears that the dynamic patterns of taxi needs are mostly expressed by the observations made from periodic timestamps. Consequently, this technique adds a second CGRNN branch that receives periodic data as input. It is shown in equation (16),

$$I^{QH}_{j,:} = LSTM\left(\bar{Y}^{(u')}_{j,:}, \bar{Y}^{(u'+q)}_{j,:}, \bar{Y}^{(u'+2q)}_{j,:}, \ldots, \bar{Y}^{(U-q)}_{j,:}, \bar{Y}^{(U)}_{j,:}; X_4\right) \tag{16}$$

Here, $I^{QH}_{j,:}$ represent the single vector, $\hat{Y}^{(u)}_{j,:}$ signifies t-th observation, U represents temporal observation, q represent the periodic interval, $LSTM$ denotes data continuity in temporal dimension and X_3 denotes the weight. Depending on the features of the data, the periodic interval can be configured to be one day, one week and so on. Afterwards, this technique combines the data from two branches to generate the final temporal encoded feature. It is shown in equation (17),

$$I^{E}_{j,:} = X^{H} I^{H}_{j,:} + X^{QH} I^{QH}_{j,:} + c \tag{17}$$

Here, $I^{E}_{j,:}$ represent the single vector, X^{H} denotes the weight and c denotes the bias. The data is pre-processed before being sent to the Network DTG-MGCN. Anticipating and analyzing data associated with International trade data and categorizing it into many areas, including financial, global trade, KYC data and bank data, is the aim of the advanced neural network architecture.

D. Optimization using Giraffe Kicking Optimization Algorithm

In this section, Giraffe Kicking Optimization Algorithm (GKOA) [31] is discussed. By tweaking its settings, GKOA is utilized to improve the DTG-MGCN's performance and raise its accuracy in data analysis and prediction related to International commerce. The GKOA is a unique meta-heuristic inspired by giraffe kicking behavior. The mother giraffe will lick the residual amniotic fluid off her new-born calf in the first few minutes of life as a sign of affection. Additionally, she will be observed encouraging the calf to stay by giving it three kicks in a row and taking its first steps, allowing the young giraffe to nurse for the first time. This is used for practical purposes including predicting and analyzing data from international trade.

Step 1: Initialization

The giraffe mother's method of kicking to wake the baby from its resting state is initially described in the inspiration. Giraffes are the tallest creatures on Earth; infant giraffes are taller than most people. Giraffes' great size serves as trans-formative adaptation enables them to survive on tall trees, other vegetable sources. A giraffe's mother would occasionally kick her new-born repeatedly to keep it active after giving birth. After a half-hour after birth, the new-born giraffe is eager to chase other giraffes in the vicinity for the following ten hours. Mother giraffes are in charge of patrolling borders of their area, alerting their offspring if they see any threats. Thus it is given the equations (18) and (19),

$$\vec{Em}\alpha = \left|\vec{G} \cdot \vec{LQ}(uj) - \vec{L}(uj)\right| \tag{18}$$

$$\vec{L}(uj+1) = \vec{LQ}(u) - \vec{X} \cdot \vec{Em}_{\alpha} \tag{19}$$

Here, uj represents current position of giraffe, $\vec{X}$ and $\vec{G}$ denotes the coefficient vectors, $\vec{Em}$ represent space among baby giraffe, mother giraffe, $\vec{LQ}$ position vector of baby and $\vec{L}$ position vector of giraffe.

Step 2: Random Generation

The weight parameters are formed randomly. The values generated randomly between 0 and 1.

Step 3: Fitness Function

Fitness function creates random solution form initialized values. It calculated using optimizing parameter. Thus it is shown in equation (20),

$$Fitness\ Function = optimizing\left[\hat{Y}_{j,:}^{(u)}\ and\ G_H^{L'}\right] \tag{20}$$

Step 4: Exploration phase

Information on obtaining or pursuing further prizes can be found via exploration. They separate to find the new-born giraffe and then reunite to kick it. By utilizing coefficient vectors with random features more important than the majority, the pursuing expert may be driven to seek from the baby giraffe; this technique beats PSO and SSA in multimodal capabilities. Moreover, GKOA performs aggressively compared to DE and GA and can even outperform them at times. These findings indicate that more investigation into the GKOA algorithm has promise. Vectors are determined in equation (21) and (22),

$$\vec{X} = 5 \cdot \vec{\alpha} \cdot \vec{s1} - \vec{\alpha} \tag{21}$$

$$\vec{G} = 5 \cdot \vec{s2} \tag{22}$$

Here, $\vec{X}$ and $\vec{G}$ denotes the coefficient vectors and $s1$ & $s2$ are denotes the arbitrary vectors or random vectors.

Step 5: Exploitation phase

Exploitation explains the moment at which a better or more convergent solution is obtained. Furthermore, the coefficient's vacillation choice is less. Stated differently, an uneven incentive in the interval [- 5a, 5a] is represented by coefficient [0, 1]. Where is reduced throughout periods from 5 to 0. With these administrators, the process tends to stall in close quarters. Giraffe can attain any state between the two designated positions with the use of random vectors. Therefore, by using equations (23), (24) and (25) giraffe enliven its location intimate space towards youngster in arbitrary zone.

$$\vec{Em}_{\alpha} = \left|\vec{G1} \cdot L\alpha - \vec{L}\right| \tag{23}$$

$$\vec{L}1 = \vec{L} - \vec{X} \cdot \left(\vec{Em}\alpha\right) \tag{24}$$

$$\vec{L}(uj+1) = \frac{\vec{L}1 + \vec{L}2 + \vec{L}3}{3} \tag{25}$$

Here, $\vec{Em}$ represents space among baby giraffe with mother giraffe, $\vec{X}$ and $\vec{G}$ denotes coefficient vectors, $\vec{L}$ position vector of giraffe and uj represents current position of giraffe. The GKOA optimization technique improves DTG-MGCN's capacity to predict and analyze data related to International trade data.

Step 6: Termination

In the DTG-MGCN, the weight parameters for generators are optimized using the GKOA, dynamically adjusting weights inspired by celestial mechanics. The iterative refinement, guided by halting criteria $\vec{Em}\alpha = \vec{Em}\alpha + 1$, ensures optimal weight convergence, maximizing DTG-MGCN's generator performance. Then flowchart of GKOA for optimizing the weight parameters of DTG-MGCN for enhances forecast, analysis of International trade data. Figure 2: shows Flowchart of GKOA for optimizing weight parameters of DTG-MGCN for improve prediction with analysis of International trade data

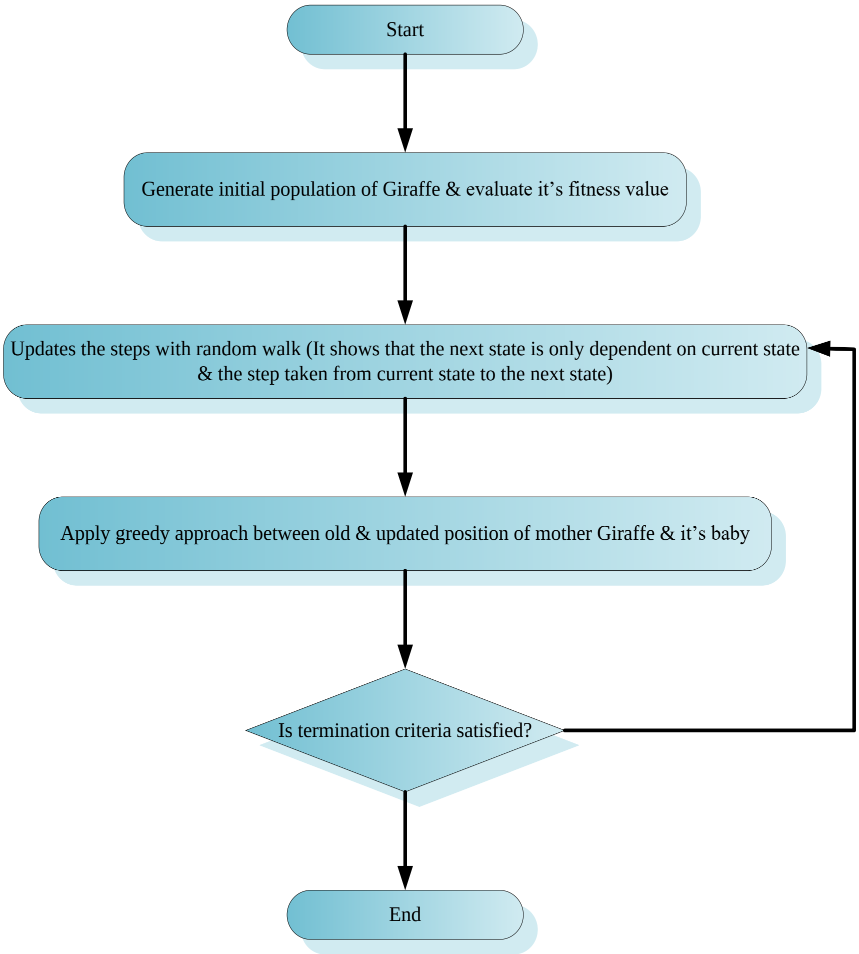

Figure 2: Flowchart of GKOA for optimizing weight parameters of DTG-MGCN for improve prediction with analysis of International trade data

IV. RESULT AND DISCUSSION

In this paper, Prediction with Analysis of ITD Based on Optimized Dual Temporal Gated Multi-Graph Convolutional Recurrent Network is discussed. The PA-ITD-DTG-MG-CRN technique is implemented in python and evaluated by utilizing numerous performance metrics such as accuracy, precision, sensitivity, specificity, FI-score, Computational time, error rate. The result of PA-ITD-DTG-MG-CRN approaches was compared with existing PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM techniques.

A. Performance measures

This is a crucial step for determining the exploration of optimization algorithm. Performance measures to evaluate to access performance likes accuracy, precision, sensitivity, specificity, FI-score, computational time, error rate.

1) Accuracy

The value of accuracy is calculated as ratio of the number of samples accurately categorized by scheme with total count of samples, it is given in equation (26),

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{26}$$

Here, TP denotes true positive, TN signifies true negative, FN denotes false negative and FP signifies false positive.

2) Precision

Precision computes number of true positives divided through true positives plus number, false positive number and it is given by the equation (27),

$$precision = \frac{TN}{FP + TN} \tag{27}$$

Here, TN denotes true negative, FP represents false positive.

3) F1 score

A popular statistic for assessing the performance of the model in binary classification issues is FI-score. The harmonic mean of recall and precision is what it is. It is shown in equation (28),

$$F1-score = 2\times\frac{\Pr ecision\times\operatorname{Re}call}{\Pr ecision+\operatorname{Re}call} \tag{28}$$

4) Computational time

It is amount of time required to complete computational process. A calculation is represents sequence of rule applications, with computation time proportional to number of rule applications.

5) Sensitivity

Sensitivity finds the proportion of positive instances and it is given in equation (29),

$$sensitivity = \frac{TN}{TN+FN} \tag{29}$$

Here, TP denotes true positive, TN signifies true negative, FN denotes false negative, FP denotes false positive.

6) Specificity

Specificity estimates proportions of negative, given in equation (30),

$$specificity = \frac{TP}{FN+TP} \tag{30}$$

Here, TP denotes true positive, FN signifies false negative

7) Error rate

It is used to scale degree of prediction error of method made regarding true method. It is given in equation (31),

$$Error\ Rate = 100 - Accuracy \tag{31}$$

B. Performance Analysis

Figure (3 to 9) depicts the simulation results of proposed PA-ITD-DTG-MG-CRN method proposed. Proposed PA-ITD-DTG-MG-CRN method is compared with existing as PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM methods.

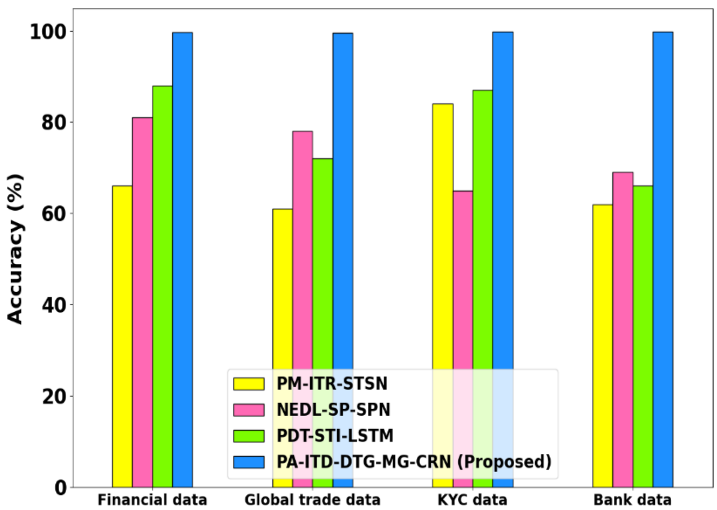

Figure 3: Accuracy analysis

Figure 3 depicts accuracy analysis. Here, proposed PA-ITD-DTG-MG-CRN technique attains 31.89%, 25.45% and 19.32% higher accuracy for Financial data; 34.58%, 23.24% and 28.68% higher accuracy for Global trade data; 22.98%, 32.49% and 19.31% higher accuracy for KYC data; 33.79%, 26.82% and 29.33% higher accuracy for Bank data; to enhances prediction with analysis of International trade data; as compared to existing PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM methods respectively.

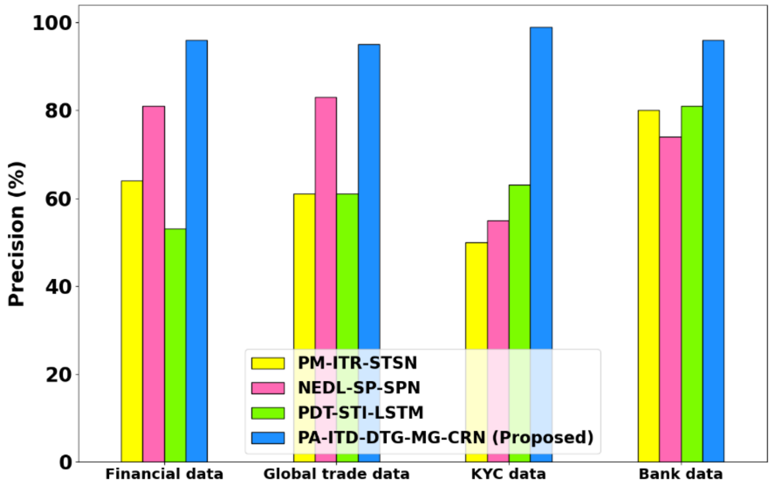

Figure 4: Precision analysis

Figure 4 depicts precision analysis. Here; proposed PA-ITD-DTG-MG-CRN technique attains 27.73%, 20.45% and 33.77% higher precision for Financial data; 32.12%, 23.49% and 30.94% higher precision for Global trade data; 34.45%, 28.52% and 24.11% higher precision for KYC data; 26.79%, 30.82% and 24.88% higher precision for Bank data; to enhances prediction with analysis of ITD; as compared to existing PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM methods.

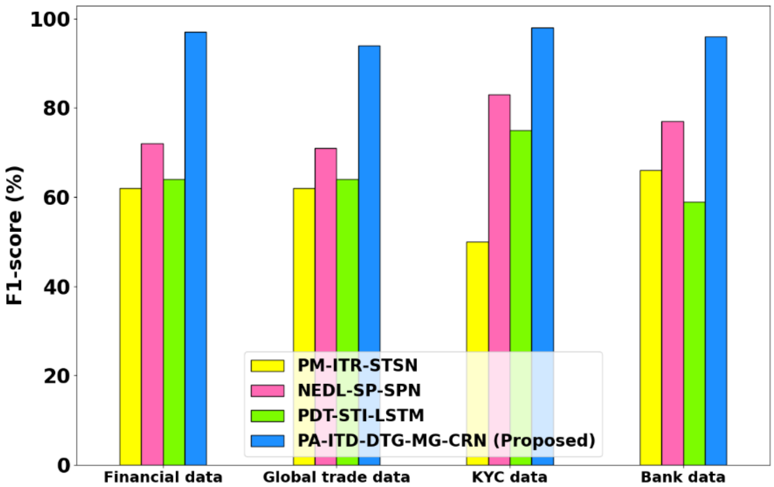

Figure 5: F1-score analysis

Figure 5 depicts F1-score analysis, Here; proposed PA-ITD-DTG-MG-CRN technique attains 32.61%, 18.96% and 25.75% higher f1-score for Financial data; 32.12%, 23.49% and 30.94% higher f1-score for Global trade data; 32.45%, 21.12% and 27.11% higher f1-score for KYC data; 28.78%, 20.51% and 34.77% higher f1-score for Bank data; to enhances prediction with analysis of ITD; as compared to existing PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM methods respectively.

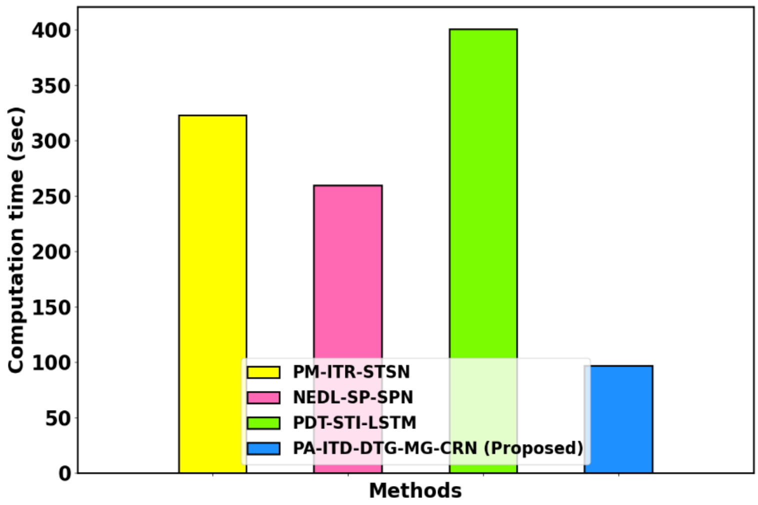

Figure 6: Computational time analysis

Figure 6 depicts computational time analysis, Here; proposed PA-ITD-DTG-MG-CRN technique attains 25.56%, 17.24% and 29.85% lower computational time for improves prediction with analysis of ITD; as compared to the existing PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM methods respectively.

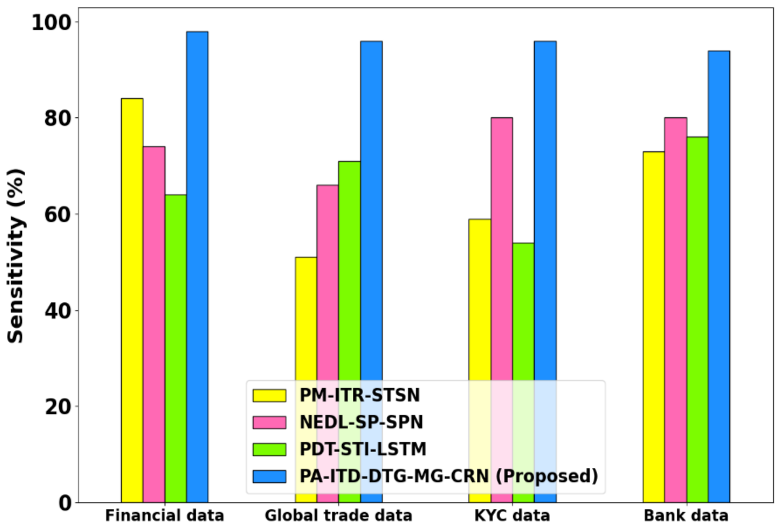

Figure 7: Sensitivity analysis

Figure 7 depicts sensitivity analysis, Here; proposed PA-ITD-DTG-MG-CRN technique attains 19.97%, 27.68% and 33.18% higher sensitivity for Financial data; 32.12%, 23.49% and 30.94% higher sensitivity for Global trade data; 32.45%, 21.12% and 27.11% higher sensitivity for KYC data; 28.78%, 20.51% and 34.77% higher sensitivity for Bank data; to enhances prediction with analysis of ITD; as compared to existing PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM methods respectively.

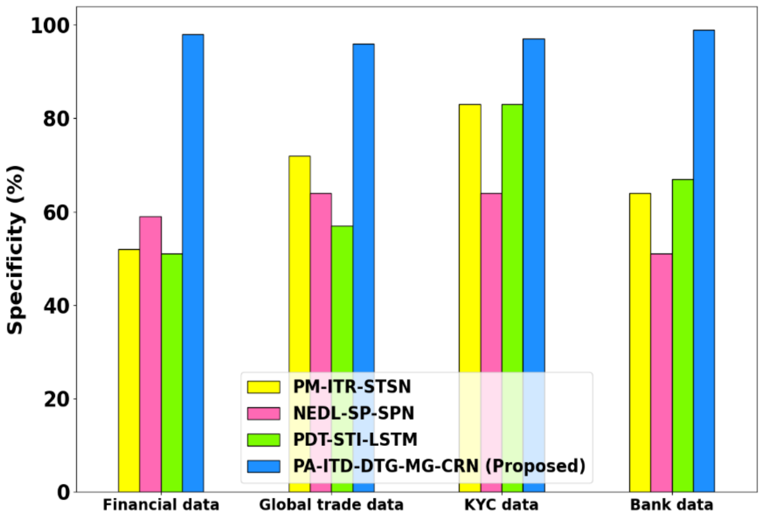

Figure 8: Specificity analysis

Figure 8 depicts specificity analysis, Here; proposed PA-ITD-DTG-MG-CRN technique attains 28.46%, 23.68% and 34.79% higher specificity for Financial data; 22.53%, 28.76% and 31.46% higher specificity for Global trade data; 31.45%, 33.12% and 30.11% higher specificity for KYC data; 25.79%, 34.51% and 22.81% higher specificity for Bank data; to enhances prediction, analysis of ITD; as compared to existing PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM methods respectively.

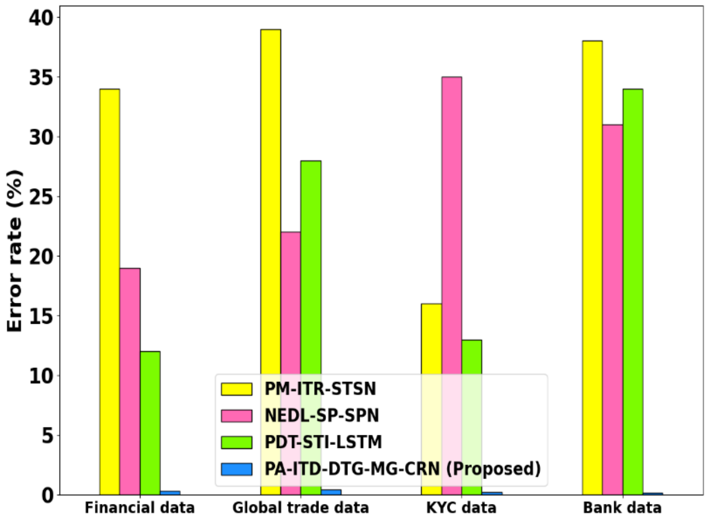

Figure 9: Error rate analysis

Figure 9 depicts error rate analysis, Here; PA-ITD-DTG-MG-CRN technique attains 34.46%, 28.68% and 22.79% lower error rate for Financial data; 33.49%, 20.76% and 27.96% lower error rate for Global trade data; 26.87%, 34.65% and 23.94% lower error rate for KYC data; 32.79%, 25.15% and 29.32% lower error rate for Bank data; to enhances prediction, analysis of ITD; as compared to existing PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM methods respectively.

C. Discussion

The data used in this proposed PA-ITD-DTG-MG-CRN approach are taken from the Import Genius Trade Dataset and sent to another location for preliminary processing. The pre-processing unit uses the dataset's collected data for tokenization, stop word removal, and text vectorization for analyses and predictions related to international trade. The DTG-MGCN predicts and categorizes international trade data using the pre-processed data, and GKOA improves the DTG-MGCN's effectiveness in predicting and analyzing international trade data. From analysis of outcomes, it has been observed proposed system technique performed well than the others. In the instance of result, the average highest outcomes of the approach were compared to average results in existing methods like PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM respectively. The accuracy values of PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM are lower than proposed approach. The proposed framework attains average accuracy of 99.92%, analyzed with accuracy of 92.85% for comparison methods. Similarly, specificity value of proposed method is 97.92% analyzed with average specificity value of comparison methods of 94.42%. The proposed method QGAN-AVOA-SDP has high accuracy and specificity evaluation metrics than existing methods. Hence, comparative methods are expensive than the proposed method. Accordingly, proposed method predict and analyze International trade data more efficiency.

V. CONCLUSION

In this section, Prediction and Analysis of International Trade Data Based on Deep Learning was successfully implemented. This proposed method using the MWSGF for Tokenization, removing stop words and text vectorization of data from Import Genius Trade Dataset, DTG-MGCN for prediction and GKOA for enhance the performance of the DTG-MGCN. The predictability and analysis of data on International commerce are improved by this innovative methodology. When compared to existing approaches such as PM-ITR-STSN, NEDL-SP-SPN and PDT-STI-LSTM, the proposed PA-ITD-DTG-MG-CRN model outperform them. Notably, it increases specificity by 22.53%, 28.76% and 31.46%, while increasing sensitivity by 19.97%, 27.68% and 33.18%. Moreover, the proposed PA-ITD-DTG-MG-CRN approach accomplishes a noteworthy reduction in computational time with respect to its counterparts, exhibiting reductions of 25.56%, 17.24%, and 29.85%. This validates its effectiveness in enhances the prediction and analyzes of the International trade data.

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