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Enhancing Supply Chain Performance through AI: A Predictive Analytics Approach Using Weighted Regularized Extreme Learning Machine Model

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Abstract: Supply chain management (SCM) is a crucial component of any competitive strategy aimed at increasing organizational profitability and productivity. The discipline of SCM has a wealth of literature on strategies and technologies for effective SCM. There has been a deluge of academic and professional activity in recent years devoted to metrics and evaluations of organizational effectiveness. Training the model, selecting features, and preprocessing are its main components. There are three types of normalization used in data preprocessing: min-max, z-score, and decimal scaling. The most accurate method is z-score normalization. To pick features, we employ the sine-cosine algorithm. For this purpose, we trained the model using the WRELM framework. It makes ELM and RELM look antiquated in comparison. According to the numbers, the accuracy rate is 96.20%.

Keywords: Supply Chain Performance, Weighted Regularized Extreme Learning Machine (WRELM), Sine Cosine Algorithm (SCA).

Introduction

Ignoring a major word about block chain technology that we overheard in the corporate world is perhaps the best course of action. A number of business-related modules have contributed to the phrase "block chain's recent rise to prominence in the IT industry. Many companies are looking to this technology to revolutionize their operations. Many sectors, like healthcare, banking, and business, stand to be profoundly affected by block chain technology in the not-too-distant future. Block chain technology allows database programmers to connect to multiple sets of computers at once. Data recording and all the steps involved are ongoing operations. Every block has its own distinct set of data and programming; these blocks also talk to each other and connecting the building blocks. The program's database is integrated with all networks and divisions, thus it handles more than just one group are able to access all databases. While adding new blocks to the database, the data from earlier blocks is safely preserved. It is not necessary to falsify transactions or information in order to produce documents and files on the block chain. Economic development is the most important factor in determining a nation's well-being and the longevity of its political systems. The nations' development plans, however, are running into unexpected roadblocks due to the recent coronavirus outbreak. Given the current situation, it is crucial to reconsider what factors lead to economic growth. The emergence of the coronavirus has caused some nations to realize that lockdowns pose problems for their supply chains. People and companies are already having a hard time because of supply chain interruptions, and the situation could get far worse if the current crisis drags on. This is especially the case with vaccines and other safety-related medical equipment. Even more mysterious is the question of whether or not supply chains can work effectively, simultaneously, and according to plan after the lockdowns are finally lifted. Determining the possible consequences of interruptions under different scenarios can benefit in planning and recuperation once the uncertainty is gone. An issue in one country that provides critical inputs can impact supply chains worldwide due to increased international trade and manufacturing specialization. "Data sets whose size is beyond the ability of typical database software tools to capture, store, manage and analyze", the supply chain analytics strategy combines big data with analytics. We are now able to supply management with thorough and trustworthy information that can guide their decisions by utilizing the enormous quantities and kinds of data that are available to us. Here is where the viewpoint of analytics becomes useful. The business climate is more challenging now than it was in the past due to factors such as intense competition, fast changes in consumer tastes, globalization, shorter product life cycles, and unexpected customer satisfaction. The pressure on businesses to handle these issues properly is growing. With all these concerns in mind, it's natural to want to know how to improve the supply chain's efficiency and agility by integrating digital technologies. Digital technology improves supply chain capabilities, which boosts competitive advantage and long-term performance for businesses. In order to understand the impact of digital technology on supply chain performance, this study explores the ready-made garments (RMG) industry in Bangladesh. When it comes to the production of garments, Bangladesh is well-known as a global leader and the number two supplier in the world. Companies need supply chain skills that prioritize fast delivery to minimize costs, decrease lead times, and assure customer satisfaction in order to stay up with the ever-changing demands of the business world.

Literature survey

The significance of digitalization has led some to call it "the fourth industrial revolution", drawing comparisons to the previous three industrial revolutions: mechanization, electrification, and information technologies. Many of today's most valuable companies have integrated the newly-emerged "Industry 4.0" into their supply chains and business models, heavily utilizing cutting-edge digital technology[1]. The adoption of Industry 4.0 technologies is the only way to fully experience the advantages of digital servitization, which is described as the "transformation in processes, capabilities, and offerings [2]within industrial firms and their associate ecosystems to progressively create, deliver, and capture increased service value arising from a broad range of enabling digital technologies". The authors [3]state that digital servitization faces several challenges due to contacts with outside parties and disagreements amongst companies. Businesses can overcome these difficulties with the use of Industry 4.0 technologies, which enable the realization of interorganizational logics. The authors [4]suggest that in order to improve supply chain management, businesses should alter their protocol. In recent years, the number of research investigating how Industry 4.0 will influence supply networks has skyrocketed. Although these investigations have provided many useful findings, they have also led to a fragmentation of the literature and a blurring of the boundaries between known and unknown information[5]. Two current tendencies in the research make definitive findings difficult to reach. Sustainable agriculture is essential if we are to provide food security and end world hunger in the face of a rapidly expanding human population. Several studies have shown that global food production has to be increased. [6] Therefore, a shift in thinking from focusing on increasing agricultural output to promoting sustainable agriculture is essential. Sustainable agriculture strategies seek to increase agricultural productivity while decreasing negative effects on the environment. According to[7], ASCs that support sustainable agriculture rely on the knowledge, skills, and attitudes of everyone engaged. More information about sustainable agriculture practices (SAPs) leads to their wider adoption by farmers. [8]that ASCs are under immense pressure to increase farming efficiency due to issues like as drying up water and fossil fuels, shrinking amounts of arable land, and growing customer demand for more ethical and environmentally friendly food supply chains. [9]The capacity of ASCs to adjust to fluctuating market prices and growing supply-and-demand imbalances are critical components impacting agricultural output. Recent studies on sustainable inventory and transportation management of perishable goods have been published by[10], ASCs are being affected by digital technologies including the IoT, data analytics, digitally supplied services, mobile devices and technologies, artificial intelligence (AI), and other applications. Several examples show how ASC uses digital technologies. For example, agricultural machinery can be automated to reduce labour input. Sensors and remote satellite data can improve monitoring of crops, land, and water.A number of books and articles on the subject of supply chain management tackle the challenging subject of supply chain performance. Respondence, quality, dependability, flexibility, and asset management are the aspects that [11]use to assess the performance of the supply chain. Comparatively, considers efficiency, reactivity, quality, and adaptability as performance metrics. Utilizing the research of [12]as a springboard, an alternate approach proposes measuring performance gains in terms of availability, variety, innovation, time, and price. One of the most critical aspects of supply chain relationship management and successful performance is the exchange of pertinent information, say[13]. Companies are investing in technological advances to build effective communication channels and collaboration mechanisms to improve supply chain performance through better information sharing. An additional requirement for effective business performance is a system of interdependent processes. In terms of technology, the introduction of the internet a few decades ago was revolutionary, and it rocked several industries to their foundations. [14]state that this disruption reorganized whole value networks and impacted many supply chains. Particularly among corporate software engineers, the term "block chain" has become a byword in the IT world. This technology will be crucial to the operations of various kinds of organizations, say[15]. In the coming years, block chain technology is expected to be widely used by businesses, healthcare providers, and other financial institutions[16]. A block chain is an application that functions like a database. In addition, a modern business's inventory management system is a brilliant strategy for increasing productivity and keeping track of products' whereabouts and quantities before they sell out[17]. Employing analytical management approaches and intelligently integrating inventory, retail sectors are able to connect available stock with stock removal. Promptly satisfying consumer demand in today's competitive business environment requires effective inventory management. Furthermore, as stated by[18], performance in supply chain management is characterized by the extent to which operations are structured to fulfil the needs of consumers. Previous research on SCPM in its native context has been conducted by various authors, according to the literature review. [19] Although some choose to reveal their approach, others utilized one or more methods to assess their performance in a particular case study. Using three separate methodologies—approaches, data analysis techniques, and data collection tools—this work evaluates the papers. Because various researchers have different perspectives, the methodologies utilized to evaluate performance can change among studies. For example, in their methods section, [20]defines the performance variables from seven different angles. Second, the authors have laid out the revised objectives and KPIs for the perspective change. Furthermore, they have enhanced the performance measurement system and checked that it aligns with its objectives and KPIs. Third, we observed numerous outcomes after receiving the goal weights. There are four steps to evaluating performance, as stated by[21]. The initial step is to find and learn about the indicators using exploratory factor analysis.

Proposed system

In today's market, supply chain performance is becoming more important than company performance in determining success. Supply chain performance encompasses all activities along the extended supply chain that contribute to meeting the demands of the end customer. Maintaining an adequate inventory and the ability to react swiftly to client requests are all part of this. So is making sure that products are available and delivered on time.

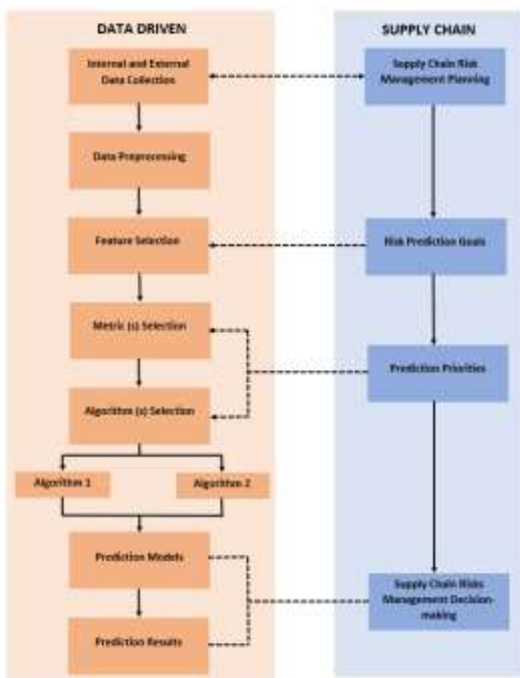

Fig. 1. Data Driven Risk Prediction System

Figure 1 shows the workflow of the framework. You can see the main roles of a data-driven strategy on the left side of the diagram. You may observe the standard steps of an SCRM procedure on the right-hand side. Experts in data-driven decision-making and supply chain risk management clearly collaborated to build this approach.

Data Preprocessing

All three of these methods—ANN, clustering, and classification software—benefit greatly from normalization. Using tanned faces data features normalization for backpropagation NN algorithms may speed up the learning process.

Min-Max Normalization:

The min-max normalization method scales the b values of a numerical feature U using the interval $[\mathrm{new}-\mathrm{max}_{\mathrm{U}}, \mathrm{new}-\mathrm{min}_{\mathrm{U}}]$ to generate a range. To modify o to o' by plugging it into the following equation, this gives us the updated value:

$$\mathrm{o}' = \frac{\mathrm{o}-\mathrm{min}_{\mathrm{U}}}{\mathrm{max}_{\mathrm{U}}-\mathrm{min}_{\mathrm{U}}}.(\mathrm{new}-\mathrm{max}_{\mathrm{U}}, \mathrm{new}-\mathrm{min}_{\mathrm{U}}) + \mathrm{new}-\mathrm{min}_{\mathrm{U}} \qquad (1)$$

ln where $\mathrm{max}_{\mathrm{U}}$ denotes the highest feature value and $\mathrm{min}_{\mathrm{U}}$ mean the lowest. The typical intervals in normalization are [0, 1] or [−1, 1], where $[\mathrm{new}-\mathrm{max}_{\mathrm{U}}, \mathrm{new}-\mathrm{min}_{\mathrm{U}}]$ is equal to [0, 1]. This normalization process is commonly applied to datasets that will be utilized with algorithms for distance learning [22]. Features with a big $\mathrm{max}_{\mathrm{U}}-\mathrm{min}_{\mathrm{U}}$ difference will not have an advantage in the distance computation if the data is normalized to the same range of values. [23] Because the older characteristics aren't given significant weight, the learning process is unaffected. It is also known to help ANNs learn faster because the weights can converge more swiftly.

Z-Score Normalization:

It is not possible to use min-max normalization without first determining the minimum and maximum values. Although these values may be known, outliers might still cluster them, reducing the computational precision that can be used to represent them and so distorting the min-max normalization.

$$\mathrm{o}' = \frac{(\mathrm{o}-\overline{\mathrm{m}})}{\mathrm{i}_{\mathrm{m}}} \qquad (2)$$

The sample mean is represented by $\overline{\mathrm{m}}$.

$$\bar{m} = \frac{1}{c}\sum_{s=1}^{c} o_s \qquad (3)$$

Additionally, the mean absolute deviation of m is denoted by i_m.

$$i_m = \frac{1}{c}\sum_{s=1}^{c}(o_s - \bar{m}) \qquad (4)$$

Decimal Scaling Normalization:

One way to reduce the absolute feature values is to normalize the numerical feature values. This is done by dividing the decimal point by 10th power, so that the maximum value after transformation is 1.

$$o' = \frac{o}{10^t} \qquad (5)$$

where t is the smallest integer necessary to ensure that $new - max_U$ is smaller than 1.

Feature Selection:

The original intent of the basic Sine Cosine Algorithm was to solve optimization problems. Initially, the sine and cosine oscillation functions served as the basis of the algorithm by adjusting the positions of the potential solutions. By employing a set of random variables to indicate the direction of movement and the suitable distance to go, SCA is able to highlight or downplay the impact of the destination, as well as switch between the cosine and sine components. The following mathematical form is used by SCA to update the positions of different solutions:

$$M_s^{k+1} = \begin{cases} M_s^k + j_1 \times \sin(j_2) \times \left|j_3 D_s^k - M_s^k\right| j_4 < 0.5 \\ M_s^k + j_1 \times \cos(j_2) \times \left|j_3 D_s^k - M_s^k\right| j_4 \geq 0.5 \end{cases} \qquad (6)$$

where D_s^k represents the ideal solution in the s th dimension and M_s^k represents the position of the s th-dimensional current solution. The values of j_2, j_3, and j_4 can be anything from 0 to 1. As can be seen in Eq. 1, the positions of the agents are updated based on the optimal solution [24]. A compromise between the exploration and exploitation stages can be achieved by adjusting the SCA algorithm's parameter j_1 during iterations, as:

$$j_1 = y - \frac{y \times k}{k_{max}} \qquad (7)$$

in where k stands for the iteration number, y is a constant, and k_{max} is the maximum iteration number.

The SCA approach, as shown, starts with a randomly generated set of n agent population locations. Step 5 concludes the process of finding the best solution by computing the objective function for every agent. In Step 6, the ideal response is represented by P. The seventh step is to use Eq. (7) to change the value of r1. The positions of the different agents are updated in Eq. (6) in Steps 8–13. Repetition of stages 4–16 is proportional to the number of iterations. The optimal solution is refined with each iteration. In contrast to many other meta-heuristics, the original SCA algorithm shows substantial search space exploitation due to its use of a single optimal solution to guide additional candidate solutions. This results in a memory-and convergence-speed-efficient approach. However, this method may perform slightly worse in cases where there are many locally optimal alternatives. This motivated us to address the issue with the proposed Sine Cosine Dynamic Group algorithm.

Model Training:

RELM:

Overfitting occurs naturally when deciding on output weights during ELM training because to their infamously poor generalizability. When the training error and the norm of the weights both reach their minimal values simultaneously, the FFNN achieves its maximum generalizability. The "regularization parameter" (N) is an extra parameter that is used to find the ratio of these two variables. The following is the RELM loss function, which minimizes both the training error and the norm of weights, as defined by the RELM regularization parameter (N).

$$Z_{RELM} = \min_{\alpha} N\|a - Q\alpha\|_2^2 + \|\alpha\|_2^2 \qquad (8)$$

The second term, however, is novel, and it receives the parameter N just like the first term. An updated version of the previous formula is this:

$$Z_{RELM} = \min_{\alpha} N\|z\|_2^2 + \|\alpha\|_2^2 \qquad (9)$$

The applicable Lagrangian can also be expressed as

$$Z_{RELM} = \min_{\alpha} N\|z\|_2^2 + \|\alpha\|_2^2 + \lambda^T(a - Q\alpha - z) \qquad (10)$$

where the Lagrangian multiplier is represented by the matrix λ and the value of e is equal to $z = [z_1, \ldots, z_c]^T$. Here are the best conditions for solving the given relationship:

$$\begin{cases} \dfrac{\partial W}{\partial \alpha} = 0 \Rightarrow 2\alpha - Q^T\lambda = 0 \\ \dfrac{\partial W}{\partial z} = 0 \Rightarrow 2Nz - \lambda = 0 \\ \dfrac{\partial W}{\partial \lambda} = 0 \Rightarrow a - Q\alpha - z = 0 \end{cases} \tag{11}$$

Here is Equation 10 for calculating the best output weights:

$$\hat{\alpha} = \left(Q^TQ + \frac{S}{N}\right)^{-1} Q^T a \tag{12}$$

where S is the unit matrix. The output weights are determined using the previous equation when the hidden layer neuron count is fewer than the training sample count. In all other cases, this is the form the equation takes:

$$\hat{\alpha} = Q^T \left(QQ^T + \frac{S}{N}\right)^{-1} a \tag{13}$$

WRELM:

The WRELM modeling procedure consists of three steps: Starting with the RELM techniques, construct the network from the bottom up. Due to the fact that ELM-based methods adjust the computational procedure of output weights throughout their whole training cycle, the WRELM model updates the output weights to make the model more stable. This is essential to ensure the model's generalizability and prevent instability caused by outliers in the output weights. The second step is to give the model some weights. The second phase involves updating the output weights using data from the weighting in step 2 and a process similar to the RELM approach. This will help reduce the impact of outliers. The third step involves assigning modest weights to each training sample that has high modeling mistakes.

The WRELM differs from the RELM in that its development was based on the idea of using input weights to edit output weights [25]. So, it is possible to assign weights to various kinds of data. If the weight factor l_s is applied to the error z_s from the RELM, the value of $\|z\|_2^2$is provided as $l = diag(l_1, \ldots, l_c)\|z\|_2^2$in the ELM. The standard deviation of RELM's errors for accurate weight computation is defined as follows:

$$\hat{s} = \frac{IQR}{2 \times 0.6745} \qquad (14)$$

Here, the 80th and 20th percentiles represent the two ends of the distribution, and the interquartile range (IQR) measures the distance between them. The value of w can be determined using the following equation once the aforementioned parameter has been defined:

$$l_s = \begin{cases} 1 & \left|\frac{z_s}{\hat{\imath}}\right| \leq 1 \\ \frac{n_2 - \left|\frac{z_s}{\hat{\imath}}\right|}{n_2 - n_1} & n_1 \leq \left|\frac{z_s}{\hat{\imath}}\right| \leq n_2 \\ 10^{-4} & \text{otherwise} \end{cases} \qquad (15)$$

Other ways of calculating w can be defined by setting the parameter j. Notably, the values were arrived at by an iterative process of trial and error.

$$j = \frac{e}{\text{tune} \times \hat{\imath}} \qquad (16)$$

Here is an explanation of the Z_{RELM}loss function based on the L calculation equations:

$$Z_{RELM} = \min_{\alpha} N\|Lz\|_2^2 + \|\alpha\|_2^2 \qquad (17)$$

where the most effective methods for determining output weights are as follows:

$$\hat{\alpha} = \left(Q^T L^2 Q + \frac{S}{N}\right)^{-1} Q^T L^2 a \qquad (18)$$

Result and Discussion

Despite the claims made by supply chain management experts, few businesses actually achieve the competitive advantage they seek. This might be because current methods of supply chain analysis aren't comprehensive enough to understand the complexities of SCM and organizational performance as a whole.

TABLE I. MSE, MAE AND R² VALUE (%)

Models	MSE	MAE	R^2
ELM	4.22	1.65	2.57
RELM	2.14	1.15	0.99
WRELM	1.40	1.03	0.37

The ELM, RELM, and WRELM models demonstrated encouraging outcomes when it came to Supply chain forecasting as illustrated in table I.

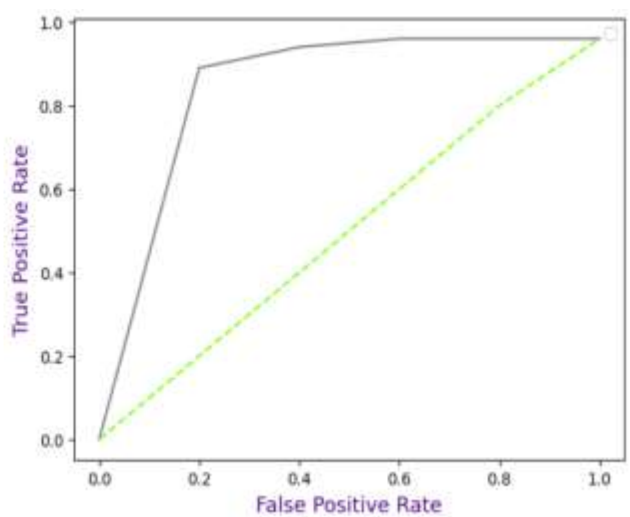

Fig. 2. ROC Curve of Proposed Model

The ROC Curve of the WRELM model is shown graphically in Figure 2. The supply chain information collaboration performance training accuracy was 96.20%.

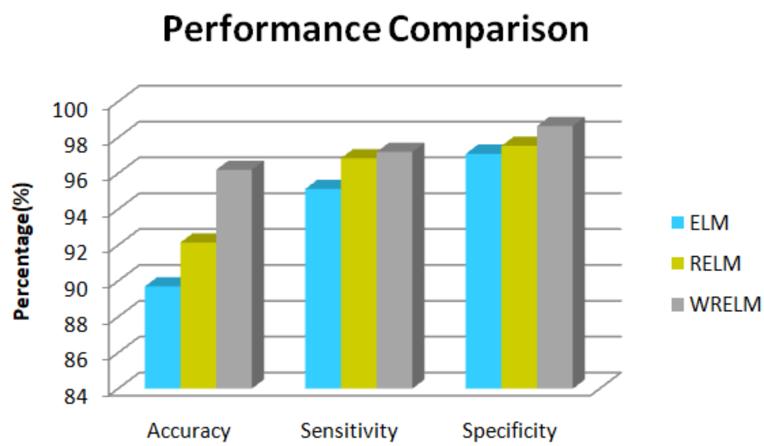

Fig. 3. Performance Comparison of the Model

Figure 3 shows the numerical and graphical explanations of the ELM, RELM, and WRELM data's specificity, sensitivity, and accuracy.

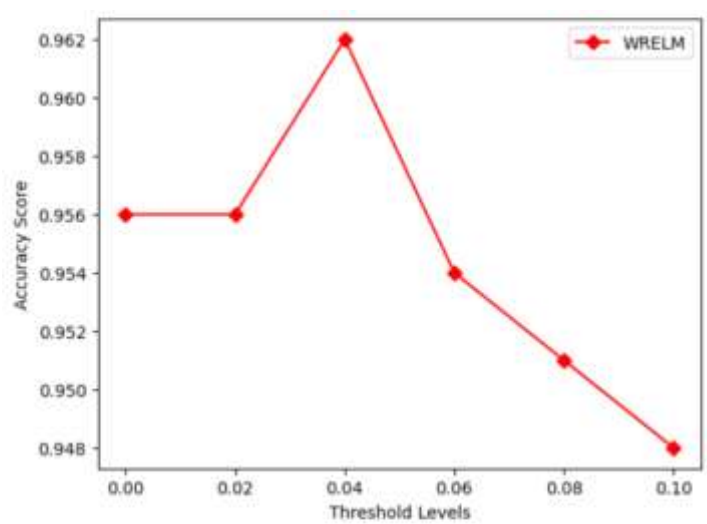

Fig. 4. Model Accuracy in Different Threshold Level

Our investigation into the assessment's precision at different levels yielded the results shown in Figure 4. As the threshold is raised, more unnecessary features are removed, and the model's accuracy increases with each iteration, reaching a peak of 0.03 (with an average accuracy of 0.962) when tested.

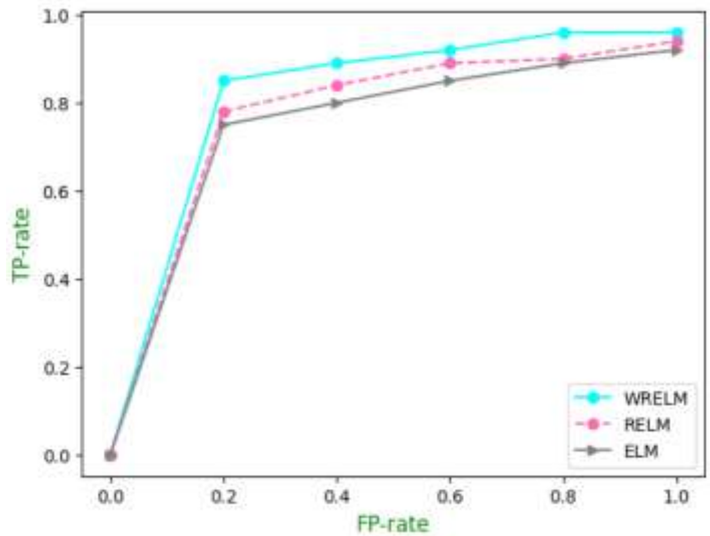

Fig. 5. Data Classification Comparison Results

Figure 5 shows the findings of a study that compared ROC curves using ELM, RELM, and WRELM after controlling the number of positive and negative samples and studying the created data set.

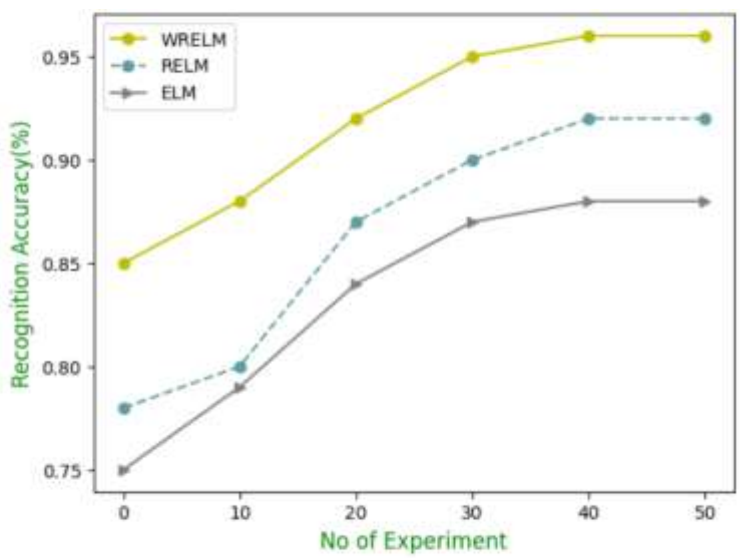

Fig. 6. The Accuracy of Different Epoch

Figure 6 then shows a comparison of WRELM to the preexisting ELM and RELM. The experiment is carried out fifty times for each model, and the results may be seen in figure 6.

Conclusion

Organizations, customers, and others all benefit from well-managed supply chains. Given the critical nature of supply chains, monitoring their efficiency is of the utmost importance. When it comes to how companies measure employee performance, modern models vary in a number of areas. These include corporate structure, the distribution of responsibilities, and the maturity of the supply chain. During data preprocessing, three different methods of normalization are employed: min-max, z-score, and decimal scaling. Using z-score normalization is the most precise approach. The sine-cosine algorithm is used for feature selection. A technique known as A-WRELM is used to train the model. The suggested strategy consistently achieves a higher level of accuracy (96.20 percent) than the RELM and ELM models.

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