ISSN: 2752-3829 Vol. 3 No.2, (December, 2023)

Stochastic Modelling and Computational Sciences

REVOLUTIONIZING WAREHOUSE MANAGEMENT: INTEGRATION OF ROBOTICS AND ENTERPRISE RESOURCE PLANNING TO BUILD MODERN WAREHOUSE USING TRANSFER LEARNING ASSISTED MODEL

Sohit Reddy Kalluru[1,*], Prasanna Kumar Reddy Gurijala[1], Pavana Kumari Gavva[2] and Lohith Reddy Kalluru[3]

[1]MYGO Consulting Inc, SAP Solution Architect, Naperville, Illinois, USA - 60563
[2]Nextgen IT Solutions, Plainfield, Illinois, USA – 60544
[3]Hewlett Packard Enterprise, 1701 East Mossy Oaks Road, Spring, TX 77389-1767

ABSTRACT

Today, the warehouse plays an essential part in the victory of businesses. And also plays a significant intermediate role among supply chain members, imitating supply chain service and cost. To enhance supply chain procedures and to accomplish them better, numerous businesses have set up federal manufacturing and warehouse amenities over the past few years. Despite the significance of warehousing to the customer service and cost levels of numerous businesses, there is presently not a complete systematic model for originating warehouses. Enterprise Resource Planning (ERP) is a tactical device, which aids a business to attain economic benefit by combining business methods and enhancing the resources accessible. New technologies like ERP systems, computerized equipment, barcodes, and many others have made warehousing more effective and accurate in business processes. With the growth of ERP services, more selections and dissimilar kinds of software started to be accessible for businesses. This manuscript presents an Integration of Robotics and Enterprise Resource Planning to Build Advanced Warehouse Management (IRERP-BAWM) technique. The main intention of the IRERP-BAWM model is to modernize warehouse management using the transfer learning model. In the first stage, the presented IRERP-BAWM technique utilizes a data preprocessing by employing Z-score normalization to measure the input data into a beneficial format. In addition, the IRERP-BAWM method employs a deep neural network (DNN) technique for the classification process. At last, for the hyperparameter fine-tune process of DNN model, the improved dung beetle optimization (IDBO) algorithm can be exploited. The experimental analysis of IRERP-BAWM algorithm is tested on a benchmark database and the outcomes are measured with respect to various features. The simulation outcome emphasized the improvement of IRERP-BAWM system over the recent techniques.

Keywords: Enterprise Resource Planning; Transfer Learning; Dung Beetle Optimization; Warehouse Management; Deep Neural Network

1. INTRODUCTION

Nowadays, the Enterprise Resource Planning (ERP) system can combine every financial action and information of firms, like billing, wage payment, sales, taxes, purchasing, communication costs, and utilities, particularly in the exchange of information within and across organizational limitations [1]. Hence, firms are executing ERP systems to increase their enterprise performance and strengthen their competition in the fast-increasing global competitiveness among industries. Present ERP systems play a significant part in fundamental choices in technology development or trade-offs implied in novel product development [2]. At present, an ERP system is more than only an accounting information system extensively recognized by enterprises [3].

Presently, all companies struggle to take a top position in the global or local market, based on the enterprise's size and, thus, development opportunities [4]. Presently, all of the units have warehouses to store products that are acquired or produced. Therefore, organizations that are involved in logistics aren't excluded [5]. Therefore, to construct a successful and sustainable company, inner modules like production when there is one, stock management, and warehouse processes, must be finely managed. Warehouses are the nodes that support a company's supply chain strategies [6]. They strongly impact the costs and maintenance of the network. Today companies must have well-developed and technologically updated warehouses to support market requirements

[7]. For sure, this means good information share and software in the companies and the warehouse in particular. Selecting a good ERP system and executing it is the major component of the expenses of all companies nowadays [8]. ERP applications normally assist health service organizations in incorporating several hospital functions namely patient scheduling, hospital decision-making, human resource management, and workflow management [9]. Moreover, ERP systems have exceeded the organization and managed to concentrate on resources, but ERP systems also aid planning like operating management, controlling, finance, reporting and analyzing, and decision-making tasks [10].

This manuscript presents an Integration of Robotics and Enterprise Resource Planning to Build Advanced Warehouse Management (IRERP-BAWM) technique. The main intention of the IRERP-BAWM model is to modernize warehouse management using the transfer learning model. In the first stage, the presented IRERP-BAWM technique utilizes data preprocessing by employing Z-score normalization to measure the input data into the beneficial format. In addition, the IRERP-BAWM method employs a deep neural network (DNN) technique for the classification process. At last, for the hyperparameter fine-tune process of the DNN model, the improved dung beetle optimization (IDBO) algorithm can be exploited. The experimental analysis of the IRERP-BAWM algorithm can be verified on a benchmark database and the outcomes are measured with respect to various aspects.

2. RELATED WORKS

Kunduru [11] proposed to study artificial intelligence (AI) and in what way enterprise resource planning uses it. This study inspects several online pieces and books about AI in ERP based on existing articles. Based on the study, the impact of AI is deceptive as businesses attain a novel study-level efficacy in different ERP fields owing to incredible developments in AI, and ML. The major inspiration of the study is to progress an appropriate another selecting approach based upon principles for warehouse managers. The study is executed in various phases. In the initial phase, the selecting standards of software have been identified based on the article study. In the secondary phase, the criteria were weighted with the criteria importance through the inter-criteria correlation (CRITIC) technique based on single-valued neutrosophic sets (SVNSs).

Tong et al. [12] proposed the execution of an automatic warehouse based on the incorporation of WMS and ERP with the technology and method. Additionally, MES is the intellect and the central part of a maintainable digital factory. The enterprise implements innovative smart create and execute the MES, understand good management and responsive productivity, and see the modified requirements of the market. Liang et al. [13] proposed the standard association of picker-routing and load-assignment difficulties can be analyzed. A varied integer numerical method can be determined based on wave-picking warehouse features. To overcome the difficulty produced by the routing decision of the presented issue, a group of effectually adapted estimation distribution methods can be advanced. Legowo and Wijaya [14] presented to examine the current warehousing system performance in the company utilizing the adaptable IT-BSC perception. From the presented method of statistical and hypothesis tests, it is created that dual variables can affect the warehousing system performances, i.e. the Operational Excellence and Business Contribution variables.

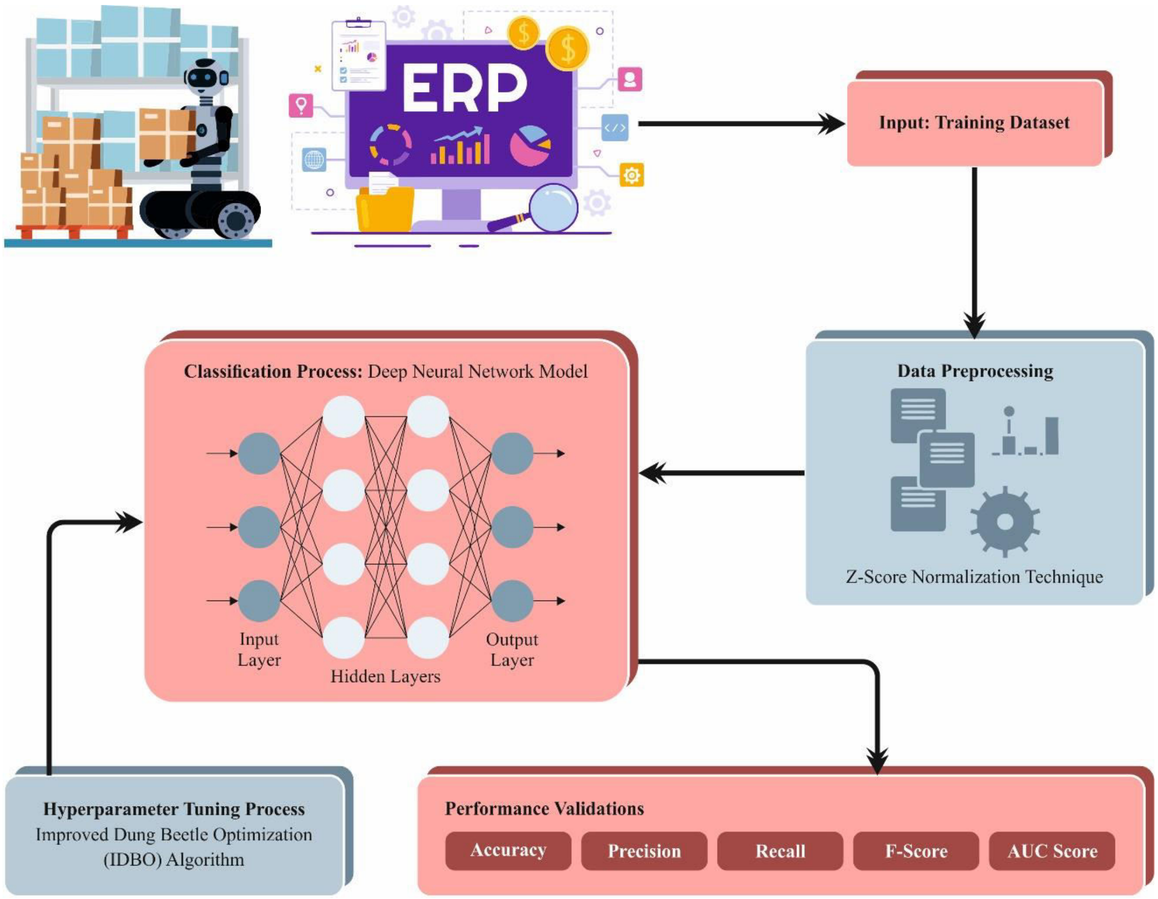

Fig. 1: Workflow of IRERP-BAWM technique

3. THE PROPOSED METHOD

In this manuscript, we have presented an IRERP-BAWM model. The main intention of the IRERP-BAWM model is to modernize warehouse management using the transfer learning model. To accomplish that, the IRERP-BAWM technique has z-score normalization, DNN-based classification, and IDBO-based parameter tuning. Fig. 1 depicts the complete work flow of the IRERP-BAWM technique.

3.1. Z-score Normalization

In the first phase, the presented IRERP-BAWM system applies data pre-processing utilizing Z-score normalization to measure the input data into the beneficial format. Z-score normalization is a numerical method employed to normalize data by regulating for mean and standard deviation, which can improve the accuracy of data analysis [15]. When incorporating robotics and ERP systems in present warehouses, Z-score normalization aids in supporting varied data sources, enhancing inventory management, and improving operational efficacy. By regularizing data, warehouses can well analyze performance metrics, demand forecasts, and modernize robotic processes. This integration mains to more accurate decision-making and a more responsive supply chain.

3.2. DNN-based Classification Process

By definition, a DNN could understand a few intricate patterns, which are concealed in multi-modal, nonlinear, high-dimensional datasets. For that, the DNN includes a backpropagating method that is a supervised training method derived from an iterant gradient descent technique permitting global error reduction. More accurately, the proposed DNN structure is typically created from an input layer $(x_m^{[k=0]})$, numerous hidden layers (HL) $(x_n^{[k]})$, and an output layer $(\Sigma^{[K]}) - cf$.

Every HL is made of various nodes, each one being associated with the following ones over particular weight coefficients, $w_n^{[k-1,k]}$ that conduct its particular significance concerning the outcome of the output. Therefore, the final arises as a weighting input layer's data amount that comprises each difficult connection happening among the nodes throughout the layers. Particularly, the transitional output attained at every node, $\Sigma_n^{[k]}$, can be used over an activation function (λ) that serves as a filter, which moderates the weight sum [27–30] :

$$\Sigma_n^{[k]} = \lambda\left(\sum_{1}^{n} w_n^{[k-1,k]} \cdot x_n^{[k]} + b_n^{[k]}\right) \qquad (1)$$

In the above equation, b_n represent a term of scalar bias that is allocated to each node to propose a further amount of independence.

To improve the DNN constancy and sturdiness, its input data have been pre-processed, and standardized to a usual zero mean distribution and unit variance e^{27-30}:

$$\langle x_m^0 \rangle = \frac{x_m^0 - \mu(x^0)}{\sigma(x^0)} \qquad (2)$$

whereas σ and μ separately stand for the standard deviation and mean describing the input dataset.

The input dataset can be shattered into 3 sub-sets that are separately dedicated to the testing, training, and validation of the DNN; The dual initial sub-sets function as a source for training the DNN that can be completed by the iterating learning. The latter search to reduce the network loss or error, L-among the validation and training data by the appropriate fine-tuning of the DNN's weight co-efficient. The network loss can be restrained by calculating the output layers prediction to the predictable outcome, later this error can be back propagated to fine-tune the weighted coefficient of the previous layers. This method can be recurrent in an iterative method till an approved conjunction level can be attained, for example, while the DNN error has condensed to a suitable threshold, or while the directed quantity of iterative cycles in every epoch or layer has been seen. The above training method has been determined by the hyperparameters depicting the DNN, for example, activation function type, loss criteria, its depth and initial weights, width, count of epochs, etc. Once the last weights were attained, the DNN was benchmarked against the test data that didn't play some role in the process of training, thus permitting to measurement of the model precision in an unbiased method. So, this benchmark evaluates how much the DNN efficiently attained a relationship overall knowledge among each output and input, after the modest memorizing of particular input-output pairs that would relatively resemble an input data overfitting, subsequent in a DNN specially qualified for predicting the trained dataset but not the tested one.

3.3. Hyperparameter Tuning Process

At last, for the hyperparameter tuning model of the DNN method, the IDBO algorithm can be exploited. The DBO model mimics the dung beetle's behaviors namely dancing, foraging, ball-rolling, breeding, and stealing. The population of a model is separated into 4 sections: brood balls, stealing, small, and ball-rolling DBs. The complete explanation is the following.

Ball-Rolling DBs

Lacking problems, DBs use the sun to find and retain the dung ball rolled in a straight line. This model accepts that light power affects the path of DBs. Now, the location upgrade of the ball-rolling DBs has been formulated in Eq. (3).

$$x_i(t+1) = x_i(t) + \alpha \times k \times x_i(t-1) + b \times \Delta x \qquad (3)$$

$$\Delta x = |x_i(t) - X^W| \qquad (4)$$

α is controlled over a probabilistic method to imitate the complex states in the regular environment. A larger value of Δx denotes a low-powerful light source.

If DBs meet obstacles that prevent them from roll forwarding, they require dancing to relocate. A tangent function pretends these behaviors. The updating of the position now is designed by Eq. (5).

$$x_i(t+1) = x_i(t) + tan(\theta)\,|x_i(t) - x_i(t-1)| \qquad (5)$$

θ represents the defection angle affiliated to $[0, \pi]$. This position should be affected if θ equals 0, π, or $\pi/2$.

Brood Balls

Selecting spawn locations is critical. Dung balls are hidden after being rolled to a safer position. The boundary selection approach has been accepted for modeling the spawning region of female DBs. This area can be limited by Eqs. (6) and (7).

$$Lb^* = \max(X^* \times (1-R), Lb) \qquad (6)$$

$$Ub^* = \min(X^* \times (1+R), Ub) \qquad (7)$$

$$R = 1 - \frac{t}{T_{\max}} \qquad (8)$$

Once describing the region, the female DBs pick the brood balls for spawning. The DBO technique accepts that every female DB lone breeds once in every iteration. Additionally, the range of boundaries is changing dynamically, generally resolved in the R-value. Hence, the location of brood balls is also unpredictable throughout the iterations. The location updated is considered by Eq. (9).

$$B_i(t+1) = X^* + b_1 \times (B_i(t) - Lb^*) + b_2 \times (B_i(t) - Ub^*) \qquad (9)$$

Small DBs

Small DBs would dig out of the ground for searching food. This DBO model determines an optimum area of foraging. The boundary area is limited by Eqs. (10) and (11). The location update of small DBs is designated by Eq. (12).

$$Lb^b = \max(X^b \times (1-R), Lb) \qquad (10)$$

$$Ub^b = \min(X^b \times (1+R), Ub) \qquad (11)$$

$$x_i(t+1) = x_i(t) + C_1 \times (x_i(t) - Lb^b) + C_2 \times (x_i(t) - Ub^b) \qquad (12)$$

Stealing DBs

Stealing dung balls from other DBs is known as the behavior of stealing. This DBO method adopts that the locality of X^b represents the optimum position for scrambling for food. The location upgrade of stealing DBs' is measured in Eq. (13).

$$x_i(t+1) = X^b + S \times g \times \left(|x_i(t) - X^*| + |x_{i(t)} - X^b|\right) \qquad (13)$$

The DBO model benefits are fast convergence and outstanding optimization accuracies However, the local and global searching abilities are imbalanced. Especially to express that the DBO model endures poor exploration capacity globally and simply drops into local optimization. Therefore, they adopted 3 improvement approaches for solving the above problems. The convergence speed and accuracies of swarm intelligence optimization methods are generally closely connected to the structure and quality of the initial population. The random initialization in the conventional DBO model results in an uneven distribution of samples. When the diversities and qualities of the primary population can't be assured, the effectiveness of the algorithm's search should be considerably affected. LHS understands non-overlapped sampling depending on the standard of stratified sampling, that may provide the samples distributed evenly in the searching space. The upgraded stages to initialize the population in the following:

- Control the hyperparameter counts D demonstrating the optimization dimension of the problem.

- Fixed the range $[Lb, Ub]$ for each hyperparameter, whereas Lb and Ub represent lower and upper boundaries.
- The range $[Lb, Ub]$ of every hyperparameter is separated into N equal sub-intervals. N represents the DBO algorithm's population size.
- Generate a matrix of dimension $N \times D$. Every column ordering the numbers at random 1, 2, $\cdots$, N. Formerly, a sample has been produced at random in the equivalent sub-interval depending on the number of rows. The last resultant makes a primary population.

During LHS, the sampled values are generally in the interval of $[0,1]$. Nevertheless, they should be transformed to the range fixed by the resultant hyperparameters within the problem of optimization. The ith sample value of the jth hyperparameter is represented as shown in Eq. (14).

$$X_{ij} = Lb_j + LHS_{ij} \times \left(Ub_j - Lb_j\right) \quad (14)$$

The IDBO method creates a fitness function to reach enhanced classifier efficiency. It determines an optimistic numeral to signify the improved performance of the candidate solution. In this article, the reduction of the classifier rate of error was measured as FF and expressed in Eq. (15).

$$fitness\,(x_i) = ClassifierErrorRate(x_i)$$

$$= \frac{no.of\ misclassified\ samples}{Total\ no.of\ samples} * 100 \quad (15)$$

4. EXPERIMENTAL VALIDATION

The simulation valuation of the IRERP-BAWM algorithm has been inspected under Warehouse-dataset-2023 [16]. The dataset comprises 1500 samples under 3 class labels is depicted in Table 1.

Table 1 Details of Dataset

Priority	No. of Samples
High	641
Low	413
Medium	446
Total Samples	**1500**

Fig. 2 provides the classifier results of the IRERP-BAWM model on the test database. Figs. 2a-2b validates the confusion matrices with precise classification of 3 number of classes on a 70:30 TRAP/TESP. Fig. 2c presents the PR study, illustrating the greatest performance over all sum of classes. Finally, Fig. 2d shows the study of ROC, demonstrating effectual outcomes with great values of ROC for numerous numbers of classes.

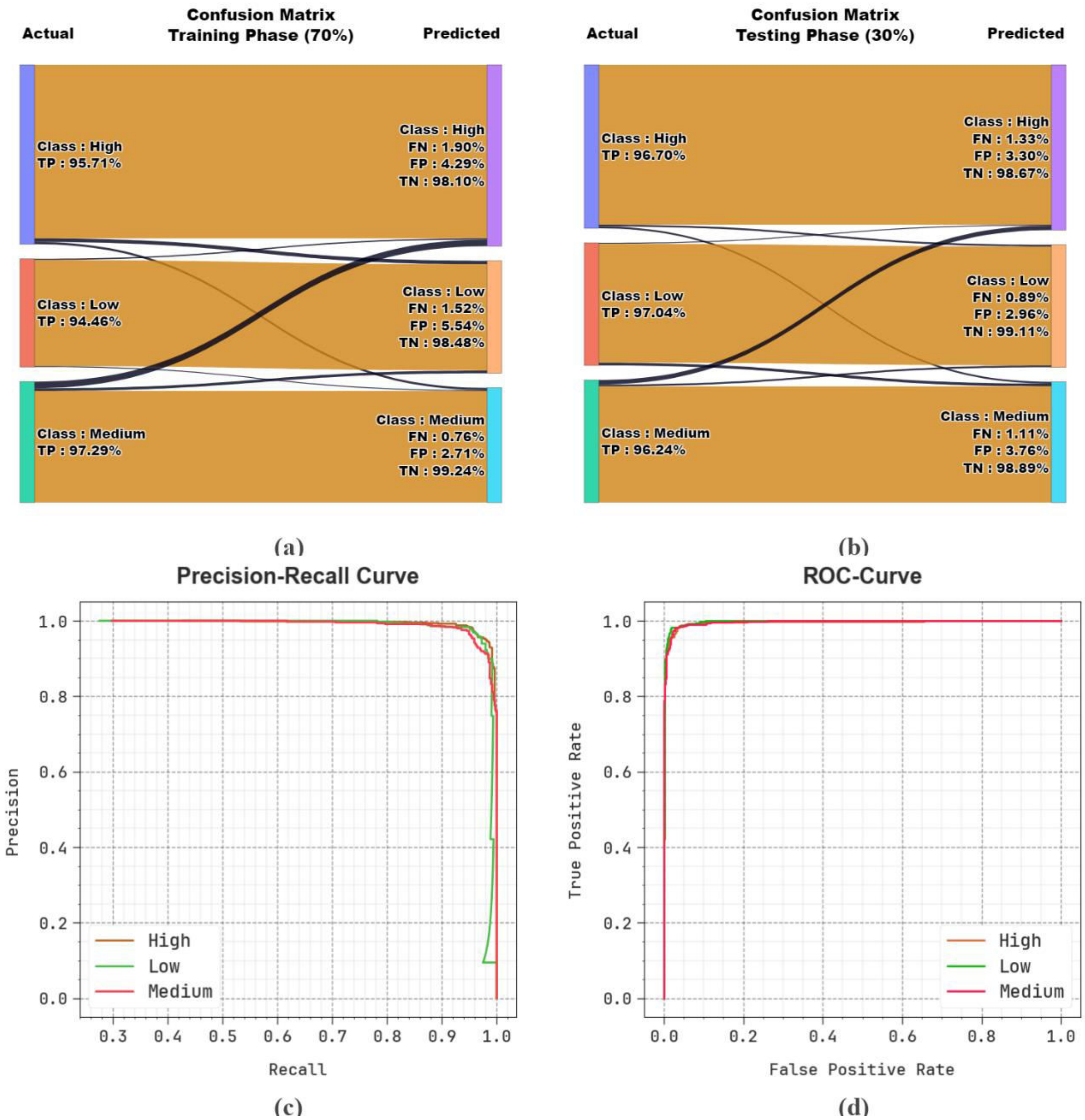

Fig. 2: Classifier outcomes of (a-b) 70%TRAP and 30%TESP of confusion matrices and (c-d) PR and ROC curves

The classifier results of the IRERP-BAWM system on 70%TRAP and 30%TESP are portrayed in Table 2. Fig. 3, the average outcomes given by the IRERP-BAWM approach on 70% of TRAP is underlined. The outcomes define that the IRERP-BAWM method correctly recognized the samples. With 70%TRAP, the IRERP-BAWM algorithm provides average $accu_y$ of 97.21%, $prec_n$ of 95.82%, $reca_l$ of 95.74%, F_{score} of 95.75% and AUC_{score} of 96.78%.

The average result of the IRERP-BAWM system under 30%TESP has been described in Fig. 4. The outcomes define that the IRERP-BAWM method correctly recognized the samples. According to 30%TESP, the IRERP-BAWM method presents average $accu_y$ of 97.78%, $prec_n$ of 96.66%, $reca_l$ of 96.54%, F_{score} of 96.60% and AUC_{score} of 97.43%.

Table 2: Classifier outcome of IRERP-BAWM method under 70%TRAP and 30%TESP

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	AUC_{score}
Training Phase (70%)					
High	96.67	95.71	96.75	96.22	96.68
Low	98.00	94.46	98.20	96.30	98.06
Medium	96.95	97.29	92.28	94.72	95.60
Average	**97.21**	**95.82**	**95.74**	**95.75**	**96.78**
Testing Phase (30%)					
High	97.78	96.70	97.78	97.24	97.78
Low	98.22	97.04	97.04	97.04	97.88
Medium	97.33	96.24	94.81	95.52	96.61
Average	**97.78**	**96.66**	**96.54**	**96.60**	**97.43**

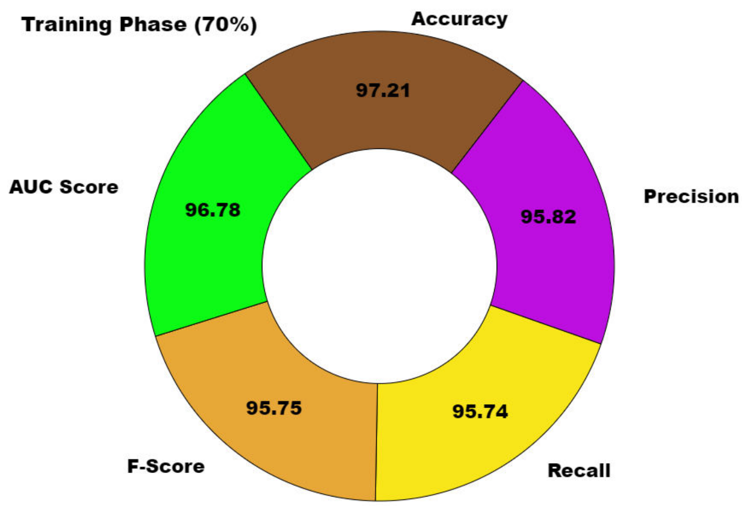

Fig. 3. Average of IRERP-BAWM technique under 70%TRAP

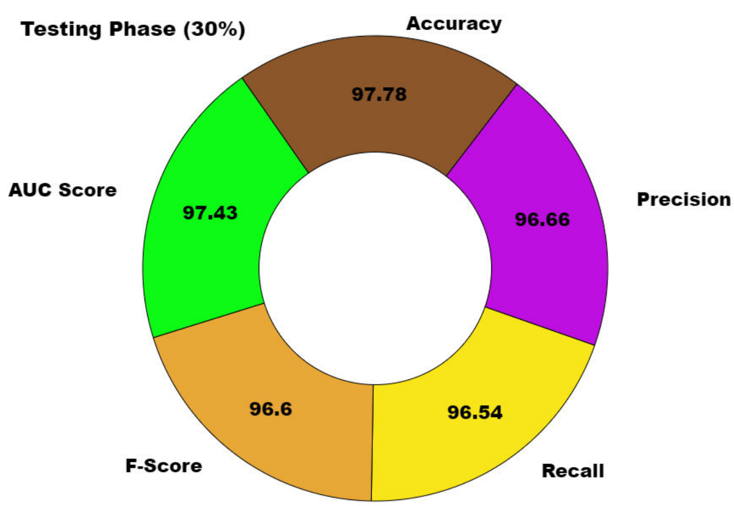

Fig. 4. Average of IRERP-BAWM technique under 30%TESP

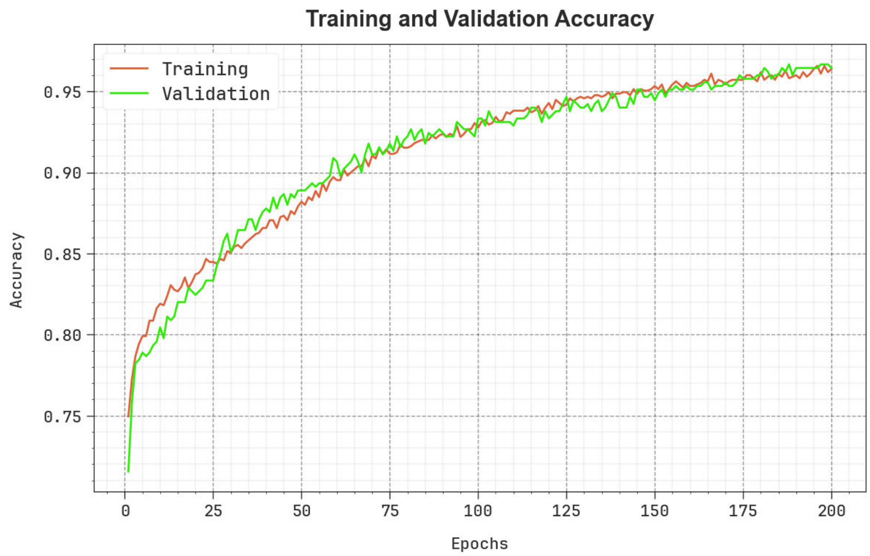

Fig. 5. $Accu_y$ curve of IRERP-BAWM technique

In Fig. 5, the training $accu_y$ (TRAAC) and validation $accu_y$ (TRAAC) accuracy results of the IRERP-BAWM system are stated. The $accu_y$values are calculated throughout 0-200 epoch counts. The figure emphasized that the TRAAC and TRAAC values demonstrated a growing trend that reports the abilities of the IRERP-BAWM technique with better performance across various iterations. Furthermore, the TRAAC and TRAAC stay nearer over the number of epochs, which illustrates less minimum overfitting and shows the superior performance of the IRERP-BAWM technique, guaranteeing steady prediction on hidden instances.

In Fig. 6, the TRA loss (TRALS) and VLA loss (VLALS) graph of the IRERP-BAWM methodology has been determined. The loss values are calculated throughout 0-200 epoch counts. It has been portrayed that the TRALS and VLALS values point out a decreasing trend, notifying the capabilities of the IRERP-BAWM system to balance a trade-off between data fitting and generalization. The constant decline in loss values moreover promises the superior performance of the IRERP-BAWM algorithm and fine-tune the prediction outcomes on time.

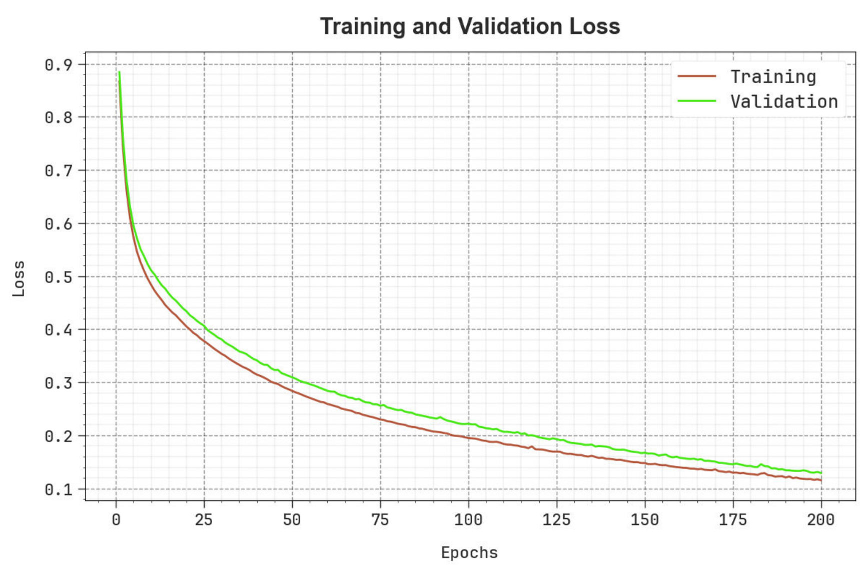

Fig. 6. Loss curve of IRERP-BAWM technique

The comparison study of IRERP-BAWM algorithm with recent techniques is described in Table 3 and Fig. 7. The experiment result illustrated that the IRERP-BAWM model outshined superior performances. According to $accu_y$, the IRERP-BAWM method has greater $accu_y$ of 97.78% while the RF, DT, KNN, SVM, NB, LR, and AlexNet techniques have lower $accu_y$ of 93.37%, 96.42%, 90.90%, 88.86%, 91.32%, 90.98%, and 92.34%, respectively. Similarly, depending on $prec_n$, the IRERP-BAWM system has better $prec_n$ of 96.66% however the RF, DT, KNN, SVM, NB, LR, and AlexNet models have the least $prec_n$ of 90.30%, 93.36%, 89.79%, 92.74%, 95.78%, 95.08%, and 88.77%, individually. Lastly, according to F_{score}, the IRERP-BAWM methodology has maximum F_{score} of 96.60% but the RF, DT, KNN, SVM, NB, LR, and AlexNet approaches have minimum F_{score} of 90.27%, 92.27%, 94.93%, 90.94%, 89.88%, 89.64%, and 93.65%, correspondingly.

Table 3: Comparative analysis of IRERP-BAWM technique with recent models

Techniques	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
IRERP-BAWM	97.78	96.66	96.54	96.60
Random Forest	93.37	90.30	95.14	90.27
Decision Tree	96.42	93.36	88.28	92.27
KNN Algorithm	90.90	89.79	93.24	94.93
SVM Classifier	88.86	92.74	88.93	90.94
Naïve Bayes	91.32	95.78	94.30	89.88
Logistic Regression	90.98	95.08	88.33	89.64
AlexNet Model	92.34	88.77	93.72	93.65

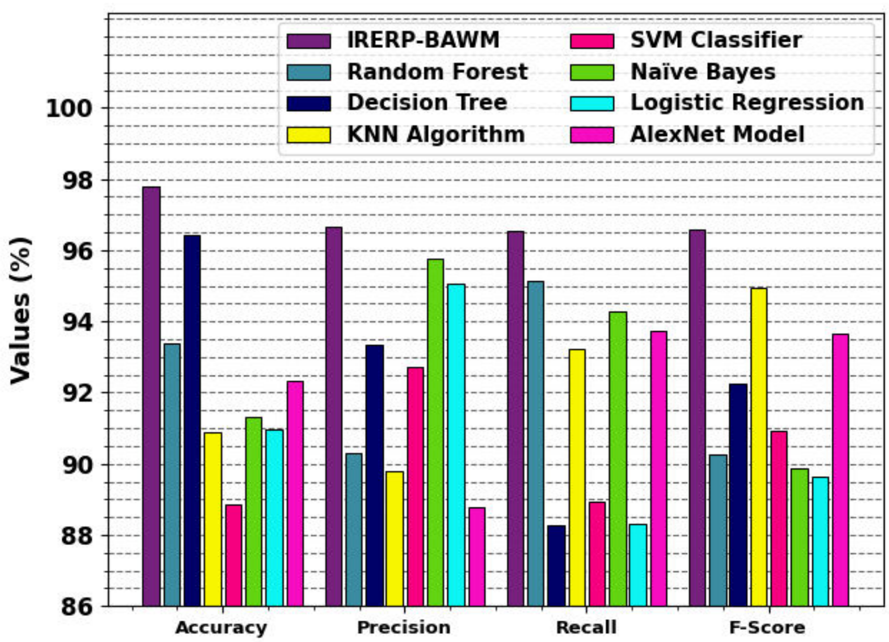

Fig. 7: Comparative analysis of IRERP-BAWM approach with existing models

Fig. 8 establishes the correlation matrix formed by the IRERP-BAWM technique. The figure demonstrated effective outcomes of the IRERP-BAWM technique under various features such as Order_ID, Order_Quantity, Priority, Product_Type, Weight, and Size.

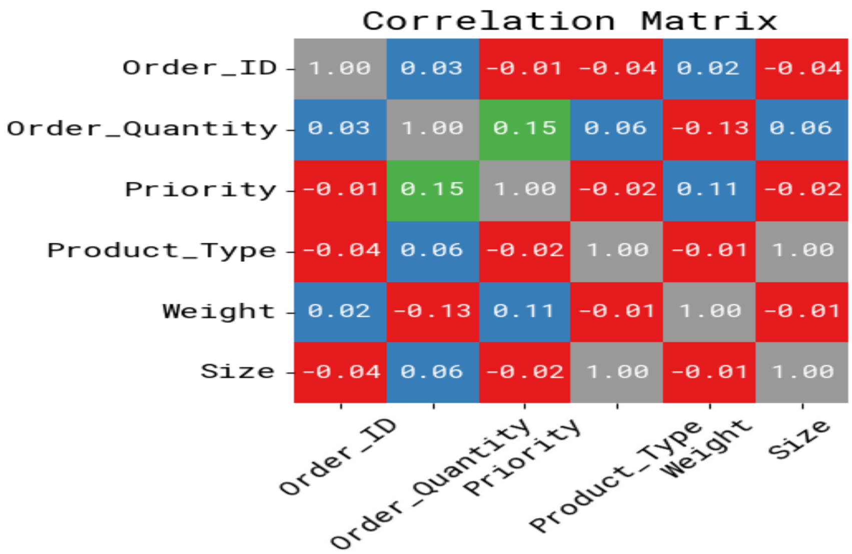

Fig. 8: Correlation matrix of IRERP-BAWM approach

5. CONCLUSION

In this manuscript, we have presented an IRERP-BAWM technique. The main intention of the IRERP-BAWM model is to modernize warehouse management using the transfer learning model. To accomplish that, the IRERP-BAWM technique has z-score normalization, DNN-based classification, and IDBO-based parameter tuning. In the first stage, the presented IRERP-BAWM technique employs data pre-processing utilizing Z-score normalization to measure the input data into a beneficial format. In addition, the IRERP-BAWM method employs the DNN technique for the classification process. At last, for the hyperparameter fine-tune process of the DNN model, the IDBO algorithm can be exploited. The experimental validation of the IRERP-BAWM algorithm can be tested on a benchmark database and the outcomes are measured with respect to numerous features. The simulation outcome emphasized the improvement of the IRERP-BAWM system over the recent techniques.

REFERENCES

[1] Žunić, E., Delalić, S., Hodžić, K., Beširević, A. and Hindija, H., 2018, November. Smart warehouse management system concept with implementation. In *2018 14th Symposium on Neural Networks and Applications (NEUREL)* (pp. 1-5). IEEE.

[2] Andiyappillai, N., 2020. Factors influencing the successful implementation of the warehouse management system (WMS). *International Journal of Computer Applications*, *177*(32), pp.21-25.

[3] Kučera, T., 2017. Logistics cost calculation of implementation warehouse management system: a case study. In *MATEC Web of Conferences. Vol. 134 (2017): 18th International Scientific Conference-LOGI 2017*. EDP Sciences.

[4] Istiqomah, N.A., Sansabilla, P.F., Himawan, D. and Rifni, M., 2020, July. The implementation of barcode on warehouse management system for warehouse efficiency. In *Journal of Physics: Conference Series* (Vol. 1573, No. 1, p. 012038). IOP Publishing.

[5] Pane, S.F., Awangga, R.M. and Azhari, B.R., 2018. Qualitative evaluation of RFID implementation on warehouse management system. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *16*(3), pp.1303-1308.

[6] Anđelković, A. and Radosavljević, M., 2018. Improving order-picking process through implementation of warehouse management system. *Strategic Management-International Journal of Strategic Management and Decision Support Systems in Strategic Management*, *23*(1).

[7] Li, M., Gu, S., Chen, G. and Zhu, Z., 2011, October. A RFID-based intelligent warehouse management system design and implementation. In *2011 IEEE 8th International Conference on e-Business Engineering* (pp. 178-184). IEEE.

[8] Atieh, A.M., Kaylani, H., Al-Abdallat, Y., Qaderi, A., Ghoul, L., Jaradat, L. and Hdairis, I., 2016. Performance improvement of inventory management system processes by an automated warehouse management system. *Procedia Cirp*, *41*, pp.568-572.

[9] Zhang, Y. and Pan, F., 2022. Design and implementation of a new intelligent warehouse management system based on MySQL database technology. *Informatica*, *46*(3).

[10] Vatumalae, V., Rajagopal, P. and Sundram, V.P.K., 2020. Warehouse management system of a third party logistics provider in Malaysia. *International Journal of Economics and Finance*, *12*(9), p.73.

[11] Kunduru, A.R., 2023. Effective usage of artificial intelligence in enterprise resource planning applications. *International Journal of Computer Trends and Technology*, *71*(4), pp.73-80.

[12] Tong, Q., Ming, X. and Zhang, X., 2023. Construction of sustainable digital factory for automated warehouse based on integration of ERP and WMS. *Sustainability*, *15*(2), p.1022.

[13] Liang, J., Wu, Z., Zhu, C. and Zhang, Z.H., 2022. An estimation distribution algorithm for wave-picking warehouse management. *Journal of Intelligent Manufacturing*, pp.1-14.

[14] Legowo, N. and Wijaya, W., 2022. Measurement of warehouse management system performance using it-BSC method in the FMCG industry. *Journal of System and Management Sciences*, *12*(5), pp.230-251.

[15] Henderi, H., Wahyuningsih, T. and Rahwanto, E., 2021. Comparison of Min-Max normalization and Z-Score Normalization in the K-nearest neighbor (kNN) Algorithm to Test the Accuracy of Types of Breast Cancer. *International Journal of Informatics and Information Systems*, *4*(1), pp.13-20.

[16] https://www.kaggle.com/datasets/metztl1/warehouse-dataset-2023