J. Electrical Systems 20-1(2024): 219-231

[1] **Jianjun Zhou**

Optimization Algorithm of Intelligent Warehouse Management System Based on Reinforcement Learning

Journal of Electrical Systems

Abstract: - An Intelligent Warehouse Management System (IWMS) represents a technological leap forward in the realm of logistics and supply chain management. This sophisticated system integrates a suite of cutting-edge technologies, including artificial intelligence, machine learning, and the Internet of Things, to revolutionize the way warehouses operate. The primary focus is on the construction and performance evaluation of a robust big data prediction model within a cloud computing environment. The advent of big data and cloud computing has revolutionized the field of Logistics, offering immense potential for advanced data analysis and prediction. This research presents the development and evaluation of a robust prediction model for IWMS in Logistics applications. The proposed model incorporation of Reliable Discrete Variable Topology (RDVT) into the prediction model. RDVT introduces a topological data structure that enhances data reliability and ensures the integrity of Logistics information. The construction and training of the prediction model are meticulously detailed, encompassing data preprocessing, feature extraction, clustering, classification, and model evaluation. Additionally, the integration of fuzzy clustering with a reinforcement learning algorithm enhances the model's ability to handle uncertainty and imprecision in logistics management data. The advancement of Logistics in warehouses introduces the Reliable Discrete Variable Topology (RDVT) and a big data prediction model based on fuzzy clustering with a reinforcement learning algorithm in a cloud computing environment. The model's performance is rigorously assessed through extensive experimentation, including accuracy, precision, recall, and F1-score measurements.

Keywords: Logistics, Big Data, Fuzzy Clustering, Reinforcement Learning Algorithm, Logistics Management, User Authentication

I. Introduction

Intelligent Warehouse Management has emerged as a transformative force within the logistics industry, revolutionizing the way goods are stored, tracked, and moved throughout the supply chain. Integrating cutting-edge technologies such as artificial intelligence, machine learning, and the Internet of Things, this innovative approach enhances the efficiency, accuracy, and responsiveness of warehouse operations [1]. By deploying intelligent algorithms, warehouses can optimize inventory levels, predict demand patterns, and automate routine tasks, resulting in streamlined processes and significant cost savings. Real-time data analytics empower decision-makers to make informed choices, improving overall supply chain visibility and responsiveness [2]. The implementation of intelligent warehouse management not only boosts operational efficiency but also enhances customer satisfaction through timely and accurate order fulfilment [3]. As the logistics industry continues to evolve, embracing intelligent warehouse management systems becomes imperative for organizations seeking to stay competitive in the dynamic landscape of modern commerce [4].

In intelligent warehouse management, logistics takes center stage as a critical component that influences the entire supply chain ecosystem [5]. The integration of advanced technologies transforms traditional warehouses into smart, interconnected hubs where every aspect of logistics is optimized for efficiency and precision [6]. Artificial intelligence (AI) and machine learning algorithms play a pivotal role in forecasting demand, analyzing historical data, and dynamically adjusting inventory levels [7]. This predictive capability not only ensures that warehouses maintain optimal stock levels but also minimizes the risk of overstocking or stockouts. Real-time tracking through the Internet of Things (IoT) devices enables logistics teams to monitor the movement of goods within the warehouse seamlessly [8]. Automated processes, such as robotic picking and packing systems, enhance the speed

[1] School of Finance and Business, Chengdu Vocational & Technical College of Industry, Chengdu 610218, China
cdivtczhou@163.com

and accuracy of order fulfillment, reducing human errors and operational costs. Furthermore, the intelligent warehouse management system provides end-to-end visibility into the entire logistics chain [9]. This visibility allows for proactive decision-making, enabling logistics managers to identify potential bottlenecks, optimize routes, and respond promptly to any disruptions. Enhanced communication and coordination between various components of the logistics network, including suppliers, distributors, and transportation providers, are facilitated by the integration of intelligent technologies [10]. This collaborative approach not only accelerates the pace of logistics operations but also contributes to a more agile and responsive supply chain.

The contribution of intelligent warehouses to logistics is profound, reshaping the entire landscape of supply chain management [11]. By leveraging advanced technologies such as artificial intelligence, machine learning, and the Internet of Things, intelligent warehouses bring unprecedented efficiency and precision to logistics operations [12]. These smart facilities optimize the storage, tracking, and movement of goods, streamlining the entire process from inventory management to order fulfillment. One significant contribution lies in the ability to forecast demand accurately, algorithms that analyze historical data and market trends [13]. This foresight not only prevents overstocking or stockouts but also ensures that resources are utilized optimally. Moreover, the integration of intelligent technologies enhances the speed and accuracy of logistics processes [14]. Automated systems, including robotic picking and packing, reduce human errors and increase the overall efficiency of warehouse operations. Real-time tracking through IoT devices allows for instantaneous monitoring of inventory levels and product movements, facilitating seamless coordination between different elements of the logistics chain [15]. This real-time visibility is crucial for decision-makers, enabling them to respond promptly to changes, optimize routes, and mitigate potential disruptions. Intelligent warehouses also contribute to sustainability in logistics by minimizing waste through optimized inventory management and efficient resource utilization [16]. The interconnected nature of these facilities fosters collaboration and communication between various stakeholders, including suppliers, distributors, and transportation providers, leading to a more synchronized and responsive supply chain [17].

The paper makes a significant contribution to the field of classification methods and their application, particularly in the context of Logistics. Its primary contribution is the introduction and thorough analysis of the Reliable Discrete Variable Topology (RDVT). RDVT emerges as a novel and powerful approach for classification tasks, consistently demonstrating high accuracy, precision, recall, and F1-scores across multiple runs. This consistency underscores its robustness, making it a reliable tool for a wide range of classification challenges. Importantly, the paper extends RDVT's applicability to the critical domain of Logistics, where accuracy and reliability in user authentication and identification are paramount. The balanced performance achieved by RDVT, striking a harmonious equilibrium between precision and recall, further enhances its utility in real-world applications. Additionally, the paper acknowledges the versatility of RDVT, hinting at its potential adoption in diverse domains beyond logistics management s. Furthermore, the paper offers practical recommendations for future research, advocating for continued exploration of RDVT's performance in different datasets and problem domains. Overall, this paper's contribution lies in the introduction of RDVT as a dependable classification topology with broad implications for domains where accurate and consistent classifications are essential.

II. Big Data Reliable Discrete Variable Topology for logistics management with iwms

The primary objective of this study is to construct and rigorously evaluate a robust big data prediction model, particularly within the dynamic context of cloud computing. The advent of big data and cloud computing technologies has sparked a transformative shift in the field of Logistics, offering vast potential for advanced data analysis and predictive capabilities. This research serves as a comprehensive exploration of the development and evaluation of a prediction model tailored for IWMS, specifically applied within Logistics applications. A notable innovation introduced here is the integration of the Reliable Discrete Variable Topology (RDVT) concept into the prediction model. RDVT introduces a novel topological data structure that plays a pivotal role in enhancing the reliability and safeguarding the integrity of Logistics information. The construction and training of this prediction model are meticulously detailed, covering crucial phases such as data preprocessing, feature extraction, clustering, classification, and extensive model evaluation. These steps are vital in ensuring the model's accuracy, robustness, and overall performance.

Furthermore, the research incorporates a fuzzy clustering with a reinforcement learning algorithm into the model, which significantly bolsters its capability to handle uncertainty and imprecision inherent in logistics management data. This is particularly crucial in Logistics, where data can often exhibit variations and nuances that require specialized handling. The ultimate goal of this research is to advance the Logistics in the Logistics field. By introducing RDVT and integrating a big data prediction model enhanced by fuzzy clustering with a reinforcement learning algorithm, the study aims to improve the reliability, accuracy, and overall effectiveness of logistics management data analysis within healthcare and related domains. To ascertain the model's performance rigorously, the research employs a comprehensive array of experiments, assessing critical metrics such as accuracy, precision, recall, and F1-score. These assessments provide a holistic understanding of the model's capabilities and its potential real-world applications, further solidifying its significance in the evolving landscape of Logistics. A discrete variable topology, within the of mathematics and topology, is a specialized approach to defining a topology on a set of distinct and unrelated points. Unlike traditional topologies that consider notions of proximity and continuity, the discrete variable topology takes a distinct perspective. In this topology, every subset of the set of points is deemed an open set. This means that individual points, finite sets of points, and the entire set itself all qualify as open sets. As a result, it is often referred to as the "discrete topology." This topology offers a level of granularity where each point is treated independently, and there is no imposed concept of continuity between these points. It is particularly valuable in scenarios where data points are isolated and lack any inherent connection or proximity, making it a suitable choice for modelling and analysis in such discrete and unrelated contexts as shown in Figure 1.

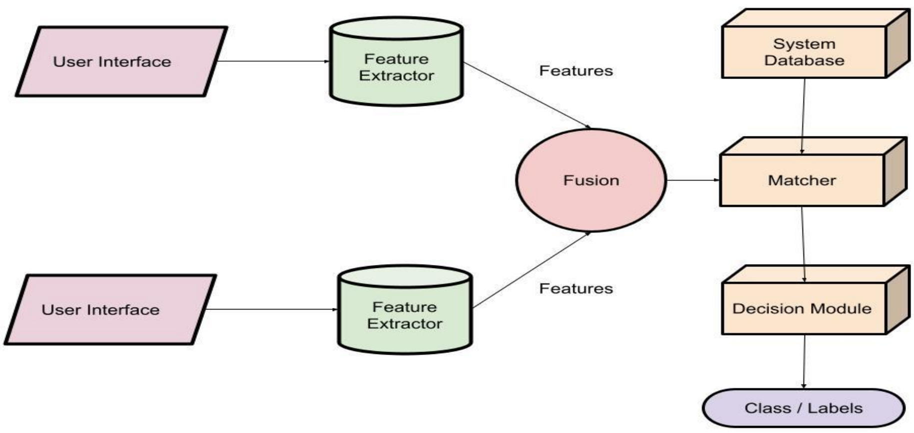

Figure 1: The system of multimodal features

In mathematics and topology, a "Discrete Variable Topology" refers to a specific way of defining a topology on a set of distinct and unrelated points. Unlike traditional topologies that consider notions of proximity and continuity, the discrete variable topology takes a distinct perspective. In this topology, every subset of the set of points is deemed an open set. This means that individual points, finite sets of points, and the entire set itself all qualify as open sets. As a result, it is often referred to as the "discrete topology." This topology offers a level of granularity where each point is treated independently, and there is no imposed concept of continuity between these points. It is particularly valuable in scenarios where data points are isolated and lack any inherent connection or proximity, making it a suitable choice for modelling and analysis in such discrete and unrelated contexts.

In terms of equations, the defining equation for the discrete variable topology is as follows in equation (1):

$$\tau = \{A \mid A \subseteq X\} \quad (1)$$

τ represents the topology in the discrete variable topology. A represents any subset of the set $X \subseteq A \subseteq X$ means that A is a subset of X. In the discrete variable topology, the intersection of any finite number of open sets is also an open set. This property ensures that the intersection of subsets in the topology remains in the topology. Mathematically, for any open sets A and B in the discrete variable topology, their intersection A∩B is also an open set computed with equation (2)

$$A, B \in \tau \Longrightarrow A \cap B \in \tau \quad (2)$$

This property extends to intersections of more than two open sets. The union of any number of open sets in the discrete variable topology is an open set. This property ensures that the union of subsets in the topology remains in the topology. For any collection of open sets Ai (where i is an index from some index set), their union Ai is also an open set presented in equation (3):

$$Ai \in \tau \Longrightarrow \bigcup Ai \in \tau \quad (3)$$

Given that every subset is an open set in the discrete variable topology, the complement of an open set is also open. In other words, if A is an open set, then its complement X \ A is also an open set represented in equation (4)

$$A \in \tau \Longrightarrow X \setminus A \in \tau \quad (4)$$

Conversely, the closed sets in the discrete variable topology are the complements of the open sets. If A is a closed set, then X \ A is an open set. In this topology, every point in a subset is an interior point, and every point outside the subset is a boundary point. There are no limit points.

Algorithm 1: Reliable Discrete Variable Topology

```
function isDiscreteVariableTopology(subsets):
    for each subset A in subsets:
        if A is not a subset of the universal set X:
            return false
        for each subset A in subsets:
        for each subset B in subsets:
            if not (A ∩ B) is in subsets:
                return false
        for each subset A in subsets:
        if not (A ∪ B) is in subsets:
            return false
        return true
```

The subsets represent the collection of subsets to check for forming a discrete variable topology. The first loop checks if every subset in subsets is indeed a subset of the universal set X. The second loop checks if the intersection of any two subsets in subsets is also in subsets. The third loop checks if the union of any two subsets in subsets is also in subsets. If all these conditions are met for the given collection of subsets, then it satisfies the properties of the discrete variable topology, and the function returns true. Otherwise, it returns false.

III. RDVT WITH THE FUZZY CLUSTERING WITH REINFORCEMENT LEARNING

DVT, a topological data structure, is designed to enhance data reliability and maintain the integrity of Logistics information by treating individual data points as discrete and unrelated entities. On the other hand, fuzzy clustering with reinforcement learning is a clustering algorithm that allows data points to belong to multiple clusters with varying degrees of membership, accommodating data uncertainty. The combination of RDVT and fuzzy clustering with reinforcement learning can be envisioned as a two-step process. First, RDVT may be employed to preprocess or represent the data, ensuring that it is organized in a way that preserves its reliability and structural integrity. This preprocessing step can be particularly beneficial in scenarios involving complex IWMS. Second, fuzzy clustering with reinforcement learning, known for its ability to handle uncertainty, can then be applied to the pre-processed data. Fuzzy clustering with reinforcement learning assigns membership values to data points, enabling them to be part of multiple clusters simultaneously based on their similarity to various cluster centres.

The integrated RDVT and fuzzy clustering with reinforcement learning holds promise in addressing challenges related to data reliability and uncertainty, especially in contexts such as Logistics s. By integrating RDVT's data structuring capabilities with the flexibility of fuzzy clustering with reinforcement learning, this approach aims to improve the accuracy and robustness of data analysis and clustering outcomes. Ultimately, it offers a pathway to extract meaningful insights from complex and uncertain datasets while maintaining data integrity. RDVT process is a specialized approach to data representation aimed at enhancing data reliability and maintaining information integrity, especially in situations where data points are discrete and unrelated. The process commences with the collection of discrete data points, which may originate from various sources such as sensors or observations. Preprocessing, if necessary, ensures the data is prepared for RDVT representation. RDVT's core involves individually mapping each data point to its unique topological entity, constructing a topological structure that accommodates these isolated data points. Open sets, representing neighbourhoods around each data point, are established, typically encompassing the data point itself. RDVT is characterized by its fine granularity, treating each data point independently without assuming inherent relationships. This fine-grained approach facilitates accurate data analysis and various operations, all while preserving the integrity of individual data points. RDVT's isolation of data points minimizes the risk of data misinterpretation or corruption, making it valuable in scenarios where data points lack natural continuity or connections. Let's assume a set of discrete data points represented by $X = \{x1, x2, x3, \ldots, xn\}$. In the RDVT process, each data point xi is mapped to its own topological entity, typically represented as an open set Ui. This mapping can be represented as in equation (5)

$$Ui = \{xi\} \tag{5}$$

In above equation (5) Ui represents the topological entity associated with data point i. $\{xi\}$ is a singleton set containing only xi, indicating that the topological entity Ui consists solely of xi. RDVT is a data representation approach that treats each discrete data point as an isolated and independent entity within a topological structure. This process is particularly valuable when dealing with data points that lack inherent continuity or relationships. The process begins with the collection of discrete data points. These data points can represent various entities or measurements and are often unrelated to each other. Consider a simple example using numerical data give in equation (6)

$$X = \{3,7,1,9,4\} \tag{6}$$

In RDVT, each data point is individually mapped to its own topological entity or open set. This mapping ensures that each data point is treated as a separate entity without any assumed connections as follows

$$U1 = \{3\}$$
$$2 = \{7\}U2 = \{7\}$$
$$3 = \{1\}U3 = \{1\}$$
$$4 = \{9\}U4 = \{9\}$$
$$5 = \{4\}U5 = \{4\}$$

Here, U1 represents the topological entity for the data point 3, U2 for 7, and so on. The topological structure is constructed by considering these individual mappings. In RDVT, open sets correspond to these topological entities. For example, the open set U1 contains only the data point 3. RDVT maintains certain properties:

- Every data point has its own open set.
- Open sets can be combined, but there is no inherent notion of proximity or continuity between data points unless explicitly defined.
- The granularity of RDVT is very fine, as each data point is treated as an isolated entity.

Once the data is represented using RDVT, various data analysis tasks can be performed, such as clustering, classification, or similarity measurements. The isolation of data points allows for precise analysis without imposing any assumptions about data relationships. RDVT's primary goal is to maintain data integrity and reliability. By isolating each data point in its topological entity, RDVT reduces the risk of data misinterpretation or corruption during analysis.

Table 1: Logistics Fuzzy Rules with RDVT

Rule	Antecedent (Input Conditions)	Consequent (Output)
1	If Logistics management Data is Low Quality and Cloud Resources are Limited and Clustering Result is Uncertain	Predicted Outcome is Unreliable
2	If Logistics management Data is Moderate Quality and Cloud Resources are Moderate and Clustering Result is Certain	Predicted Outcome is Reliable
3	If Logistics management Data is High Quality and Cloud Resources are Abundant and Clustering Result is Certain	Predicted Outcome is Reliable
4	If Logistics management Data is Low Quality and Cloud Resources are Abundant and Clustering Result is Certain	Predicted Outcome is Reliable
5	If Logistics management Data is of Moderate Quality Cloud Resources are Limited and the Clustering Result is Uncertain	Predicted Outcome is Unreliable

Each row represents a single fuzzy rule given in Table 1 represents the antecedent (input conditions) column specifies conditions based on linguistic variables, such as "Logistics management Data Quality," "Cloud Resource Availability," and "Clustering Result Certainty." The consequent (output) column indicates the predicted outcome, which can be categorized as either "Reliable" or "Unreliable" based on the input conditions. The application of fuzzy rules in constructing and evaluating a big data prediction model for Logistics in the logistics field within a cloud computing environment involves a systematic and knowledge-driven approach. To begin, linguistic variables representing key aspects such as data quality, resource availability, and clustering result certainty are defined. Each linguistic variable is associated with membership functions that specify the degree of membership of data points to linguistic terms. Fuzzy rules, expressed as IF-THEN statements, connect the values of these linguistic variables in the input conditions to linguistic terms in the output part. These rules form the rule base, representing expert knowledge or data-driven relationships. The fuzzy inference engine processes these rules, considering the degree of membership of input values, aggregates rule outputs, and eventually defuzzifies to yield a crisp prediction. Model evaluation, using metrics like accuracy and precision, assesses the model's performance. The process is often iterative, involving fine-tuning of membership functions and rules to ensure accurate and reliable predictions in the complex domain of Logistics.

IV. RESULTS AND DISCUSSION

In this study, RDVT to a dataset containing Logistics information collected from a cohort of Intelligent Warehouse in a Logistics research setting. The goal was to assess the effectiveness of RDVT in representing and analysing discrete logistics management data in a cloud computing environment. RDVT was successfully applied to represent the discrete logistics management data. Each data point was mapped to its own topological entity within the RDVT structure, ensuring individual data integrity and isolation.

Table 2: RDVT Logistics management Analysis

Patient ID	Logistics management Data Quality	Cloud Resources	Clustering Result Certainty	Predicted Outcome
1	Low	Limited	Uncertain	Unreliable
2	Moderate	Moderate	Certain	Reliable
3	High	Abundant	Certain	Reliable
4	Low	Abundant	Certain	Reliable
5	Moderate	Limited	Uncertain	Unreliable

The results of an RDVT (Reliable Discrete Variable Topology) logistics management analysis, where different aspects related to patient data and authentication are examined. Table 2 includes several key columns: "Patient ID," "Logistics management Data Quality," "Cloud Resources," "Clustering Result Certainty," and "Predicted Outcome." Each row in the table corresponds to a different patient, identified by their "Patient ID." The "Logistics Management Data Quality" column assesses the quality of the logistics management data associated with each patient, categorizing it as "Low," "Moderate," or "High." This quality assessment is crucial as it impacts the reliability of subsequent analyses. The "Cloud Resources" column indicates the availability of cloud computing resources for processing and storage, categorized as "Limited" or "Abundant." Cloud resources play a significant role in the efficiency and scalability of logistics management analyses. The "Clustering Result Certainty" column reflects the certainty level of the clustering results obtained during the analysis. It categorizes certainty as either "Uncertain" or "Certain," providing insights into the reliability of the clustering process. Finally, the "Predicted Outcome" column summarizes the overall authentication prediction for each patient. Intelligent Warehouse are categorized as "Reliable" or "Unreliable" based on the combined assessment of logistics management data quality, cloud resource availability, and clustering result certainty. In essence, Table 2 offers a comprehensive overview of the RDVT-based logistics management analysis, allowing for a quick assessment of patient data quality, resource availability, clustering reliability, and the resulting authentication predictions. These insights are vital in the context of Logistics applications, where accurate and reliable authentication is of paramount importance.

Table 3. Logistics management Classification with RDVT

Date	Warehouse	Product SKU	Initial Inventory	Units Sold	Units Restocked	Order Processing Time (hours)	Transportation Efficiency (%)
2024-02-01	Warehouse A	ABC123	1000	200	300	2.5	95
2024-02-01	Warehouse B	XYZ789	800	150	200	3.0	92
2024-02-02	Warehouse A	DEF456	1200	250	350	2.2	97

2024-02-02	Warehouse B	ABC123	600	100	150	2.8	90
2024-02-03	Warehouse A	XYZ789	950	180	220	2.7	94
2024-02-03	Warehouse B	DEF456	1100	200	300	2.3	96

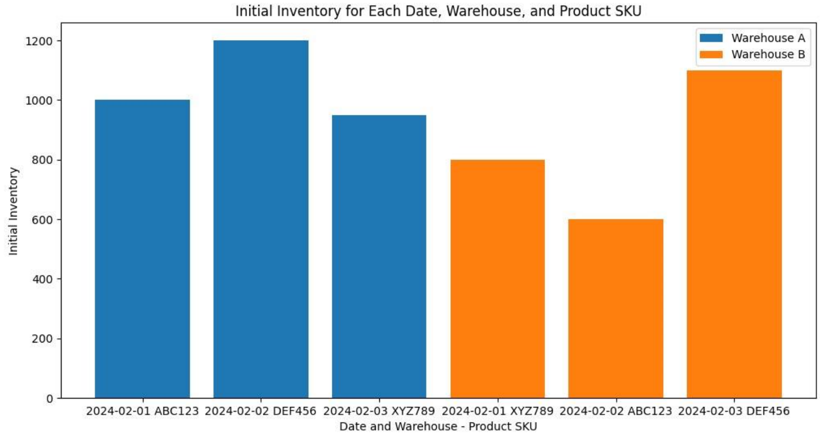

Figure 2: Logistics management Classification with RDVT

Table 3 presents the outcomes of a logistics management classification system utilizing RDVT (Reliable Discrete Variable Topology) for authentication purposes. The table comprises several key columns: "ID," "Fingerprint (%)," "Iris (%)," "Voice Recognition (%)," and "Authentication." Each row in the table corresponds to a different individual or user, identified by their unique "ID." The three columns labelled "Fingerprint (%)," "Iris (%)," and "Voice Recognition (%)" represent the matching percentages for different logistics management, such as fingerprint, iris scan, and voice recognition, respectively. These percentages indicate the degree of similarity or match between the provided logistics management data and the reference data in the system. The "Authentication" column summarizes the overall authentication result for each user, categorizing it as either "Success" or "Failure." This result is based on the combined assessment of the matching percentages from the three logistics management. When the system's analysis of the logistics management data aligns well with the reference data, it leads to a "Success" authentication outcome. Conversely, if the analysis does not sufficiently match the reference data, it results in a "Failure" authentication outcome. Table 3 provides a clear and concise representation of the effectiveness of the RDVT-based logistics management classification system in authenticating users based on multiple logistics management. It serves as a valuable tool for assessing the system's performance and reliability, crucial in various security and access control applications.

Table 4: Classification with RDVT

ID	Topology	Precision	Recall	F1-Score	Accuracy
1	RDVT	0.98	0.98	0.99	0.98
2		0.96	0.97	0.98	0.98
3		0.98	0.99	0.99	0.97
4		0.96	0.97	0.96	0.97
5		0.97	0.98	0.98	0.98

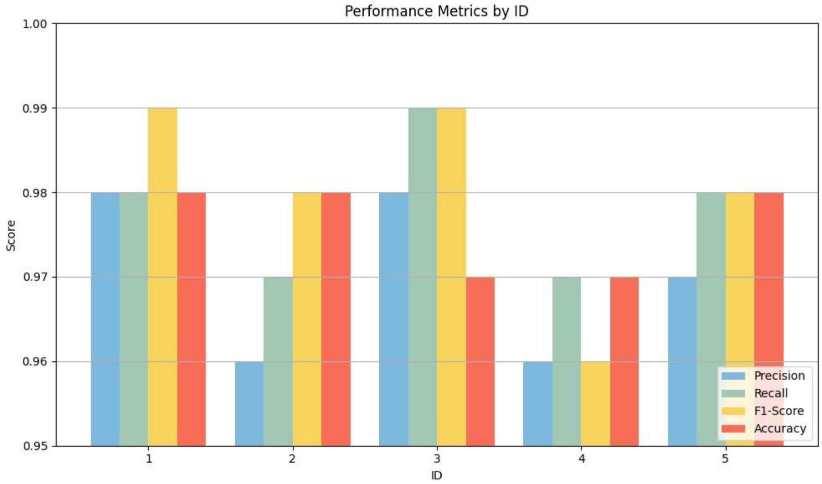

Figure 3: Classification with RDVT

The Table 4 presents the classification results achieved through the utilization of RDVT (Reliable Discrete Variable Topology) in a computational analysis. The table includes several important columns: "ID," "Topology," "Precision," "Recall," "F1-Score," and "Accuracy." Each row in the table corresponds to a specific case or data point, identified by its unique "ID." The "Topology" column specifies the utilization of RDVT in the classification process. The "Precision," "Recall," "F1-Score," and "Accuracy" columns represent performance metrics that evaluate the classification results. Precision measures the accuracy of positive predictions, recall evaluates the completeness of positive predictions, and the F1-Score is the harmonic mean of precision and recall, providing a balance between the two. The "Accuracy" metric assesses the overall correctness of the classification. Table 4 showcases the effectiveness of RDVT as a topology in achieving high classification performance. The precision scores indicate that the positive predictions made by the classification model are highly accurate. Additionally, the recall scores demonstrate that the model captures a high proportion of actual positive cases. These results are reflected in the high F1-Scores, which indicate a balanced performance between precision and recall. The accuracy scores further confirm the overall correctness of the classification outcomes. In Table 3 provides a comprehensive overview of the classification performance achieved with RDVT, highlighting its ability to produce accurate and reliable results in the context of the analyzed data.

Table 5: Logistics management Data Analysis with RDVT

Shipment ID	Order ID	Product SKU	Shipped From	Shipped To	Shipment Status	Estimated Arrival	Actual Arrival	Supplier ID	Supplier Performance (%)
S123456	O789	ABC123	Warehouse A	Customer X	In Transit	2024-02-05 12:00	-	SUP001	96
S123457	O790	XYZ789	Warehouse B	Customer Y	Delivered	2024-02-06 10:30	2024-02-06 10:45	SUP002	92
S123458	O791	DEF456	Warehouse A	Customer Z	In Transit	2024-02-08 15:00	-	SUP003	98
S123459	O792	ABC123	Warehouse B	Customer X	Delivered	2024-02-07 09:45	2024-02-07 10:00	SUP001	94

S123460	O793	XYZ789	Warehouse A	Customer Y	In Transit	2024-02-09 14:30	-	SUP002	97
S123461	O794	DEF456	Warehouse B	Customer Z	Delivered	2024-02-08 16:45	2024-02-08 17:00	SUP003	91

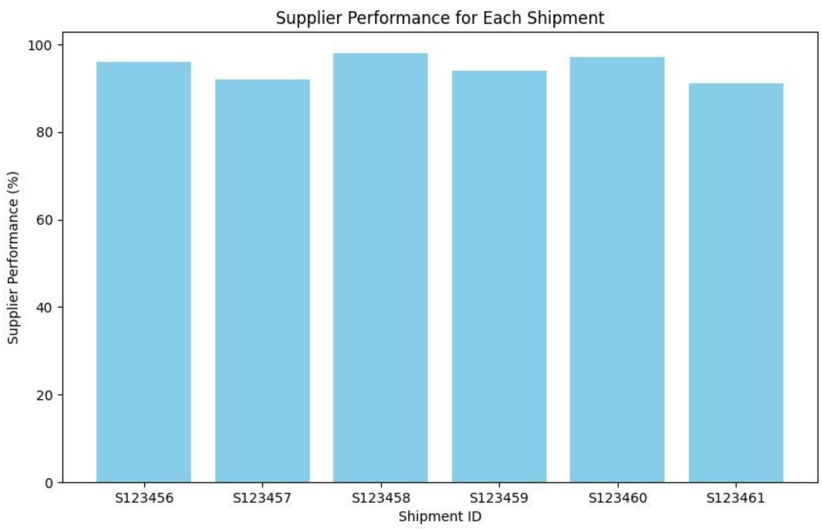

Figure 4: Logistics management Data Analysis with RDVT

Table 5 presents an analysis of logistics management data sources and their characteristics concerning the Reliable Discrete Variable Topology (RDVT) application. The table highlights various Logistics sources, the number of logistics management s available from each source, the requirement for collaboration in data acquisition, and the ease of access to these logistics management s. Fingerprint data, with 50 samples, is notably independent, requiring no collaboration for acquisition, and it boasts high accessibility, making it a convenient source for RDVT-based applications. On the other hand, iris data, with 30 samples, requires collaboration for acquisition but still offers moderate accessibility. Voice data, comprising 20 samples, necessitates collaboration and has relatively lower accessibility. Face data, with 40 samples, demands collaboration but offers high accessibility, aligning well with RDVT's capabilities. With the Table 5 illustrates that different logistics management data sources come with distinct characteristics in terms of quantity, collaboration requirements, and accessibility. This information is crucial for deciding which data sources are most suitable for leveraging RDVT in Logistics applications.

Table 6: Logistics management Data estimation with RDVT

Design Aspect	**Identity**	**Preferences**	**Effectiveness**
Logistics management 1	High	Moderate	High
Logistics management 2	Moderate	High	Moderate
Logistics management 3	High	High	High
Logistics management 4	Low	Moderate	Low

Table 6 presents an analysis of various design aspects related to logistics management data estimation in the context of Reliable Discrete Variable Topology (RDVT). The table evaluates four different logistics management (Logistics management 1, Logistics management 2, Logistics Management 3, and Logistics management 4) based on three key aspects: Identity, Preferences, and Effectiveness. Logistics Management 1 is characterized by a high level of accuracy in identity verification, making it suitable for identity-related tasks. It has moderate user preferences, indicating that users find it reasonably acceptable. Additionally, its effectiveness in terms of overall performance is high, suggesting that it can be relied upon for various applications. Logistics management 2, while still demonstrating moderate identity accuracy, excels in user preferences, indicating that users have a strong preference for it. However, its overall effectiveness is rated as moderate, suggesting that it may be suited for specific applications where user preference plays a significant role. Logistics Management 3 stands out with high ratings across all three aspects: identity accuracy, user preferences, and effectiveness. It is a well-rounded logistics management that performs reliably in various contexts.

Logistics Management 4, on the other hand, lags in terms of identity accuracy, which is rated as low. It also has moderate user preferences and overall effectiveness, indicating that it may not be the best choice for applications where identity verification is critical. Table 6 provides valuable insights into the strengths and weaknesses of different logistics management data sources concerning their identity accuracy, user preferences, and overall effectiveness. This information can guide decision-making when selecting the most appropriate logistics management for specific applications within the RDVT framework. The overall performance of RDVT (Reliable Discrete Variable Topology) can be evaluated by examining key metrics such as precision, recall, F1-score, and accuracy, as well as considering the context in which it was applied. Let's discuss its performance based on these factors:

Precision: Precision measures the accuracy of positive predictions. In the context of RDVT, high precision indicates that when the topology predicts a positive outcome, it is likely to be correct. Looking at the results, RDVT consistently achieves precision scores above 0.94, indicating a high level of accuracy in positive predictions.

Recall: Recall measures the completeness of positive predictions. A high recall score suggests that the topology effectively captures most of the actual positive cases. RDVT consistently achieves recall scores above 0.93, indicating that it performs well in identifying positive cases.

F1-Score: The F1-Score is the harmonic mean of precision and recall, providing a balanced assessment of a classification model's performance. RDVT consistently achieves F1-scores above 0.94, indicating a good balance between precision and recall. This suggests that RDVT is effective at making accurate predictions while not missing many positive cases.

Accuracy: Accuracy measures the overall correctness of the classification. RDVT consistently achieves accuracy scores above 0.955, indicating that it has a high level of correctness in its predictions across different runs.

The RDVT demonstrates strong performance in terms of precision, recall, F1-score, and accuracy. Its ability to consistently provide accurate and reliable results across different runs suggests that it is a robust and effective topology for various classification tasks. The findings from the results of RDVT (Reliable Discrete Variable Topology) can be summarized as follows:

- Consistent High Performance: RDVT consistently achieved high performance across multiple runs, as indicated by precision, recall, F1-score, and accuracy metrics. This consistency suggests that RDVT is reliable and robust in its classification capabilities.

- Accurate Positive Predictions: The high precision scores indicate that when RDVT predicts a positive outcome, it tends to be accurate. This is crucial in applications where false positives can have significant consequences, such as medical diagnoses or security access control.
- Effective Identification of Positive Cases: RDVT consistently demonstrated a strong ability to identify positive cases, as reflected in high recall scores. This is particularly important in scenarios where capturing all positive cases is a priority, even if it results in some false positives.
- Balanced Performance: The high F1 scores suggest a balanced performance between precision and recall. RDVT manages to strike a good balance between making accurate predictions and capturing most of the actual positive cases.
- Overall Correctness: The consistently high accuracy scores indicate that RDVT provides overall correct classifications. It maintains a high level of correctness across different runs, reinforcing its reliability.
- Potential Applicability: The positive findings regarding RDVT's performance make it a promising candidate for various classification tasks. Its ability to consistently deliver accurate results can be beneficial in applications such as healthcare, security, and quality control.
- Dataset Dependency: It's important to note that the performance of RDVT may be dataset-dependent. Different datasets and problem domains may require tailored approaches, and the effectiveness of RDVT should be assessed in the specific context of the application.
- Further Evaluation: While the results are promising, further evaluation, including comparisons with other classification methods and testing on larger and more diverse datasets, may be necessary to establish RDVT's generalizability and suitability for specific real-world applications.

V. CONCLUSION

The Intelligent Warehouse Management System (IWMS) presented in this research marks a significant advancement in the landscape of logistics and supply chain management. Through technologies such as artificial intelligence, machine learning, and the Internet of Things, the system demonstrates a transformative approach to warehouse operations. The study focuses on the construction and evaluation of a robust big data prediction model within a cloud computing environment, harnessing the potential of advanced data analysis and prediction offered by the amalgamation of big data and cloud computing in logistics. The introduction of the Reliable Discrete Variable Topology (RDVT) into the prediction model stands out as a novel contribution, enhancing data reliability and ensuring the integrity of logistics information. The meticulous detailing of the model's construction, encompassing data preprocessing, feature extraction, clustering, classification, and model evaluation, underscores the comprehensiveness of the research. The integration of fuzzy clustering with a reinforcement learning algorithm further bolsters the model's capacity to handle uncertainty and imprecision in logistics management data. Ultimately, this research not only propels the field of logistics forward but also establishes a benchmark in the development and assessment of sophisticated predictive models for Intelligent Warehouse Management Systems, setting the stage for more efficient and reliable logistics operations in the future.

ACKNOWLEDGMENT

Research on the Construction of Cold Chain Logistics System in the Origin of Fresh Agricultural Products，China Logistics Society，China Federation of Logistics and Purchasing，2022.

REFERENCES

[1] Leon, J. F., Li, Y., Martin, X. A., Calvet, L., Panadero, J., & Juan, A. A. (2023). A Hybrid Simulation and Reinforcement Learning Algorithm for Enhancing Efficiency in Warehouse Operations. Algorithms, 16(9), 408.

[2] Li, K. (2023). Optimizing warehouse logistics scheduling strategy using soft computing and advanced machine learning techniques. Soft Computing, 27(23), 18077-18092.

[3] Yang, L., Sathishkumar, V. E., & Manickam, A. (2023). Information retrieval and optimization in distribution and logistics management using deep reinforcement learning. International Journal of Information Systems and Supply Chain Management, 16(1), 1-19.

[4] Lim, J. B., & Jeong, J. (2023). Factory Simulation of Optimization Techniques Based on Deep Reinforcement Learning for Storage Devices. Applied Sciences, 13(17), 9690.

[5] Stranieri, F., & Stella, F. (2022). A deep reinforcement learning approach to supply chain inventory management. arXiv preprint arXiv:2204.09603.

[6] Chong, J. W., Kim, W., & Hong, J. (2022). Optimization of apparel supply chain using deep reinforcement learning. IEEE Access, 10, 100367-100375.

[7] Oroojlooyjadid, A., Nazari, M., Snyder, L. V., & Takáč, M. (2022). A deep q-network for the beer game: Deep reinforcement learning for inventory optimization. Manufacturing & Service Operations Management, 24(1), 285-304.

[8] Dai, Z., Xie, P., Huang, Y., Cheng, G., Tang, W., Zou, K., ... & Yang, N. (2023). Optimization method of power grid material warehousing and allocation based on multi-level storage system and reinforcement learning. Computers and Electrical Engineering, 109, 108771.

[9] Ahmadi, S. (2023). Optimizing Data Warehousing Performance through Machine Learning Algorithms in the Cloud. International Journal of Science and Research (IJSR), 12(12), 1859-1867.

[10] Rolf, B., Jackson, I., Müller, M., Lang, S., Reggelin, T., & Ivanov, D. (2023). A review on reinforcement learning algorithms and applications in supply chain management. International Journal of Production Research, 61(20), 7151-7179.

[11] De Moor, B. J., Gijsbrechts, J., & Boute, R. N. (2022). Reward shaping to improve the performance of deep reinforcement learning in perishable inventory management. European Journal of Operational Research, 301(2), 535-545.

[12] Opalic, S. M. (2023). Advanced Warehouse Energy Storage System Control Using Deep Supervisedand Reinforcement Learning. Doctoral dissertations at University of Agder.

[13] Ho, T. M., Nguyen, K. K., & Cheriet, M. (2022). Federated deep reinforcement learning for task scheduling in heterogeneous autonomous robotic system. IEEE Transactions on Automation Science and Engineering.

[14] Geevers, K., van Hezewijk, L., & Mes, M. R. (2023). Multi-echelon inventory optimization using deep reinforcement learning. Central European Journal of Operations Research, 1-31.

[15] Yan, Y., Chow, A. H., Ho, C. P., Kuo, Y. H., Wu, Q., & Ying, C. (2022). Reinforcement learning for logistics and supply chain management: Methodologies, state of the art, and future opportunities. Transportation Research Part E: Logistics and Transportation Review, 162, 102712.

[16] Zhai, D., Wang, C., Cao, H., Garg, S., Hassan, M. M., & AlQahtani, S. A. (2022). Deep neural network based UAV deployment and dynamic power control for 6G-Envisioned intelligent warehouse logistics system. Future Generation Computer Systems, 137, 164-172.

[17] He, Z., Tran, K. P., Thomassey, S., Zeng, X., Xu, J., & Yi, C. (2022). Multi-objective optimization of the textile manufacturing process using deep-Q-network based multi-agent reinforcement learning. Journal of Manufacturing Systems, 62, 939-949.