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CUCKOO SEARCH SUPPORT VECTOR MACHINE FOR SUPPLY CHAIN RISK MANAGEMENT

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ABSTRACT

Supply chain interruptions have been identified as a key risk factor. Supply chain risk management has been driven by technological advancements, an increase in information overload, and a greater exposure to risk. Data mining uses a variety of analytical methods to make intelligent and fast decisions; yet, its utility in supply chain risk management has yet to be fully realized. The risk in the supply chain is prioritized using machine learning techniques. The majority of supply chain studies, on the other hand, focus on prediction efficiency and ignore the significance of interpretability, which helps experts to mitigate or avoid risks. The goal of this study is to develop a data mining-based cuckoo search support vector machine supply chain risk management (DM-CSVM SCRM) for predicting hazards in supply chains, as well as identifying, assessing, and mitigating them. A supply chain risk prediction is done by using a machine learning algorithm in this project. A holistic approach to risk management combines risk management and DM operations into a single structure for efficient management of risk. Based on discussions, focus group interviews, and semi-structured interviews the framework is tested in this study. The research shows how DM can help you find unseen and relevant data in unstructured risk data so you can make better risk decisions.

Keywords:- *Supply Chain Risk Management, Decision Support System, Data Mining, Machine Learning, Data Analytics.*

1. INTRODUCTION

A major reason for the growing interest in managing supply chains risks locally, nationally, and globally has been the global financial ambiguity that arose after the 2009 global financial crisis. SCRM originated as a specialized field in the early 2000s, encompassing other than closely related topics like supply chain management and enterprise risk management [1]. In the SCRM, all stakeholders participating in the supply chain's collaborative and coordinated efforts identify, mitigate, monitor, and assess the risks with the goal of reducing susceptibility and improving the supply chain's robustness and resilience, ensuring stability as well as consistency. Different tactics for managing supply chain risks were presented, ranging from intra-organizational strategies to supplier management (such as alternative suppliers, supplier sustainability, and flexible sourcing) [2]. Supply Chain Risk Management includes all information, institutions, technologies, and procedures that can be utilized to reduce the risk in a supply chain on a technical, organizational and personal level.

Many businesses do not pay attention to supply chain hazards. A lack of standards in terms of system compatibility and data consistency, as well as technical problems in integrating risk management software into current information and communication systems, are frequently cited issues in addition to a lack of time and staff resources. One of the most difficult difficulties is receiving early

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notification of variations from the intended process in order to certify the timeliness of logistical processes within the supply chain [6].

This research examine the probability of using machine learning methods to develop SCRM predictive analytics which are both interpretable and perform to a high prediction accuracy level. The machine learning method is then used to implement and test a real-world study by examining a number of measures and machine learning algorithms namely support vector machines (CUCKOO SEARCH SVMs). Using classification, this case study predicts risk. To make effective, intelligent, and timely decisions, an increasing amount of groups are turning to Data Mining (DM) and Business Intelligence (BI) methodologies.

Data Mining is crucial in generating important insights about potential Supply chain risk factors, their sources, impacts, and interconnections. To construct proactive and reactive systems, DM approaches can be applied at various stages of SCRM. DM approaches are used in a variety of studies to discover and assess specific risks in various research disciplines. A systematic structure for exploiting unstructured data for SCRM is lacking. Machine Learning also used in supply chain risk management is an algorithm that generates outputs based on available data without having to program the learning outcome first. Instead, the machine learning algorithm 'learns' and assimilates its vision to the underlying real-world phenomena represented in the input data iteratively.

The remaining section of this study is demonstrated as follows. The related works is explained in Section II. The suggested techniques were shown in Section III, along with an explanation and the related algorithm. The performance outcome and their analysis are provided in Section IV. Conclusions and further work were completed in Section V.

2. RELATED WORKS

In 2021 Schroeder, M. and Lodemann, S [6] evaluated the literature to see if risks were managed in the use cases and how machine learning may affect SCRM. Based on the findings, the examples presented are mainly geared toward identifying supply chain risks early on so that they can be addressed as soon as possible. As a consequence, this research is able to determine the additional value that Machine Learning integration can provide to the SCRM.

In 2021 Tavana, M et al [7] propose an integrated method to evaluate supply chain risk benefits and select suppliers that combines fuzzy analytic hierarchy processes (AHP) and multi-objective fuzzy optimization analysis. The fuzzy AHP is utilized to rate providers and the fuzzy MULTIMOORA is utilized to quantify the crucial to the supply chain benefits and risks.

In 2020 Xu, R.Z. and He, M.K., et al [8] suggest a deep network-based Technique for assessing financial credit risk in the supply chain in online. Deep belief network assessment models are created when Restricted Boltzmann Machines (RBM) is combined with the classifier SOFTMAX. The results reveal that this technique has a 96.04 percent evaluation accuracy, which is greater than the CUCKOO SEARCH SVM method and the Logistic method and has better logic.

In 2020 Munir, M. et al [9] Developed theoretical and managerial implications by developing and empirically testing a holistic framework demonstrating the influence of SCI on SCRM and, as a result, on presentation results. According to the findings, supplier, customer integration, and internal all have the favourable impact on SCRM customer and supplier integration which play a role in the internal integration process.

In 2019 Baryannis, G. et al [10] present a comprehensive assessment of supply chain literature that uses AI-based methodologies to solve problems pertinent to SCRM. Mapping research is carried out to classify current literature based on the AI approach employed, which ranges from measured programming to Big Data Analytics and ML, as well as the task of the specific SCRM, must be handled.

In 2018 Rostamzadeh, R., et al [11] presented an integrated fuzzy multi-criteria decision-making for the long-term risk management of supply chains. The framework for identifying and analyzing SSCRM is being developed. Incorporating managerial attitudes into the review process utilizing qualitative research methodologies could improve the understandability of the solutions proposed and promote industry acceptance.

3. PROPOSED SCHEME

The purpose of our study is to create new ideas called DM-ML-based SCRM through the use of multiple activities, including predicting the probability of the risk, identifying the risk,

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translating the risk management problem into a DM problem, analyzing the information by using DM algorithms and interpreting analysis outcomes to classify risk mitigation strategies. Before that, the system model along with the objective function is defined in this work.

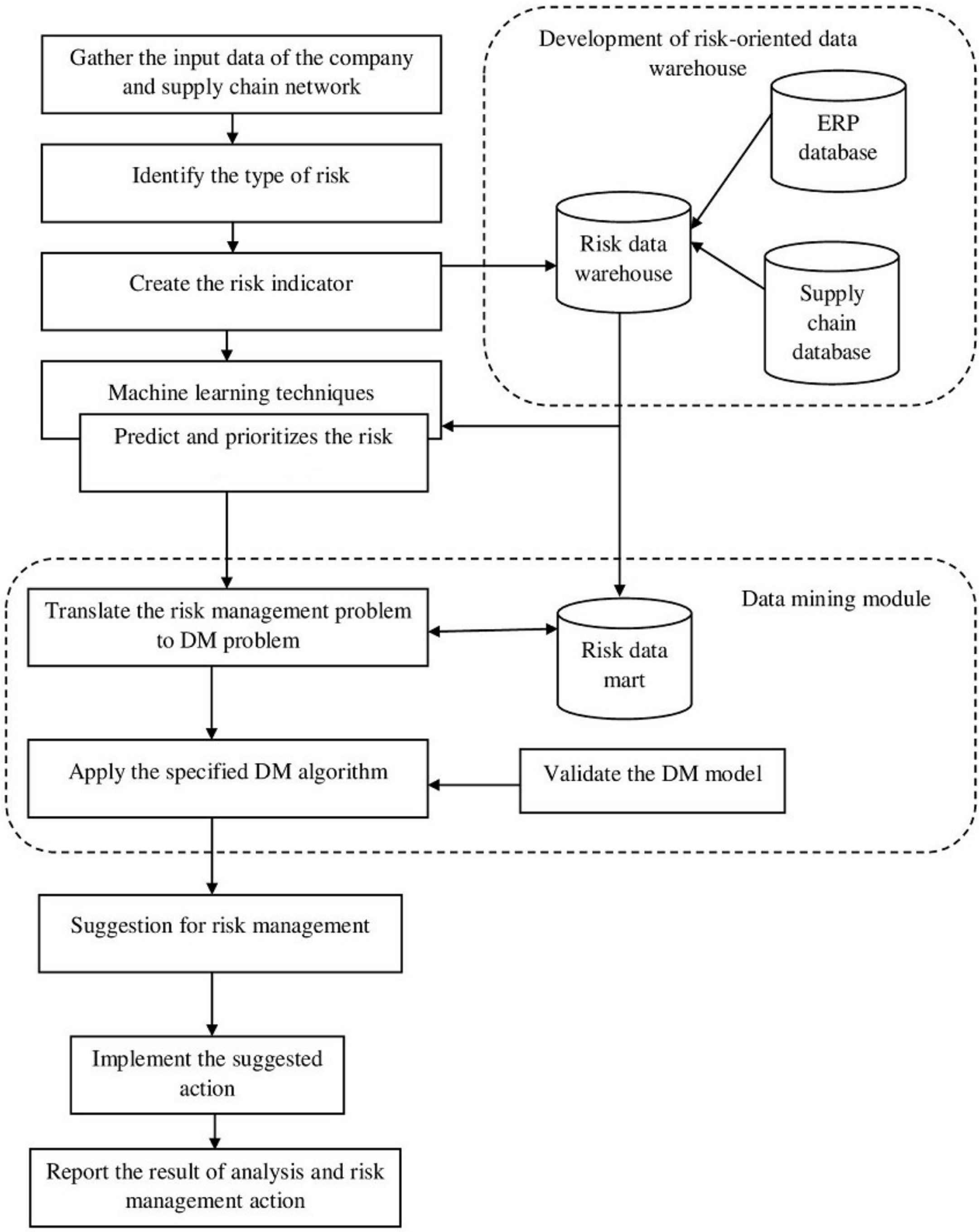

Figure 1: Proposed Methodology

Different industries, businesses, and organization structures have different types, severity, and frequency of hazards. Each organization also has a unique risk profile and approach to risk.

Obtain the information from the company:

Size, experience, industry, sector, and network structure of the firm influence the types and distribution of risks. Based on this information, every risk management model should be created and should be aligned with the mission, goals, and strategies of the company.

Identifying the major risk:

Secondly, a risk management team must be formed after analyzing the structure and gathering the information from the company. DM-based SCRM requires a multidisciplinary approach that incorporates diverse experience and expertise. To analyze risk data using DM approaches, the team needs a data analyst or DM expert. Roles and tasks should be defined in development to avoid confusion and increase worker efficiency.

Indicate the level of risk as follows:

Data warehouses are the backbone of decision support systems. It is a centralized repository for storing current and historical risk data on SC from a variation of external and internal sources. Risk data are processed, monitored, and reported by the RDW, and so the RDW's role is to help companies make data-driven decisions. Considering the difficulty and cost of building a data warehouse, a feasibility study should be conducted first.

To build a risk data analysis platform, a corporation can either construct a standalone RDW or integrate risk indicators into its existing data warehouse. A data mart is a simple data storage system that is subject-oriented and created for a particular business. Companies select risk management methods based on a variety of factors, such as the types of risks in their business, their level of exposure to risk, the amount of data about risks, and how frequently they experience risks. Risk indicators are measurements, statistics, or parameters that show the exposure level of risk factors over time. Detecting, evaluating, and monitoring risks can all be made easier with the help of these signs.

Data warehouse architecture: During this step, data flows, an ETL system, data sources, staging, metadata, data storage, frontend apps, and the presentation layer of the data warehouse are all designed and specified. In the DM-ML-based supply chain risk management model, the metadata layer contains information regarding risk indicators.

Machine learning:

The results of the monitored data are used in the next step of the framework to determine the precise aim of the risk prediction process. With a machine learning algorithm, supply chain risk is anticipated and prioritized by selecting the best algorithm for the task at hand. It is intimately related to the risk prediction task's priorities in which machine learning algorithms are utilized, as well as to measures such as false positive, true positive, false negative, and true negative. It is critical to establish whether the risk prediction method primarily aims to improve forecast accuracy.

Cuckoo search SVM:

The Cuckoo Search algorithm uses meta-heuristics to solve optimization problems. Using a new method, the cuckoo search can be used to predict multidimensional supply chain risk problems. Levy's flight process increases the likelihood of obtaining an optimal global solution by selecting the best local solution. Choosing the right parameters is crucial to the SVM's performance. In order to avoid the local minimum value that can occur when using the traditional parameter optimization procedure, the cuckoo search (CS) algorithm is used to optimize the key parameters. SVM's generalization and learning ability are both dependent on the selection of appropriate parameters. It has a strong ability to global search, requires fewer parameters, and has a good search path. In this study, radial basis functions with a single parameter γwere chosen as the kernel function. C is a more complex parameter to set. According to the unbalanced data problem, its value is determined by the number of training samples in each class. The Cuckoo search SVM is a powerful tool to predict the risk.

Data mining:

By converting expected risk data obtained by machine learning techniques into risk information, the risk knowledge module can be used to make intelligent SCRM judgments. Data from the server is collected into the DM module, which creates a data mart for the current analysis by using the RDW. Risk data marts are data marts that adhere to the DM algorithms. Data Mining techniques and tools can be employed to handle the subsequent challenges: detecting difficulties, identifying correlations among risks and other elements, identifying root causes of risk, clustering risky items, etc. Such risk issues may be solved by DM tasks. The solution to the DM problem should be used before creating the DM algorithm.

Before the risk management team interprets the results, the data mining algorithm should be authenticated, refined, and assessed by the DM expert. To guarantee the validity of the chosen DM technique, it can be compared to other approaches. Afterward, The DM algorithm, which transforms risk information into risk knowledge, can be used for interpretation and evaluation. Because the choice of DM and machine learning application for evaluation and analysis of outcomes is so important in a DL-CSVM-based supply chain, interpretation is critical. The management team and risk analysis would detect activities for mitigating focused risk aspects after analysing and assessing risk data. Domain specialists should assess alternative supply chain solutions, taking into account associated costs and advantages**.**

4. RESULTS AND DISCUSSION

This section describes the outcomes of the feature selection procedure and machine learning algorithms to predict the result of the study. Through a top-down selection process, the most critical risk indicators were selected, and a focus group study helped to develop the finishing collection of risk indicators. Researchers were able to identify the 10 problematic areas in the SC network, as well as provide empirical evidence and insight into the risk problem that would be addressed by the DM analysis.

Performance analysis:

In order to obtain optimal CUCKOO SEARCH SVM parameters C, we used scikit-learn. Misclassification penalties are referred to as C, and high values indicate a greater punishment, making the model tighter Several different metrics with 33 and 26 features are examined, so we execute grid searches for each measure independently and for both feature sets.

Here, we consider a network of 300 and 600 sensor nodes randomly distributed in a field of 250m * 250m, and the values used in the first model are described in Table 1.

Table 1: Score of Cuckoo Search SVM Prediction by 33 Features

Parameters		**Test score**				**Classification**			
C	γ	AP	F1	Recall	Accuracy	True Positive	True Negative	False Positive	False Negative
1	10^4	0.835	0.765	0.704	0.940	722	6170	154	294
10^3	10^3	0.632	0.779	0.750	0.947	749	6148	182	264
10^4	10^3	0.618	0.769	0.768	0.937	776	6089	239	239

Table 2: Score of Cuckoo Search SVM Prediction By 26 Features

Parameters		**Test score**				**Classification**			
C	γ	**AP**	**F1**	**Recall**	**Accuracy**	**True Positive**	**True Negative**	**False Positive**	**False Negative**
1	10^5	**0.851**	**0.685**	**0.557**	**0.928**	**565**	**6245**	**82**	**449**
10^2	10^4	**0.651**	**0.794**	**0.754**	**0.944**	**775**	**6142**	**184**	**239**
10^3	10^4	**0.642**	**0.785**	**0.772**	**0.941**	**781**	**6121**	**205**	**232**

From Tables 1 and 2, the results for F1 are comparable, however, the variations are more dramatic. C = 104 and = 104 have the highest values. The precision findings and the harmonic mean of precision and recall reveal that a higher misclassification penalty is required to achieve both high recall and high accuracy. Using recursive feature elimination, both feature sets achieve similar results, although the smaller set scores higher across a broader range of criteria.The performance of

CUCKOO SEARCH SVM prediction models is generally good across a variety of metrics, though they exhibit a decrease in precision for balanced metrics and recall. For all other measures, the greater the penalty level (parameter C) the lower the average precision value. The model uses C = 103 and γ =104 as a parameter and achieves the lowest number of false positives, which correctly predicts 78.1 percent of late deliveries. It is found that the parameters C = 1 and = 105 give the best results, with 88.2 percent of late delivery forecasts being accurate.

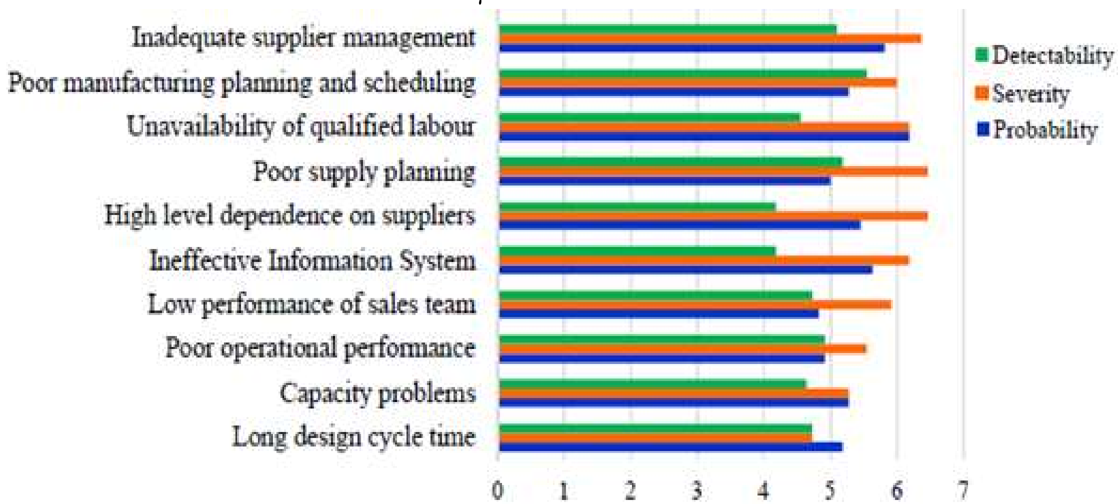

Figure 2: Ratings of the Top 10 Risks

As a result, $C = 10^2$ and $C = 10^4$ provide the optimal compromise between different classes. While both feature sets achieve near-perfect recall, correctly predicting 97.7% and 94.1 percent of provisions with 26 and 33 features correspondingly, it comes at the expense of the other measures.

The supply risk category was chosen as the subject of DM research based on respondents' evaluations and interactions with corporate managers. Inefficient supplier evaluation and selection processes, as well as the difficulty of finding an alternate provider in an emergency, are the main sources of supplier risk. Accordingly, the most important aspect of risk management is to classify suppliers according to their risk profiles. As a result, this issue has become a DM issue. We examined the risk types associated with the suppliers of a company in order to better understand how to choose DM software. Risk classifications for the company's suppliers were evaluated based on 7 qualitative and quantitative factors. Factor analysis was used to reduce the number of criteria. Using the k-means clustering technique, the primary suppliers of the company were organized according to the four risk categories determined earlier.

Table3: Mean of risk criteria

Risk criteria	**Cluster 1**	**Cluster 2**	**Cluster 3**
Manufacturing capability	4.95	4.20	5.14
Flexibility	4.85	4.29	5.10
Technological Capability	4.89	4.18	5.20
Defect rate	0.18	0.29	0.13
Lead Time variability	0.15	0.36	0.19
Reliability	4.80	3.69	4.85
Ease of Communication	3.96	3.25	4.68

Low risk Medium risk High risk

Three clusters were found, each with a different risk exposure level, and the findings were deduced to make available insights to manage supplier-related risks during the supplier evaluation and selection phase. There are 19 suppliers in the clusters, 11 suppliers in the cluster, and 42 suppliers in the cluster. Table 2 shows the mean values of the risk criteria for these clusters. For most risk types, Cluster 3 has the greatest risk ratings, Cluster 2 has medium risk scores, and Cluster 1 has the low-risk scores. The outcomes of the analysis of cluster assist the organization in eliminating riskier suppliers and obtaining smaller, more homogeneous supplier groupings that are easier to manage. The findings could potentially be utilized to create customized supplier development programs aimed at lowering supplier-related risks.

5. CONCLUSION

The aim of this study is to develop data mining and machine learning algorithms for supply chain risk management (DM-ML SCRM) in order to forecast supply chain risks as well as identify, analyses, and mitigate supply chain risk. The proposed technique provides a step-by-step guide for collecting, analyzing, monitoring, and managing SC risk data from a variety of sources. As part of this study, a machine learning-based supply chain risk prediction was created. The study illustrates how DM can help you uncover unstructured risk data that holds valuable information that can be used to make smarter decisions. The study provides a comprehensive approach that is realistic and straightforward to adopt by merging multiple process modules. A DM-ML-based risk management paradigm is designed to make businesses smarter by educating those regarding SC risks, their critical repercussions, and their interdependencies. Based on the results of tests conducted within the case study, the framework appears to perform well across a wide array of measures using both interpretable machine learning and Data Mining techniques. Future studies could concentrate on deploying the SCRM framework, which is based on data mining and machine learning, across many businesses in order to derive universal insights and explore a larger dataset with more features and a larger set of machine learning techniques.

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