# AI-Based Evaluation System for Supply Chain Vulnerabilities and Resilience Amidst External Shocks: An Empirical Approach

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**ABSTRACT**

The study focuses on the intricacies and vulnerabilities inherent in supply chains, which are often influenced by external disruptions such as pandemics, conflict scenarios, and inflation. The aim is to devise an AI-driven system that can accurately appraise these intricacies within the domain and mitigate their vulnerabilities effectively. The work employs an empirical approach utilizing datasets from various studies for developing Machine Learning (ML) and Deep Learning (DL) models. These include linear regression, deep learning, CNN networks are designed to predict supply chain risks and enhance the overall stability and performance of an industrial supply chain system. The Deep CNN regression model outperforms as compared to the other models in predicting supply chain risks, achieving an accuracy rate of approximately 90%. The developed model will be more proficient in dealing with complex and nonlinear relationships among the variables. The study introduces a novel approach to data augmentation using Fuzzy C-means in conjunction with a Deep Convolution network model. This approach expands the data size, reduces the forecast errors, and reduces the computational of the given model. The results highlight the potential of ML and DL in enhancing predictability and resilience in the face of escalating risks within supply chain networks. The findings of the work will significantly offer insights for strategists and planners in the supply chain sector to enhance their operational effectiveness and efficiency.



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## 1. Introduction

Supply Chain Risk Management (SRM) plays a crucial role in business operations, with increasing emphasis on its significance in both the academic and professional sectors. The SRM aims to identify, assess, and minimize various risks that have the potential to disrupt an organization's operational activities, thereby hampering its ability to achieve its objectives. The risks in this context are diverse, ranging from natural disasters to intentional or accidental actions that affect both internal and external facets of the supply chain.

The escalating trends of globalization, outsourcing, and the adoption of lean manufacturing methods have made Supplier Relationship Management (SRM) a vital factor in ensuring operational consistency and financial stability in unpredictable circumstances. The SRM serves to maintain uniformity and safeguard the financial viability of organizations in unpredictable business environments.

This paper delves into the theoretical foundations of the Supply Chain Risk Management (SRM) framework, its significance, and the various strategies employed to manage risks within supply chains. In recent years, a series of disruptive events have highlighted the importance of the SRM, with significant repercussions on the global economy and supply networks. The realization that an organization's susceptibility to risk hinges on multiple elements within its supply chain has accentuated the importance of Supplier Relationship Management.

Managing supply networks is a pivotal aspect of modern business. Organizations rely on efficient and productive supply chains to ensure timely delivery of goods and services to their customers. However, supply chains are vulnerable to a plethora of risks, which can obstruct their functioning and lead to significant financial consequences.

A key aspect of Supplier Relationship Management is predicting potential disruptions and assessing their harmful impacts on supply chain operations. This proactive approach to identifying and mitigating possible disruptions requires strong emphasis on risk anticipation. Machine learning techniques have emerged as highly effective tools for predicting supply chain risk.

Incorporating machine learning algorithms into risk management models can enhance the accuracy and thoroughness of predictions, enabling organizations to make informed decisions and implement appropriate strategies to manage potential dangers. These algorithms can analyze large datasets and detect patterns and correlations that may be overlooked by conventional statistical methods.

By leveraging these algorithms, organizations can achieve better control and oversight of their supply chain operations, leading to increased overall efficiency and reduced likelihood of disruptions. The integration of machine learning (ML) techniques into supply chain risk prediction enables organizations to make more informed, proactive decisions.

Figure 1 demonstrates the impact of supply chain disruptions on companies' financial performance. This reminds us of the critical importance of effective risk management in supply chain operations. Companies must understand and address the potential risks inherent in their supply chains to ensure their longevity and success in the current business landscape.

## 2. Literature Survey

Several research initiatives have explored the utilization of machine learning methodologies within this sphere, showing an enhanced capacity for accurate predictions and strategic decision-making. A key focus within the scope of supply chain risk management is the foresight of disruptions and their detrimental impact on the supply chain.The significance of striking a balance between predictive accuracy and interpretability in SRM is emphasized, ensuring that the generated outcomes can be comprehended by supply chain experts for the purpose of making educated decisions.Researchers have delved into the utilization of machine learning methods in this field, indicating a promising prospect for enhanced predictive accuracy and decision-making. One crucial aspect of supply chain risk management is forecasting potential disruptions and their detrimental effects on the supply chain.

The importance of striking a balance between predictive accuracy and interpretability in SRM is highlighted to ensure that supply chain professionals can comprehend results and make informed decisions. Delayed delivery can have substantial repercussions for a business, encompassing the possible decline in customer satisfaction and loyalty. Research indicates that customers subjected to late deliveries are less likely to be content with the company's offerings, and are more prone to opting for a rival company. Late deliveries can spur negative publicity, tarnishing a company's image and leading to the loss of prospective customers. Moreover, late deliveries can escalate business costs, such as the necessity for rush shipping or amending delivery routes. Late deliveries can also impose operational expenses on the company, especially if they depend on just-in-time inventory management. Late deliveries can interrupt the production cycle and contribute to downtime or stock shortages, which can lead to a decrease in productivity and a surge in operational costs. Moreover, late delivery can adversely affect a company's cash flow and fiscal performance. Late deliveries can result in payment deferrals or penalties levied by customers.

It has been found that maintaining higher safety stock levels necessitates the allocation of more resources and capital within the supply chain. Conversely, they also discovered that longer delivery lead-times were correlated with reduced safety stock levels, enabling businesses to better plan their inventory management and production processes (Ma et al., 2023).

Koh and Sad posit that incorporating a safety lead time into supply chain management can effectively mitigate uncertainties such as late delivery. This can lead to customer dissatisfaction, loss of trust, and potential damage to a company's reputation. Additional costs incurred owing to late delivery, such as rush order fees or expedited shipping, can strain a company's pricing strategy and overall profitability and influence its ability to set prices (Koh & Saad et al., 2006).

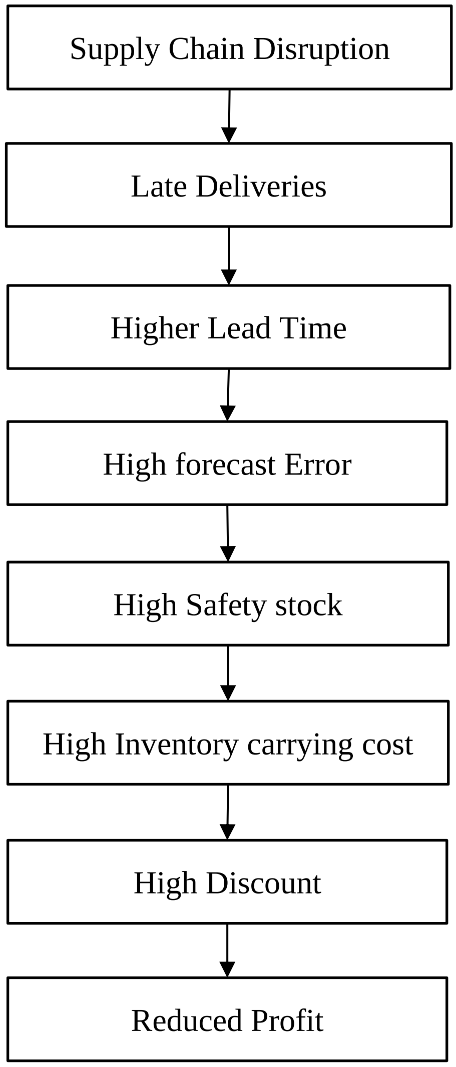


**Figure 1.** Supply Chain Disruptions impact on Companies profitability

Molinder, (1997) reinforces the link between lead time variability and optimal safety lead times and stocks. This suggests that businesses that grapple with frequent late deliveries or variability in lead times may benefit from bolstering their safety stock levels.

Louly& Dolgui, (2010) proposed that including safety stock levels in inventory planning can successfully counteract uncertainties and variability in component procurement times and simultaneously ensure a steady material flow within the supply chain. The overarching consensus is that the ability to predict delivery time accurately is a key factor in efficient supply chain management.

Mittal et al., (2008) developed a physics-based method that utilized nonlinear differential equations and a tailored objective function. This approach underscores the potency of physics-based tactics in forecasting a company’s throughput. The results are promising, indicating the potential of this method to optimize profitability through accurate throughput predictions. In another study, how hate speech could be a risk was identified, as well as the potential cause of disruption.

Gupta & Singh (2012) found that customer satisfaction is influenced by lead-time in the supply chain. Their study showed that shorter lead times can increase customer satisfaction, because customers perceive faster delivery as a sign of efficiency and reliability. Furthermore, a survey funded by Whirlpool and Sears indicated that the fulfillment of date commitments is the most important factor in customer satisfaction with appliance deliveries. This suggests that companies must prioritize timely delivery to maintain high levels of customer satisfaction. Unni et al., (2015) found that delivery time played a key role in determining overall customer satisfaction with e-retailers. Bhattacharyya et al., (2021) explored the factors, which affect the seller performance at E-Commerce market palce in India. Baryannis et al., (2021) applied machine-learning concept for predicting supply chain risks.

These studies reveal that supply chain disruptions lead to late deliveries, which have a direct and negative impact on customer satisfaction. Moreover, studies have highlighted the correlation between supply chain disruption and online marketplace sales.

Kolahi-Randji et al., (2023) employs a simulation modeling approach to evaluate supply chain performance in a multi-level, multi-commodity context. Discrete event simulation is used to model the complex workflows and dynamics in the supply chain network. This allows assessing the impacts of uncertainties, disruptions, and control policies on metrics like costs, service levels, and resilience. Simulation provides a risk-free virtual environment to gain insights and make informed decisions around mitigating supply chain vulnerabilities. Overall, simulation modeling enables comprehensive analysis of risks and tradeoffs, which is invaluable for strategic supply chain risk management.

Baker et al., (2023) employs a machine learning approach to classify Twitter posts related to COVID-19 lockdowns into "lockdown" or "recovery" categories based on when they were posted. Various classifiers like logistic regression and random forest are compared, with and without using the SMOTE technique to balance the uneven dataset. This demonstrates the impact of imbalanced data on classifier performance for sentiment analysis, an important consideration for supply chain risk monitoring using social media data.

AbdelAziz et al., (2024) proposes a framework integrating GIS, IoT, and MCDM for disaster risk management. It uses GIS and machine learning models to predict flood-prone areas. Then it selects optimal drone sites for real-time IoT data collection using MCDM. This allows proactive monitoring and rapid response to supply chain disruptions from natural disasters. Overall, it demonstrates how emerging technologies can be leveraged to build resilience against supply chain risks.

Kiptum et al., (2023) uses the interval-valued Fermatean fuzzy analytical hierarchy process (IVFF-AHP) methodology. This involves establishing a criteria framework, collecting expert opinions to compare the criteria in a pairwise manner, checking consistency, aggregating judgments, and calculating criteria weights.

Dabić & Raković (2023) proposed TOPSIS based methodology that enables a risk-based analysis of different autonomous technologies like AGVs, AMRs, drones to identify the optimal solution that improves warehouse efficiency and resilience. The ranking accounts for criteria like system disruption risks, flexibility, costs which are critical supply chain risk factors.

Mohan et al., (2023) newsvendor model using utility theory to determine optimal ordering quantities for risk-neutral and risk-averse retailers, that enables retailers to optimize inventory orders accounting for demand uncertainty risk and their own risk preferences. It supports effective management of inventory risk, shortage risk and overstocking risk in supply chains.

### 2.1. General Limitations of the existing research

In existing methodologies for predicting supply chain risk, the following three key limitations emerge.

**Absence of Risk Identification** - The current literature lacks a comprehensive frame- work for initiating supply chain risk management (SRM), particularly in the context of risk identification. This critical first step requires a thorough understanding of the diverse risk factors that influence planning, procurement, sales, and distribution, thereby affecting customer satisfaction. Notably, absent in the current research is a comprehensive treatment of ’plan risk,’ arising from inadequate supply chain planning and affecting effective management. Similarly, inadequate coverage exists for supply risk, which occurs because of material flow disruptions that hinder meeting customer demand. Process risk, stemming from manufacturing deviations leading to higher failure rates and substandard products, and delivery risk resulting from delivery disruptions affecting production and timeliness are underrepresented in the literature.

**Lower-quality predictions owing to limited information:** Predictions made with very few data points often suffer from a lack of information, leading to lower-quality outcomes. As the saying goes, "Garbage in, garbage out" the quality of the prediction is directly proportional to the quality of the input data. With limited information, the ability of the model to make accurate predictions is significantly compromised.

**Limited Scope of Current Models:** Current models often have a narrow focus that restricts the practical large proportion of the components required for the prediction. This exclusion can lead to critical gaps in the predictions, thereby reducing their usefulness and applicability in real-world scenarios. By expanding the scope of these models, businesses can gain a more comprehensive understanding of the potential delivery delays and create effective strategies to mitigate them.

## 3. Problem Formulation and Solution Methodology

The objective of this study is to develop an AI-based system to accurately evaluate supply chain risks and enhance resilience by leveraging advanced algorithms to gain insights into supply chain vulnerabilities, predict upcoming complications, and support operators in maintaining continuity and recovering rapidly from disruptions through proactive planning and optimization. The goals are

- To comprehensively identify and categorize the various risks inherent in supply chain operations such as planning, procurement, manufacturing, and distribution.
- To collect supply chain data and utilize machine learning techniques to predict potential disruptions and delays with a high degree of accuracy.
- To quantify the likelihood and severity of identified risks to determine priority areas needing mitigation.
- To design AI models using deep learning algorithms that can uncover complex nonlinear relationships between variables affecting supply chain stability.
- To augment limited training data through techniques like fuzzy clustering for improved model training.
- To evaluate different ML and DL architectures and tune hyperparameters to maximize predictive performance on unseen data.
- To test the developed models on real-world datasets to assess their effectiveness in enhancing supply chain resilience and minimizing disruptions.

The study provides an epidemiological framework for supply chain uncertainties using fuzzy clustering and a Deep CNN model. The initial building blocks for this approach are implemented using Python.

The research methodology proposed in this study followed a two-pronged phase.

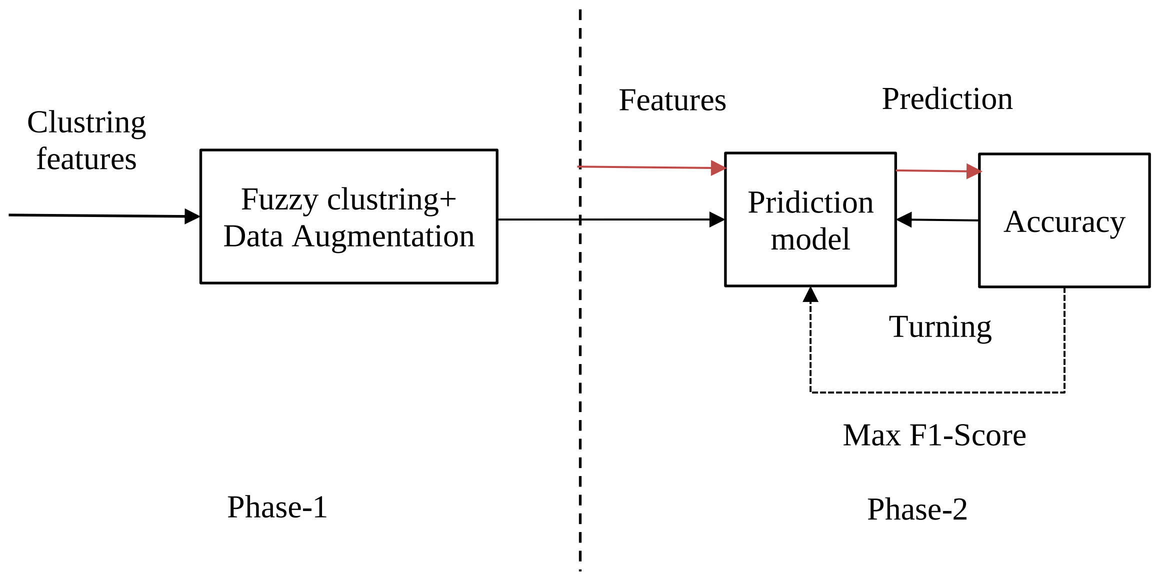


**Figure 2.** Two phase model layout

### 3.1. Phase 1: Risk Categorization using Fuzzy C-Means Clustering

After categorizing the supply chain, the output from the Fuzzy C means clustering algorithm, along with other product features, is parsed into the DCNN. This is a special type of convolution neuralclustering and data clustering. This technique allows data to belong to two or more clusters (Bezdek,1984). Unlike traditional clustering methods, where the data are assigned to a single cluster, Fuzzy C means that clustering assigns membership grades to each data point corresponding to each cluster (Romanuke, 2023). To avoid overfitting, new data points are added by adding Gaussian noise to the center of each cluster using a data augmentation technique. Each risk is assigned a membership grade to the primary, secondary, or tertiary clusters, which represent the highest and lowest severity, respectively (Daneshvar et al., 2023). This classification forms the basis for further analysis because the severity impact with respect to each influences the framing of mitigation factors.

### 3.2. Phase 1: Risk Prediction using a Deep CNN

After categorizing the supply chain, the output from the Fuzzy C means clustering algorithm, along with other product features, is parsed into the DCNN. It is a special type of convolution neural network (CNN) capable of learning long-term dependencies in data. Therefore, CNN are particularly suitable for classification, processing, and prediction.

## 4. Data

### 1. Planning Risk

Planning risk comprises potential issues that may arise owing to poor planning or lack of a comprehensive production schedule. Some of these risks include the following:

Lack of a detailed production plan: This could lead to inefficiencies, missed deadlines, and increased costs. It is crucial to outline the required production timelines and resources in detail to avoid these issues. Without a detailed plan specifying the tasks, timeframes, resource requirements, and sequencing, it will be difficult to coordinate all the required activities, materials, and personnel efficiently.

Inadequate contingency planning: Unforeseen circumstances such as supply chain disruptions, equipment malfunctions, or labor strikes can severely disrupt production. Having a solid contingency plan helps manage these unpredictable scenarios effectively so production can continue with minimal disruption. If backup options are not in place for critical production inputs like raw materials or key processes, the entire production schedule could be jeopardized when an unexpected event occurs.

Each of these risks was rated based on likelihood and severity to determine the priority. For instance, if the likelihood of a lack of a detailed production plan is considered high at 3 points, and its severity is deemed very high at 4 points, it is a critical risk at 12 points that requires immediate attention. A rigorous risk rating framework allows planners to identify and prioritize the most pressing risks needing mitigation.

### 2. Supply Risk

Supply risk involves issues related to the suppliers and raw materials required for production. Some of the risks include the following:

- **Supplier reliability:** If a key supplier fails to deliver the required raw materials or components on time or provides substandard quality materials, it can bring the entire production process to a halt. Delays or defects in supplied inputs directly impact the ability to fabricate and deliver finished products on schedule.
- **Dependence on a single supplier:** If a manufacturing company is overly reliant on one single supplier for a critical production input, any issue with that supplier - such as a facility shutdown or bankruptcy - can severely disrupt production. Sourcing from multiple redundant suppliers helps mitigate this concentration risk.
- **Inadequate supplier quality control:** If suppliers have poor quality control over their own manufacturing processes, it can result in defective components or raw materials being provided for downstream production. Stringent supplier qualifications and ongoing audits help prevent this.

The likelihood and severity of each of these supply risks were assessed to determine priority. For example, if the likelihood of supplier reliability issues is rated as two (medium risk) and the severity is four (very high impact), it is a significant risk at eight priority points that requires robust risk mitigation strategies. A balanced scorecard approach allows identification of the most crucial supply chain vulnerabilities.

### 3. Process Risk

Process risk pertains to the potential problems that can arise within the production process itself. These could include:

- **Equipment failure:** If critical machinery, tools, or equipment break down unexpectedly, it can bring production to a standstill. This results in delays, increased costs due to downtime, and potentially safety issues if hazards are created. Preventative maintenance and quick repair capabilities are essential.
- **Quality control issues:** If there are deficiencies in quality control procedures, it can result in defective and substandard finished products being passed to customers. This damages a company's reputation and brand integrity. In extreme cases, it may require a product recall which is very expensive to implement. Strong quality assurance systems and product testing methodologies help mitigate this risk.
- **Inadequate process documentation:** If manufacturing processes are not documented adequately, there could be critical tribal knowledge held by only a few employees. This can lead to errors and inefficiencies when they are absent. Thorough documentation allows smooth handovers between shifts and cross-training of employees.

By rating the likelihood and severity of each process risk, priority areas can be identified. For example, if the likelihood of critical equipment failure is rated as 1 (low probability), but its severity is 4 (very high impact), it is still an important risk to proactively manage. Strategies like preventative maintenance and keeping spare parts inventory can minimize disruptions.

### 4. Demand Risk

Demand risk arises from potential issues matching supply to market demand. Demand planning is crucial yet challenging. Key risks include:

- **Overestimating demand:** Producing excess inventory strains finances, requires storage, and risks obsolescence. This happens when forecasts are anchored on an outlier spike or high growth assumptions.
- **Underestimating demand:** Shortages lead to unfulfilled orders and lost sales. Besides revenue loss, stock-outs damage customer loyalty if consistently unable to meet demand.
- Demand volatility: Customers changing order volumes and mix frequently magnifies variability in the supply chain. This makes production planning and inventory optimization very difficult.
- **Inadequate customer analysis:** Demand forecasts based on poor customer and segmentation analysis will have a weak statistical foundation. Treating all customers homogenously overlooks distinct needs.
- **Weak forecasting methods:** Simple linear forecasting is inadequate for complex, intermittent demand patterns. Advanced quantitative models and simulations provide greater statistical accuracy.
- **Lack of real-time market data:** Relying solely on historical sales misses emerging trends or inflection points. Real-time demand signals add critical context for agile planning.

Each demand risk scenario is rated by likelihood of occurrence and severity of impact. For instance, a high likelihood but low severity risk might be prioritized below a low likelihood but very high severity risk. This provides focus on the risks that truly matter most. Mitigation strategies like improving forecasting capabilities, introducing flexibility into production, and strengthening customer analytics are crucial to minimize demand risk.

## 5. Clustering with Augmented Data

In this study, Fuzzy C means clustering is used to classify products based on Likelihood, and Severity. The risks with the highest likelihood and severity are classified as high risk and vice versa for low risk. The risks that fall in between are the medium-risk classes. Fuzzy C-means clustering has a greater advantage over other supervised learning algorithms, such as K-means, which are used to distinguish data points that overlap and belong to multiple clusters with different degrees of membership (Mohan et al., 2023). The algorithm creates soft membership instead of crisp membership for the data points within a cluster. These are termed as fuzzy clustering algorithms.

When employing Fuzzy C-means clustering to generate augmented data, the underlying concept involves the creation of novel data instances that exhibit similarities to the patterns identified within the initial data clusters. The Fuzzy C-means algorithm is used to compute the cluster centers, commonly referred to as centroids, for each cluster. The cluster centers serve as a measure of the central tendency of the data points contained within each cluster.

Employing these cluster centers as raw data points may lead to overfitting or excessive representation of the clusters. To mitigate this issue and inject diversity into the augmented dataset, a minor quantity of Gaussian noise is incorporated into every cluster centroid prior to the generation of novel data points. Gaussian noise is a prevalent form of stochastic noise that conforms to Gaussian (normal) probability distribution.

The procedure for producing more data points using Gaussian noise involves the following steps.

Cluster Centers: Following the execution of Fuzzy C-means clustering, the resultant cluster centers have been obtained for each individual cluster. These entities are depicted as vectors within the feature space.

The process of introducing noise involves the addition of a minor quantity of Gaussian noise to every vector that represents the center of each cluster. This noise is generated by sampling random values from a Gaussian distribution characterized by a mean of zero and a predetermined standard deviation. The standard deviation is a statistical measure that quantifies the dispersion or variability of data points around the cluster center, indicating the level of noise introduced.

The vectors that emerge from the clustering process and include extra noise are regarded as the novel data points. The newly created data points were distributed in proximity to the centers of the clusters, albeit with some degree of fluctuation, which was attributed to the presence of noise.

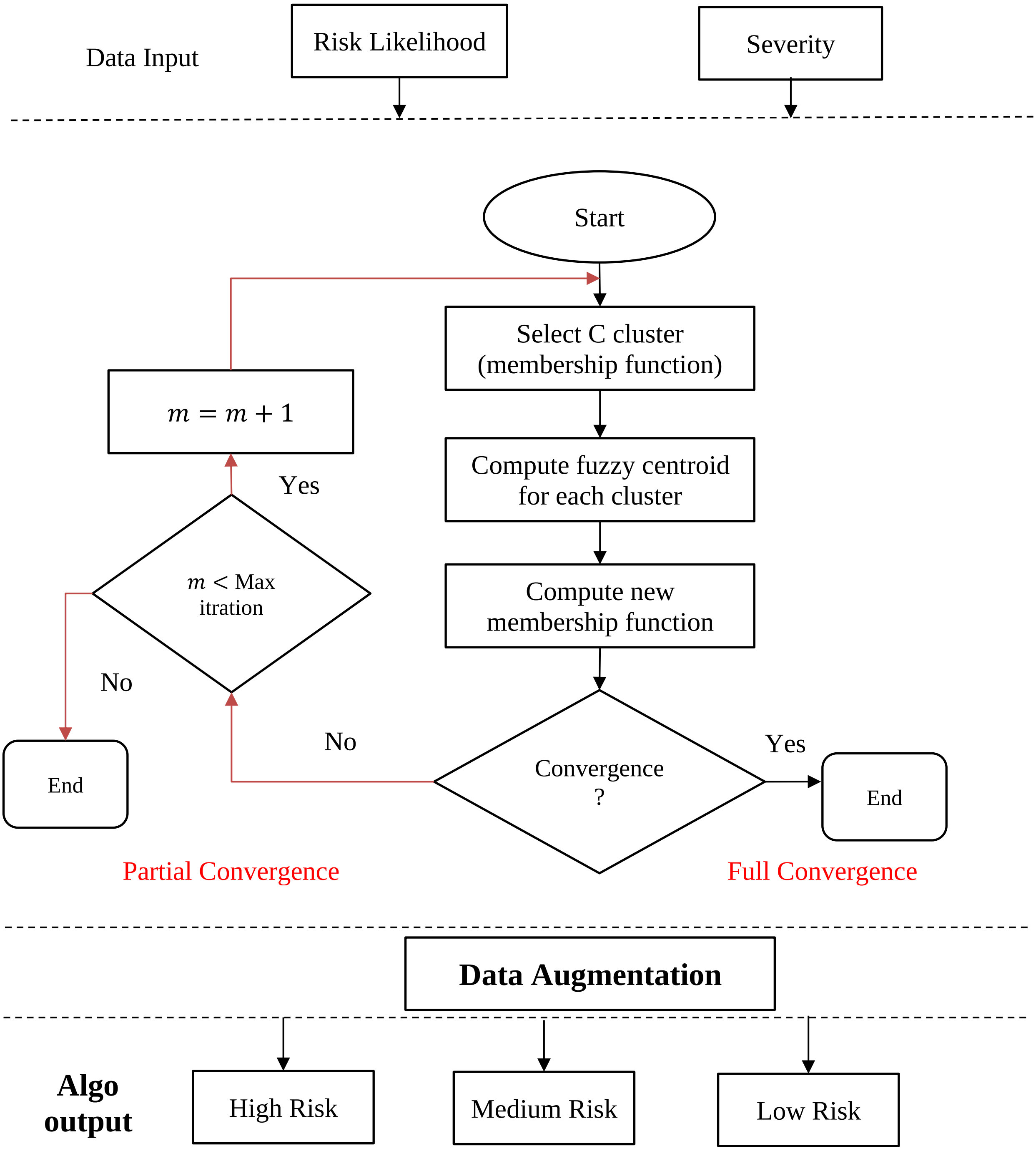


**Figure 3.** Flow chart fuzzy C-means clustering with augmented data

This procedure facilitates the generation of enhanced data points that exhibit similarities to the original data, while incorporating minor differences. The extent to which these new data points differ from the original cluster centers is dictated by the quantity of added noise, as indicated by the standard deviation. The use of noise during the data augmentation process prevents excessive similarity between the enhanced and original data, thereby enhancing the capacity of the model for generalization.

The following is a rudimentary depiction of procedural sequences.

The cluster center, excluding any noise, is represented by the coordinates [x1, x2, x3]. where x → (Risk Likelihood, Severity). Gaussian noise [n1, n2, n3] is introduced. A new augmented data point, denoted as [x1 + n1, x2 + n2, x3 + n3], is proposed.

Within the given code framework, the procedure is implemented on every cluster center produced by the Fuzzy C-means algorithm. Consequently, a collection of enhanced data points is obtained, which subsequently served as the training data for the new model.

```
Import pandas as pd
from sklearn.model_selection import train_test_split
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
import skfuzzy as fuzz# Load supply chain risk data into a
pandas DataFrame
supply_chain_data = pd.read_csv(supply_chain_risk_data.csv)#
'Risk type', 'Likelihood of risk', 'Severity of risk' with
your actual feature column names
feature_columns = [Risk type, Likelihood of risk, Severity
of risk]
label_column = cluster_label# Add a column with cluster
labels (High risk, Medium risk, Low risk)# Split data into
training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
supply_chain_data[feature_columns], supply_chain_data[
label_column], test_size=0.2, random_state=42)# Generate new
labeled data using Fuzzy C-means
X_augmented = []
y_augmented = []# Define the number of clusters for FCM
num_clusters = 3# Apply FCM clustering to the augmented data
for label in y_train.unique():
# Select augmented data for the current label
```

**Code Snippet 1.** Fuzzy C means clustering with Augmented Data

## 6. Model Evaluation Metrics

Multiple metrics such as Accuracy Rate, F-1 score, Recall, and Precision are used to measure the performance of the models.

1. Primary metrics are used to evaluate the model performance, which is based on the con- fusion matrix and the Accuracy Rate (AR) and is defined as

$$\text{AR} = \frac{(TP+NP)}{(TP+FP+TN+FN)} \tag{1}$$

In addition to accuracy, the Precision, Recall, and F-1 scores are used as secondary metrics.

2. Precision, calculated as the proportion of true positives (TP) to the sum of true positives and false positives (FP), evaluates a model's ability to accurately generate dependable positive predictions. Precision indicates the percentage of samples correctly identified as positive among all samples predicted as positive by the model. This provides an insight into the capability of the model to minimize false positives. A high-precision value signifies a low probability that the model will incorrectly classify negative samples as positive, implying that the positive predictions of the model are more likely to be accurate. Conversely, a low precision value suggests that the model has a higher rate of false positives, leading to a higher likelihood of incorrectly identifying negative data as positive data.

$$\text{Precision} = \frac{(TP)}{(TP+FP)} \tag{2}$$

3. Recall calculates the proportion of accurately predicted positive samples in the dataset. This provides insight into the model's ability to minimize false negatives. A high recall value indicates a low likelihood that the model erroneously categorizes positive data as negative, signifying its efficiency in identifying and capturing positive samples. Conversely, the low recall score demonstrates that the model had a higher rate of false negatives, suggesting that it inadequately detected certain positive data.

$$\text{Recall} = \frac{(TP)}{(TP+FN)} \tag{3}$$

4. The F1 score represents the harmonic mean of precision and recall, providing a single metric to assess the overall performance of a model while balancing the trade-off between these two factors. It was calculated using the following formula: F1 score =2 × (precision ×recall) /(Precision +Recall). The F1 score ranges from 0 to 1, with 1 indicating optimal precision and recall. A high F1 score signifies that the model is proficient in accurately predicting positive outcomes, while minimizing both false positives and false negatives.

$$\text{F1} = \frac{2*Precision * Recall}{(Precision+Recall)} \tag{4}$$

## 7. Experiments

Different experiments are conducted with varying parameters, and the models were considered to improve their accuracy, as discussed below.

### 7.1. Baseline: Ordinary Logistic Regression

Logistic regression is a member of the generalized linear regression family. The logistic regression classifier is mathematically represented as

$$h_{\theta}(x) = g(\theta^T x) = \frac{1}{1+e^{-\theta^T x}} \tag{5}$$

where g is the sigmoid function and θ is the parameter. As a baseline, an experiment is conducted using Ordinary Logistic Regression with all features. The model is optimized with a grid search and different parameters (including variations with respect to the type of regularization, size of the penalty, and type of solver used). are passed to get the best accuracy. Using the defined parameter ranges and five cross-validations, 500 potential models were evaluated.

### 7.2. Decision Tree

The experimental setup employs a decision tree as a flowchart-like configuration, with nodes representing features used for splitting and branches indicating decision-making criteria. Each terminal node represents an outcome, as stated in. The construction of decision rules involves partitioning training samples according to the data characteristics suitable for a given task, as evaluated by metrics such as index or entropy. Hyperparameter tuning is applied to mitigate and improve the efficacy of the model by limiting the maximum depth to five. This decreases the model and prevents assimilation of extraneous information in the training dataset.

### 7.3. Random Forest

Random Forest collections were used in the experimental arrangement, which incorporated numerous decision trees trained in parallel, using the bagging method. The bagging technique enables individual trees to be trained on arbitrary subsets of training data, similar to subsets of features sampled with replacement. This intrinsic randomness guarantees that each tree is distinct, and accordingly, the accumulation of these trees results in a Random Forest that is more resistant to noise in the training data than a single decision tree.

For the experiment, the maximum depth for each tree was restricted to five, which controlled and prevented model complexity. Moreover, the number of trees in the Random Forest collection was limited to 100, offering an equilibrium between computational efficiency and model performance.

### 7.4. Xgboost

The XGBoost framework was employed in this experiment. is regarded for its computational efficiency, which is achieved by optimizing specific loss functions and incorporating regularization techniques. The algorithm has various optimization techniques in place, such as a unique tree-based learning algorithm designed for sparse data and a weighted sketch method utilized to manage the instance weights. Moreover, it utilizes parallel and distributed computing, which accelerates the learning process and enables a rapid model exploration. An efficient cache-aware block structure is utilized for out-of-core tree-based learning. The loss function is defined as follows:

$$L^{(t)} = \sum_{i=1}^{n} l\left(\widehat{y_{l_i}^{t-1}}, y_i + f_t(x_i)\right) + \Omega(f_t) \quad (6)$$

$$\Omega(f_t) = YT + \frac{1}{2}\lambda|\omega|^2 \quad (7)$$

$L^{(t)}$served as a loss function that gauges the variation between the prediction and target for each instance. However, Ω acts as a penalty term that discourages an increase in model complexity.

The formulation of the objective function is an additive training scheme. It is used to train models that are difficult to optimize by using classical optimization procedures. In this case, the tree ensemble model was optimized.

The hyperparameters being tuned include estimators, which take values between 100 and 500; max depth ranging from 3 to 8; learning varying from 0.01 to 0.3; subsamples ranging from 0.5 to 1.0; col samples ranging from 0.5 to 1.0; and gamma with values of 0, 0.25, 0.5, and 1.0. The Randomized Search CV class was utilized to perform the search, with 50 iterations and 5-fold cross-validation. The evaluation metric used is accuracy. After fitting the randomized search object to the training data, the best parameters were stored.

### 7.5. Voting Classifier

The model, a voting classifier, is also experimented with, which is a machine-learning model that uses multiple separate models to generate a final prediction. The fundamental principle underlying this ensemble classifier is the amalgamation of the predictions of several models, which can lead to more precise predictions than those produced by any single model. In the present study, the voting classifier combines the predictions of three distinct models: linear SVM, XGBoost, and random forest. Each of these models possesses unique strengths and weaknesses, and the voting classifier benefits from the best aspects of each model to enhance overall performance. To generate a forecast, each component model formulates a prediction for input data. Thereafter, the voting classifier makes a final prediction using either the majority vote or the average projected probability. The majority vote entails the selection of a class label with the most votes from the individual models, whereas the average predicted-probability method considers the predicted probability of each model.

### 7.6. Neural Network

The model consists of two fully connected layers: an input layer with 72 nodes and a hidden layer containing 512 nodes. In the hidden layer, a Rectified Linear Unit (ReLU) is applied as an activation function, which is widely used in deep learning because of its efficacy. The output layer included a single node that used a sigmoid activation function. To train the model, the binary cross-entropy loss function and Adam optimizer were implemented. Binary cross-entropy is commonly used in binary-classification tasks. The model processes data with features in columns, executes a nonlinear transformation using the rectified linear unit (ReLU)activation function, and delivers a single binary classification outcome through the sigmoid activation function.

### 7.7. Dense CNN model with Pool Layer

The proposed model design comprises an embedding layer, convolution layer, max-pooling layer, and dense layer with dropout regularization. The convolutional layer employs 128 filters, also known as kernels, with a kernel size of 3. A max-pooling layer was used in all the layers of the network. The input underwent a series of three convolutional operations and three max-pooling operations. Global max pooling was employed in the final pooling layer. The model architecture includes a pair of compact layers that incorporate a dropout rate of 0.2 to mitigate the risk of overfitting. The activation function utilized in these layers is sigmoidal, which provides the likelihood of the three binary classifications. The data were partitioned into three sets, namely training, validation, and testing, with split ratios of 0.8, 0.1, and 0.1. The experimental setup involved configuring the batch size to 128 and the learning rate to 0.01 for the RMSProp optimizer. Dropout was applied at a rate of 20%, when deemed necessary. The number of epochs increased from 10 to 100. Optimal validation accuracy was attained using the RMSProp and dropout techniques. Based on the proximity of the training and validation accuracies, it was inferred that the model did not exhibit overfitting.

Full Model Architecture

```
input_ = Input(shape=(MAX_Feature_LENGTH,))
x = Embedding(input_dim=VOCAB_SIZE, output_dim=EMBED_SIZE)(input_)
x = Conv1D(128, 3, activation= relu )(x)
x = MaxPooling1D(3)(x)
x = Conv1D(128, 3, activation=relu)(x)
x = MaxPooling1D(3)(x)
x = Conv1D(128, 3, activation=relu)(x)
x = GlobalMaxPooling1D()(x)
x = Dense(128, activation=relu)(x)
output = Dense(len(possible_labels), activation=sigmoid)(x)
model = Model(input_, output)# Compile the model with binary cross entropy loss and Adam optimizer
model.compile(
     loss=binary_crossentropy,
     optimizer=adam,
     metrics=[accuracy]
)# Assuming you have df_train, MAX_Feature_LENGTH, BATCH_SIZE, and EPOCHS defined
# You might need to adjust this part according to your data setup
model, targets, data = model_cnn(df_train, MAX_Feature_LENGTH)
r = model.fit(
     data,
     targets,
     batch_size=BATCH_SIZE,
     epochs=EPOCHS
```

**Code Snippet 2.** CNN model code

## 8. Results

The Table1 provides a comparison of the performance of different machine learning algorithms on a given dataset. The performance metrics used to evaluate the algorithms are included.

**Table1.** Performance of Algorithms

| Algorithm | Dataset | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| Logistic Regression | Train | 61.2% | 62% | 51.8% | 56.8% |
| | Test | 55.2% | 61.5% | 53.1% | 57% |
| Decision Tree | Train | 61% | 59.8% | 67.1% | 63.15% |
| | Test | 60% | 59% | 57.5% | 58.7% |
| Random Forest | Train | 60.4% | 60.1% | 57.2% | 58.7% |
| | Test | 60% | 61.9% | 52.1% | 56.6% |
| Xgboost | Train | 78% | 65.7% | 59.6% | 62.5% |
| | Test | 76% | 64.4% | 58.3% | 61.4% |
| Voting | Train | 94.5% | 73.7% | 60.7% | 66.5% |

| Algorithm | Dataset | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| Classifier | Test | 93.3% | 64% | 58% | 60.9% |
| Neural | Train | 62.7% | 62.6% | 60.1% | 61.7% |
| Network | Test | 62.2% | 61.8% | 60.5% | 60.2% |
| Deep CNN | Train | 92.3% | 88.5% | 87.6% | 88.04% |
| With Pooling Layer | Test | 89.8% | 86.3% | 86.5% | 86.4% |

The Table1 provides a comparison of the performance of different machine learning algorithms on a given dataset. The performance metrics used to evaluate the algorithms included the accuracy, precision, recall, and F1-score. The best-performing algorithm on the testing set in terms of the F1-score is the Deep CNN with Pooling layer with an F1-score of 86.4%. The Voting Classifier had the highest accuracy (93.3 %), whereas the Logistic Regression had the lowest accuracy 55.6%) on the testing set.

Overall, the Deep CNN with Pooling layer seems to be the best-performing algorithm in terms of F1-score on the given dataset, while the Voting Classifier has the highest accuracy.

## 9. Conclusion

Flexible supply chains are characterized by their capacity to respond rapidly and adjust to modifications by utilizing real-time data for demand forecasting, thereby enhancing operational efficiency and customer satisfaction. The complex interconnections inherent in supply chains, coupled with external factors, such as climatic conditions or geopolitical incidents, subject them to persistent disruptions and uncertainties.

Conventional tools for supply chain visibility frequently underperform and fail to enable managers and planners to anticipate supply chain threats precisely, identify alternative measures during disruptions, and determine the fundamental reasons for these instabilities. Suggestions for enhancement have been proposed through the application of fuzzy systems and deep learning to predict supply delays and encapsulate the intricate nature of supply chains. However, current studies frequently neglect the risk severity and probability associated with supply chains and fail to guarantee prompt predictions that facilitate responsive measures.

This study addresses these issues through a two-step experimental plan using a combination of unsupervised fuzzy clustering and various machine- and deep-learning classification models. This research demonstrates that the combined approach can successfully predict supply chain risk and estimate the gravity of a delay sufficiently early to allow for necessary action. The findings of this investigation reveal that the integration of these approaches can effectively anticipate supply chain risks and quantify the severity of potential delays, thereby providing ample time for the execution of requisite measures.

It has been observed that the Deep Convolutional Neural Network (DCNN), a deep learning model, outperforms conventional classification models such as XG Boost and Random Forest. The superior performance of the DCNN (approximately 90% accuracy) can be attributed to its capability to manage intricate and nonlinear correlations among variables. This indicates the promising role of machine learning in bolstering predictability and resilience in global supply chains, particularly amid escalating digitalization in manufacturing. The implications of these findings are substantial for strategic planning within the industry as they may pave the way for enhanced operational efficiency and effectiveness.

Key Outcomes:

1. Enhanced Predictive Capabilities: Machine learning models, particularly the DCNN model, can significantly enhance the prediction of supply chain risks, leading to improved operational planning and efficiency.
2. Risk Mitigation: By accurately predicting disruptions and supplier complications, firms can better prepare for such events and mitigate their adverse effects, resulting in smoother operations.

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