



## Neutrosophic-based Machine Learning Techniques in the Context of Supply Chain Management: A Survey

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### Abstract

Supply Chain Management (SCM) plays a critical role in the success of any business organization. Individuals involved in business activities often have to make decisions regarding different aspects of the supply chain, including planning, procurement, production, inventory management, transportation, distribution, and customer relationship management. The combination of neutrosophic logic and machine learning has gained significant attention in the field of SCM as a means to tackle uncertainties and improve decision-making. This paper highlights the potential benefits and applications of integrating neutrosophic reasoning and machine learning in SCM. Neutrosophic reasoning provides a framework for handling imprecise and uncertain information, while machine learning techniques offer powerful tools for data analysis, pattern recognition, and predictive modeling. By leveraging machine learning algorithms within the context of neutrosophic logic, SCM practitioners can enhance demand forecasting accuracy, optimize inventory management, improve transportation and routing decisions, and strengthen supply chain collaboration. The integration of neutrosophic logic and machine learning enables the handling of complex supply chain data, accommodates dynamic and uncertain environments, and supports proactive decision-making. Furthermore, the combination of these approaches can contribute to improved supply chain resilience, sustainability, and customer satisfaction. This paper applied the neutrosophic AHP method as a feature selection to select the highest importance criteria as an input to machine learning. Then we applied two machine learning models named random forest and decision tree. The results show the random forest has the highest accuracy followed by a decision tree.

**Keywords:** Machine Learning; Supply Chain Management; Neutrosophic Logic; Neutrosophic AHP; SCM.

### 1. Introduction

Different authors have provided their definitions of a supply chain. For example, Mentzer, John T., et al. define the supply chain as "a collection of three or more organizations or individuals directly engaged in the upstream and downstream movement of products, services, finances, and/or information from a source to a customer." This definition emphasizes the involvement of at least three entities and the various types of flows between them[1]. Another perspective states that a supply chain encompasses the entities involved in product and service design, procurement of raw materials, transformation into intermediate or finished products, and delivery to end customers[2]. Based on these definitions, we can define a supply chain as a group of three or more entities, such as customers, retailers, warehouses, distributors, manufacturers, and suppliers, among others. These entities facilitate the upstream and downstream flow of information, finances, and materials, with the ultimate objective of fulfilling customer needs. Each entity within the supply chain performs activities like material transformation, logistics operations, customer service, and distribution[3], as illustrated in Figure 1.



Figure 1: Supply Chain Management

In the current highly competitive world, supply chain management must continuously evolve to keep pace with the escalating competition. The expectation is to generate higher profits while minimizing investments. Consequently, supply chain management becomes a critical domain that necessitates extensive research. Companies consistently face the challenge of meeting growing customer expectations while maintaining manageable costs. To address this challenge, it is essential to identify inefficient segments within the supply chain processes, identify unmet customer needs, continually enhance operations, and implement these improvements. By adopting such measures, companies can strive to fulfill customer expectations while ensuring cost-effectiveness[4].

In the past, manufacturers had control over the supply chain, determining the production volume, pace, and distribution. However, the dynamics have shifted in the present world, where customers hold the power and are in charge of the supply chain. Manufacturers are now focused on meeting customers' expectations and must adapt to their preferences, including options, styles, and features. Customers have varying demands and expect swift order fulfillment and fast deliveries. Consequently, manufacturers need to align their production activities accordingly to cater to these evolving customer needs.

In the present era, businesses face numerous uncertainties, including significant supply risks and intensifying competition. The effectiveness of a supply chain hinges on an organization's ability to efficiently manage all activities, starting from the procurement of raw materials to the transformation into valuable products and their delivery to customers. Achieving such proficiency requires seamless information flow and real-time communication among all entities involved in the supply chain. Consequently, companies are striving to enhance the information intensity of their supply chains and emphasize the sharing of real-time information with key assets like transportation, warehouses, and inventory. Recognizing the significance of information sharing, supply chain managers have explored various approaches to leverage this valuable resource for making informed business decisions. Among these approaches, one potential avenue is the utilization of Machine Learning, which has existed for some time but has not been extensively employed in supply chain management[5].

In recent times, social media has gained significant attention from organizations and researchers. Natural Language Processing (NLP) is a technique that aids in analyzing textual data from social media platforms, such as tweets on Twitter or posts on Facebook. Social media has become a crucial aspect of the modern generation, as individuals express their opinions, preferences, and viewpoints on these platforms. The research community is actively exploring the potential use of data from social media to generate new insights in various areas, including supply chain management, information diffusion and public opinions, public relations, brand management, crisis management, humanitarian relief, election predictions, early event monitoring, epidemic

prevention, and stock price predictions. Since supply chain management is largely customer-centric, social media plays a vital role by providing honest customer views and potentially influencing customer perceptions. This review focuses on the research conducted on the application of NLP in supply chain management[6].

### **1.1 Importance of Machine Learning in Supply Chain Management**

Failure to effectively manage supply chain operations can result in poor customer service, increased costs, potential revenue losses, and, most importantly, a loss of customer trust, leading to decreased profits. Supply chain processes are riddled with various uncertainties, including:

- Inventory shortages to meet demands
- Logistics uncertainties and supply shortages
- Growing order backlogs
- Fluctuations in demand
- Lack of proper communication among stakeholders
- Varying inventory quality levels

Forecasting these variations becomes challenging with predefined rules, as the reasons behind them change daily. Machine learning algorithms offer a potential solution by reducing these uncertainties and enabling precise predictions. The benefits of incorporating machine learning algorithms in supply chain management are as follows:

- Improved understanding of challenges, allowing for real-time analysis and advanced forecasting.
- Ability to process large volumes of data involved in predictions, which would be impractical to handle manually.
- Development of models using machine learning, resulting in reduced operational inefficiencies, minimized revenue losses, and on-time delivery, leading to improved customer satisfaction.
- Methodologies developed through machine learning are equipped to handle vast amounts of data and work in real time, providing proactive solutions rather than reacting after problems occur[7].

Machine Learning proves to be a valuable asset for supply chain management by mitigating uncertainties, leading to increased profits and minimized losses. Social media platforms are revolutionizing communication, collaboration, and creativity. They represent one of the most transformative impacts of information technology on business. Social media has transformed the way companies interact with society and markets, presenting new challenges and numerous opportunities across various organizational areas, including human resource management, finance, operations, and marketing. Social media provides valuable insights into recent trends and market demands. Industrial organizations have explored various potential applications of social media, such as education, sales forecasting, recruitment, customer engagement, and marketing[8].

### **1.2 Methods of Machine Learning**

Generally, Machine Learning can be likened to the innate learning process observed in animals and humans. Unlike traditional approaches that rely on fixed models or equations, Machine Learning algorithms learn directly from data. The algorithm's performance improves as more data becomes available for learning. ML algorithms play a crucial role in generating valuable insights from data by identifying patterns, thereby enabling better predictions and informed decision-making. These algorithms are widely utilized in various domains, including energy load forecasting, stock trading, and medical diagnosis.

Machine Learning encompasses two main types: Supervised Learning and Unsupervised Learning. In Supervised Learning, the model is trained using known input and output data. Once trained, the model can then be employed to predict future outputs using unknown data. On the other hand, Unsupervised Learning involves algorithms that identify hidden patterns within unknown data and make predictions based on those intrinsic patterns[9], as depicted in Figure 2.

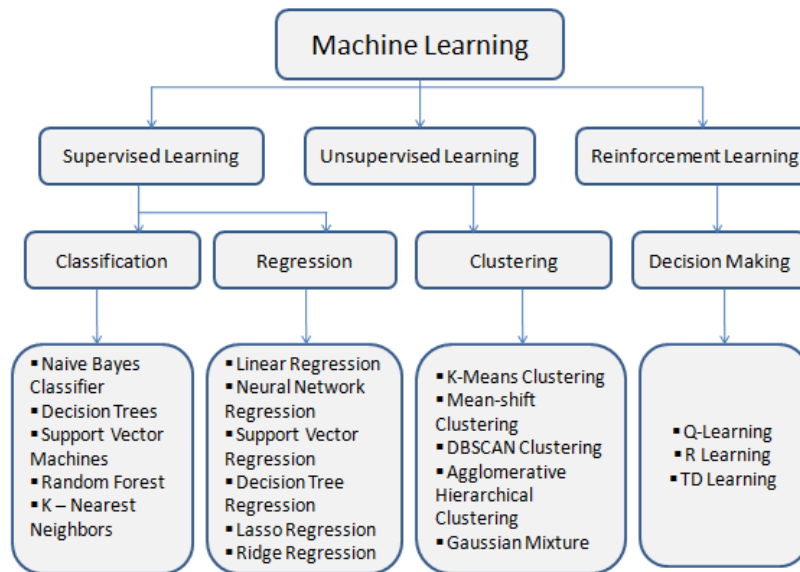


Figure 2: Methods of Machine Learning

*i. Supervised Learning:* is a method where patterns are identified based on previous outcomes, and these patterns are utilized to make future predictions. The input and output data from past instances are paired together, enabling the algorithm to forecast future occurrences. The underlying concept is to learn from historical patterns provided by a human operator to anticipate future events. Supervised Learning techniques are commonly employed in automated manufacturing processes, such as automobiles, vehicles, chatbots, and facial recognition systems. Various algorithms are utilized in supervised learning, including the Naive Bayes Classifier Algorithm, Support Vector Machine Algorithm, regression, Logistic Regression, Decision Trees, and Random Forests [10].

In Supervised Learning, prediction models are developed using two primary techniques:

- **Classification techniques:** These techniques are used to predict categorical data, such as determining whether a cancer is malignant or benign, or classifying an email as spam or legitimate. Models created using classification techniques work with discrete responses and categorize data accordingly. Applications of this technique include credit scoring, speech recognition, and medical imaging.
- **Regression techniques:** These techniques are employed when dealing with data that exhibits regular updates, such as tracking house price increases in a specific region, monitoring temperature fluctuations, or forecasting changes in power demand. Examples of applications using regression techniques include algorithmic trading and energy load forecasting [11].

*ii. Unsupervised Learning:* In the absence of a human operator providing instructions, the learning algorithm itself identifies and groups patterns. The algorithm analyzes by segmenting the data into categories. One widely used technique in unsupervised learning is clustering, which involves analyzing data and dividing it into meaningful groups based on its inherent structure. Unsupervised learning finds applications in various fields, such as object recognition, market research, and gene sequence analysis [12].

*iii. Reinforcement Learning:* Reinforcement Learning is a form of structured learning that involves providing a machine learning algorithm with a set of behaviors, parameters, and desired outcomes. The algorithm explores different options and possibilities based on specified rules, continuously monitoring and analyzing each outcome to determine the most favorable one. Reinforcement learning operates through a trial and error process, where the machine learns from previous mistakes and adjusts its strategy in response to the current situation, aiming to achieve the optimal outcome [13].

### 1.3 Applications of Machine Learning and Neutrosophic Theory in Various Aspects of Supply Chain Management

In the current era of the Fourth Industrial Revolution (4IR), ML is increasingly being adopted across various application areas. ML's ability to learn from historical data and make intelligent decisions has

contributed to its growing popularity [14]. However, the full potential of ML in solving complex problems and extracting valuable insights in Supply Chain Management (SCM) has yet to be fully explored. Neutrosophic logic is an extension of classical logic that allows for the representation and processing of uncertain, indeterminate, and inconsistent information. It can be applied to supply chain management planning to address the inherent uncertainties and vagueness associated with various factors in the supply chain. By examining the development patterns of ML applications in SCM and studying commonly used ML algorithms in SCM, we can gain insights into its potential. In this section, we will explore six SCM activities to showcase the direct correlation between ML algorithms, neutrosophic logic, and SCM [15]. Additionally, we will outline how these commonly used ML algorithms are distributed across the six SCM activities.

### 1.3.1 Inventory and Storage

The costs associated with Supply Chain Inventory Management (SCIM) and storage play a crucial role in the overall efficiency of a supply chain. The objectives of SCIM are to optimize product/service variety, enhance customer service, and minimize costs. However, traditional decision-making rules often fall short of accurately estimating, forecasting, and obtaining information related to these objectives. These rules heavily rely on the judgment and expertise of inventory managers, making it challenging to navigate the uncertainties associated with inventory management. To address this challenge, there is a need to develop methods that assist human decision-making in dealing with unknown inventory inputs.

Machine Learning (ML) algorithms, when applied to warehouse datasets, can quickly identify patterns in inventory inputs. By leveraging ML algorithms, warehouses can uncover hidden patterns in inventory data that were previously unknown, leading to cost savings [16]. ML algorithms can recognize these invisible patterns, providing valuable insights for efficient inventory management.

Neutrosophic theory can be applied to storage and inventory management within supply chain management to address uncertainties, vagueness, and imprecise information. Here are some ways in which neutrosophic logic can be used in storage and inventory management:

*Inventory Optimization:* Neutrosophic logic can assist in optimizing inventory levels by considering the imprecise nature of demand and supply parameters. By representing inventory levels, lead times, demand variations, and other relevant factors using neutrosophic numbers, planners can better assess the risks and uncertainties associated with inventory decisions. This allows for determining appropriate safety stock levels and balancing the trade-off between excess inventory and stockouts.

*Warehouse Capacity Planning:* Neutrosophic logic can aid in determining optimal warehouse capacities by considering uncertain demand patterns, product variations, and storage constraints. By representing these factors with neutrosophic numbers, planners can assess the fuzzy boundaries of warehouse capacities and make decisions that account for imprecise information. This can help in avoiding overutilization or underutilization of warehouse space.

*Inventory Replenishment:* Neutrosophic logic can be applied to inventory replenishment decisions by considering uncertain lead times, demand variability, and supplier reliability. Planners can use neutrosophic numbers to represent these factors and determine to reorder points and reorder quantities that balance the trade-off between stockouts and holding costs. This allows for more robust inventory replenishment strategies that account for the imprecision and vagueness of information.

*Quality Control:* Neutrosophic logic can be employed in quality control processes to handle imprecise and vague quality measurements. By assigning neutrosophic numbers to represent quality attributes and inspection results, planners can account for the uncertainties associated with quality assessments. This enables more effective decision-making regarding acceptance/rejection criteria and the determination of appropriate quality levels for storage and inventory items.

*Obsolescence and Expiry Management:* Neutrosophic logic can be used to manage obsolescence and expiry risks in storage and inventory. By representing product shelf lives, demand patterns, and market conditions using neutrosophic numbers, planners can assess the risks of obsolescence and take proactive measures to mitigate them. This can involve implementing dynamic pricing strategies, promotional activities, or inventory liquidation plans based on imprecise and uncertain information[17].

It is important to note that implementing neutrosophic logic in storage and inventory management requires specialized modeling techniques and algorithms. The adoption of neutrosophic logic should be based on the specific characteristics and requirements of the supply chain, as well as the availability of relevant data.

### 1.3.2 Planning

In Supply Chain Management (SCM), accurate estimation of demand and sales is crucial for effective planning. However, demand prediction can be challenging due to the complex nature of estimating sales potential, which involves multiple explanatory variables and their nonlinear relationship with the dependent variables. Conventional methods such as moving average, exponential smoothing, time-series methods, and Box-Jenkins methods heavily rely on historical data accuracy, making it difficult to achieve precise demand forecasts.

ML algorithms offer a solution to enhance the accuracy of demand prediction and forecasting in terms of revenue, demand, and inventory requirements. By employing non-linear analyses, ML algorithms can integrate various parameters and variables to improve estimation accuracy. Unlike traditional approaches, ML algorithms are not solely dependent on historical data accuracy. This makes them viable alternatives for demand forecasting and planning in SCM. ML algorithms can identify and rectify data set defects, resulting in non-linear models that better fit the demand/sales curve[18].

Here are some ways in which neutrosophic logic can be used for planning in SCM:

*Demand Forecasting:* Neutrosophic reasoning can be employed to handle uncertain demand patterns by representing the demand forecasts with neutrosophic numbers. Neutrosophic forecasting models can incorporate vague or ambiguous information, such as incomplete historical data or market fluctuations, allowing planners to make decisions based on a more comprehensive understanding of the demand scenario.

*Inventory Management:* Neutrosophic reasoning can assist in optimizing inventory levels by considering the imprecise nature of demand and supply parameters. By using neutrosophic numbers to represent inventory levels, lead times, and demand variations, planners can better assess the risks and uncertainties associated with inventory decisions and determine appropriate safety stock levels.

*Supplier Selection:* Neutrosophic reasoning can aid in supplier selection processes by accommodating imprecise information and decision-making criteria. Supply chain planners can assign neutrosophic numbers to evaluate suppliers based on various qualitative and quantitative factors, such as price, quality, reliability, and lead time. Neutrosophic decision-making techniques can then be applied to rank and select suppliers while considering the inherent uncertainties.

*Risk Assessment and Mitigation:* Neutrosophic logic enables a more nuanced approach to risk assessment in supply chain planning. Planners can represent and analyze risks using neutrosophic numbers, considering factors such as demand volatility, supplier reliability, transportation delays, and market uncertainties. This allows for more effective risk mitigation strategies, such as identifying alternate suppliers or developing contingency plans.

*Performance Evaluation:* Neutrosophic logic can be applied to evaluate the performance of different supply chains components, such as suppliers, warehouses, and transportation modes. By assigning neutrosophic numbers to performance metrics and incorporating imprecise information, planners can gain a more comprehensive view of the overall supply chain performance and identify areas for improvement[19].

It is important to note that implementing neutrosophic logic in supply chain planning requires specialized modeling techniques and algorithms. The adoption of neutrosophic logic should be based on the specific characteristics and requirements of the supply chain under consideration, as well as the availability of relevant data.

### 1.3.3 Customer Relationship Management

Gaining customer feedback is crucial for the development of a SC, as it involves aligning the SC to better cater to consumer needs. Traditionally, methods such as market analysis, surveys, and interviews have been used to collect customer input. However, these approaches often face limitations, as customers may be reluctant to provide face-to-face opinions, resulting in small sample sizes that may lead to inaccurate SC improvement decisions.

Fortunately, social media platforms offer a wealth of consumer information that can represent genuine customer opinions. However, handling this data manually is challenging due to its erratic nature, lack of

consistency, and large volume, variety, and velocity. To overcome these challenges, ML algorithms can be employed in conjunction with Internet of Things (IoT) sensors, advanced analytics, and real-time monitoring to gain comprehensive insights across SC activities[20]. For example, researchers have used ML algorithms in combination with text mining and Support Vector Machines (SVM) to analyze Twitter data and extract 133,638 customer views. This sentiment analysis helped identify the root causes of customer complaints regarding beef products, such as excessive fat, foreign particles, discoloration, and texture issues, in the upstream SC activities. In another study, researchers utilized Logistic Regression (LR), Neural Networks (NN), and Decision Trees (DT) to analyze 11,024 Amazon reviews of dishwasher brands. Their method successfully identified possible defects associated with specific keywords like "smoke" and "sparkle," achieving a 94 percent precision in predicting dishwasher defects. This approach significantly enhanced quality assurance on both the supply and demand sides. ML algorithms, in conjunction with sensor data, can enable real-time SC tracking and proactively address transportation disruptions [21].

Neutrosophic philosophy can be applied to customer relationship management (CRM) within supply chain management to address uncertainties, vagueness, and imprecise information associated with customer-related factors. Here are some ways in which neutrosophic logic can be used in CRM within the context of supply chain management:

*Customer Segmentation:* Neutrosophic logic can aid in customer segmentation by considering multiple criteria and dealing with imprecise information. Planners can assign neutrosophic numbers to represent customer attributes such as purchasing behavior, demographics, and preferences. Neutrosophic decision-making techniques can then be employed to segment customers into groups based on their characteristics, allowing for more personalized marketing and service strategies.

*Customer Demand Forecasting:* Neutrosophic logic can assist in forecasting customer demand by accounting for uncertain and imprecise information. By representing demand patterns using neutrosophic numbers, planners can consider factors such as incomplete historical data, changing customer preferences, and market fluctuations. Neutrosophic forecasting models can enable more accurate predictions and help in managing inventory levels and production planning accordingly.

*Customer Satisfaction and Feedback Analysis:* Neutrosophic logic can be used to analyze customer satisfaction and feedback data by considering the inherent vagueness and imprecision of customer opinions. Planners can assign neutrosophic numbers to represent customer feedback scores, ratings, and survey responses. This enables a more comprehensive assessment of customer satisfaction levels, identifying areas for improvement and facilitating targeted actions to enhance customer experience.

*Customer Relationship Analysis:* Neutrosophic logic can aid in analyzing and managing customer relationships by accommodating imprecise and uncertain information. Planners can use neutrosophic numbers to represent relationship metrics such as customer loyalty, engagement, and profitability. Neutrosophic analysis techniques can assist in understanding the complex dynamics of customer relationships, identifying key factors impacting customer loyalty, and developing strategies to strengthen those relationships.

*Customer Retention and Churn Prediction:* Neutrosophic logic can be applied to predict customer retention and churn by considering various customer-related factors and uncertainties. Planners can assign neutrosophic numbers to represent customer characteristics, purchase history, engagement levels, and other relevant variables. Neutrosophic predictive models can help in identifying customers at risk of churn and designing targeted retention strategies to mitigate the churn risk.

It is important to note that implementing neutrosophic logic in CRM requires suitable modeling techniques and algorithms. The adoption of neutrosophic logic should be based on the specific characteristics of the customer data, the available information, and the CRM objectives within the supply chain management context.

### **1.3.4 Transportation and Distribution**

Vehicle routing problems are widely recognized as one of the prominent applications of ML in SCM. Selecting the optimal routes for transporting vehicles from multiple options is crucial in ensuring that goods are delivered to the right customers within the SC. However, determining these routes often exceeds the capabilities of the human brain.

ML algorithms have proven to be highly effective in analyzing vast and complex datasets, enabling them to swiftly generate accurate demand forecasts. By diligently and promptly examining patterns in consumer behavior, vehicles, transportation, and infrastructure, ML algorithms can produce improved delivery routes. These algorithms excel at processing large amounts of data and leveraging it to enhance the efficiency and effectiveness of distribution and transportation in SCM[22]. Neutrosophic philosophy can be applied to distribution and transportation management within supply chain management to address uncertainties, ambiguities, and imprecise information associated with these activities. Here are some ways in which neutrosophic logic can be used in distribution and transportation:

*Route Planning:* Neutrosophic logic can assist in optimizing route planning by considering uncertain factors such as traffic conditions, weather conditions, and delivery time windows. By representing these factors using neutrosophic numbers, planners can account for imprecise and incomplete information when determining the most efficient routes. Neutrosophic route planning techniques can help in minimizing transportation costs, improve delivery reliability, and accommodate dynamic changes in the transportation environment.

*Mode Selection:* Neutrosophic logic can be employed in mode selection decisions by considering multiple criteria and dealing with imprecise information. Planners can assign neutrosophic numbers to represent factors such as cost, transit time, capacity, and service levels associated with different transportation modes. Neutrosophic decision-making techniques can then be applied to evaluate and select the most suitable transportation mode based on the imprecision and uncertainty of the information.

*Vehicle Load Planning:* Neutrosophic logic can aid in optimizing vehicle load planning by considering uncertain demands, product characteristics, and capacity constraints. By representing these factors using neutrosophic numbers, planners can assess the fuzzy boundaries of vehicle load capacities and make decisions that account for imprecise information. This can help in maximizing vehicle utilization, minimizing transportation costs, and improving overall efficiency in distribution.

*Delivery Time Estimation:* Neutrosophic logic can be used to estimate delivery times by considering uncertain factors such as distance, traffic, and unforeseen delays. By assigning neutrosophic numbers to represent these factors, planners can account for imprecise information and provide more accurate delivery time estimates. Neutrosophic estimation techniques can help in setting realistic customer expectations and managing delivery performance.

*Risk Assessment and Mitigation:* Neutrosophic logic can assist in risk assessment and mitigation in distribution and transportation. Planners can represent risks using neutrosophic numbers, considering factors such as delivery delays, transportation disruptions, and inventory losses. By incorporating neutrosophic risk assessments into decision-making processes, proactive risk mitigation strategies can be developed to minimize the impact of uncertainties. This can involve contingency planning, alternative route selection, and the use of backup transportation options.

It is important to note that implementing neutrosophic logic in distribution and transportation management requires suitable modeling techniques and algorithms. The adoption of neutrosophic logic should be based on the specific characteristics of the distribution network, transportation data, and the decision-making context within the supply chain management framework.

### 1.3.5 Production

ML algorithms have the potential to enhance the accuracy of factory scheduling and production planning by considering diverse conditions. Manufacturers utilizing build-to-order and make-to-stock production processes can particularly benefit from ML algorithms as they enable more efficient management of various conditions compared to traditional approaches. ML can assist manufacturers in minimizing supply chain latency for components and parts required in highly customized products. By utilizing ML algorithms, manufacturers can predict lead times in production with faster response times, thus optimizing their production processes and improving overall efficiency. This capability is highlighted as a valuable application of ML in the realm of supply chain management[23].

Neutrosophic logic can be applied to production management within supply chain management to address uncertainties, ambiguities, and imprecise information. Here are some ways in which neutrosophic logic can be used in production planning and control:

*Production Planning:* Neutrosophic logic can assist in production planning activities by considering uncertain demand forecasts, resource availability, and production capacity. By representing demand patterns, resource

constraints, and production parameters using neutrosophic numbers, planners can account for the imprecision and variability of information. This allows for more robust production plans that consider multiple scenarios and their associated probabilities.

*Production Scheduling:* Neutrosophic logic can aid in production scheduling by handling uncertain processing times, machine breakdowns, and other operational disruptions. Planners can represent these factors using neutrosophic numbers, enabling the consideration of imprecise and incomplete information when creating production schedules. Neutrosophic scheduling techniques can help in optimizing production sequences and allocating resources efficiently.

*Capacity Management:* Neutrosophic logic can be employed in capacity management to handle uncertain production capacities, equipment utilization rates, and resource availability. Planners can assign neutrosophic numbers to represent capacity constraints, considering factors such as machine reliability, maintenance schedules, and workforce variability. Neutrosophic capacity management techniques can aid in balancing production requirements with resource limitations while accounting for the imprecise nature of capacity-related information.

*Quality Control:* Neutrosophic logic can be used in production quality control processes to deal with imprecise quality measurements and subjective assessments. By assigning neutrosophic numbers to represent quality attributes and inspection results, planners can account for the uncertainties associated with quality assessments. This allows for more effective decision-making regarding acceptance/rejection criteria and the determination of appropriate quality levels in production processes.

*Process Improvement and Optimization:* Neutrosophic logic can assist in process improvement and optimization efforts by considering uncertain process parameters and performance indicators. Planners can represent process inputs, outputs, and performance metrics using neutrosophic numbers, allowing for a comprehensive assessment of process efficiency and variability. Neutrosophic optimization techniques can help in identifying areas for improvement and making informed decisions to enhance production performance. Implementing neutrosophic reasoning in production management requires suitable modeling techniques and algorithms. It is crucial to consider the specific characteristics of the production system, the available data, and the decision-making context when applying neutrosophic logic to production planning and control processes.

### **1.3.6 Procurement and supply management**

The procurement and supply management performance of any organization heavily relies on the ability to produce high-quality products at low costs and deliver them to customers promptly, without any delays. In the field of SCM, ML applications play a crucial role in assessing and selecting suppliers. Traditionally, suppliers were considered suitable if they could provide the right quantity of the right product at the right time and place. However, distinguishing potential suppliers from their competitors is often not straightforward. To address this challenge, many businesses implement supplier scoring or appraisal processes, which require information on the performance history, creditworthiness, and other relevant personal details of potential suppliers. Access to such information is often limited, resulting in issues such as incomplete data sets, inconsistent values, and errors.

One advantage of certain ML algorithms is their ability to handle missing values effectively. Given the complexities and uncertainties involved in supplier selection, systematic decision-aid ML algorithms, such as Support Vector Machines (SVMs), are widely utilized in make-or-buy decisions. ML algorithms can handle large volumes of supplier data and provide effective analytical decision-making capabilities, contributing to improved procurement and supply management practices in SCM[24]. Neutrosophic reasoning can be utilized in procurement and supply management within supply chain management to address uncertainties, vagueness, and inconsistencies that arise in decision-making processes. Here are some ways in which neutrosophic logic can be applied specifically to procurement and supply management:

*Supplier Evaluation and Selection:* Neutrosophic logic can help in assessing and selecting suppliers by considering multiple criteria and dealing with imprecise information. Planners can assign neutrosophic numbers to evaluate potential suppliers based on factors such as price, quality, delivery time, financial stability, and past performance. Neutrosophic decision-making techniques can then be employed to rank and select suppliers, taking into account the uncertainties associated with supplier performance.

*Contract Negotiation:* Neutrosophic reasoning can be employed during contract negotiations to handle imprecise and vague terms and conditions. Neutrosophic numbers can represent different aspects of the contract, such as pricing, delivery schedules, quality standards, and penalties. This allows for a more comprehensive representation of the negotiation space, facilitating more effective and flexible agreements.

*Demand and Supply Planning:* Neutrosophic logic can support procurement and supply management in demand and supply planning activities. Uncertain and imprecise demand forecasts can be represented using neutrosophic numbers, enabling planners to consider multiple scenarios and their associated probabilities. Similarly, supply uncertainties, such as lead times, production capacities, and supplier reliability, can be modeled using neutrosophic numbers to account for vagueness and variability.

*Risk Management:* Neutrosophic logic can aid in risk assessment and mitigation in procurement and supply management. Planners can represent risks using neutrosophic numbers, capturing uncertainties related to supplier performance, market fluctuations, logistics disruptions, and other factors. By incorporating neutrosophic risk assessments into decision-making processes, proactive risk mitigation strategies can be developed to minimize the impact of uncertainties.

*Performance Measurement:* Neutrosophic logic can be used for evaluating and monitoring supplier performance and overall supply management effectiveness. Key performance indicators (KPIs) can be assessed using neutrosophic numbers, considering imprecise data and subjective evaluations. This approach allows for a more comprehensive and accurate assessment of performance, considering the uncertainties and ambiguities inherent in supply chain operations.

**2. Methods**

This section introduced the method of machine learning and the neutrosophic AHP method. The neutrosophic AHP method is used as a feature selection, then the two machine learning models are used as a prediction in sales on the supply chain dataset. Figure 3 shows the steps of the proposed method.

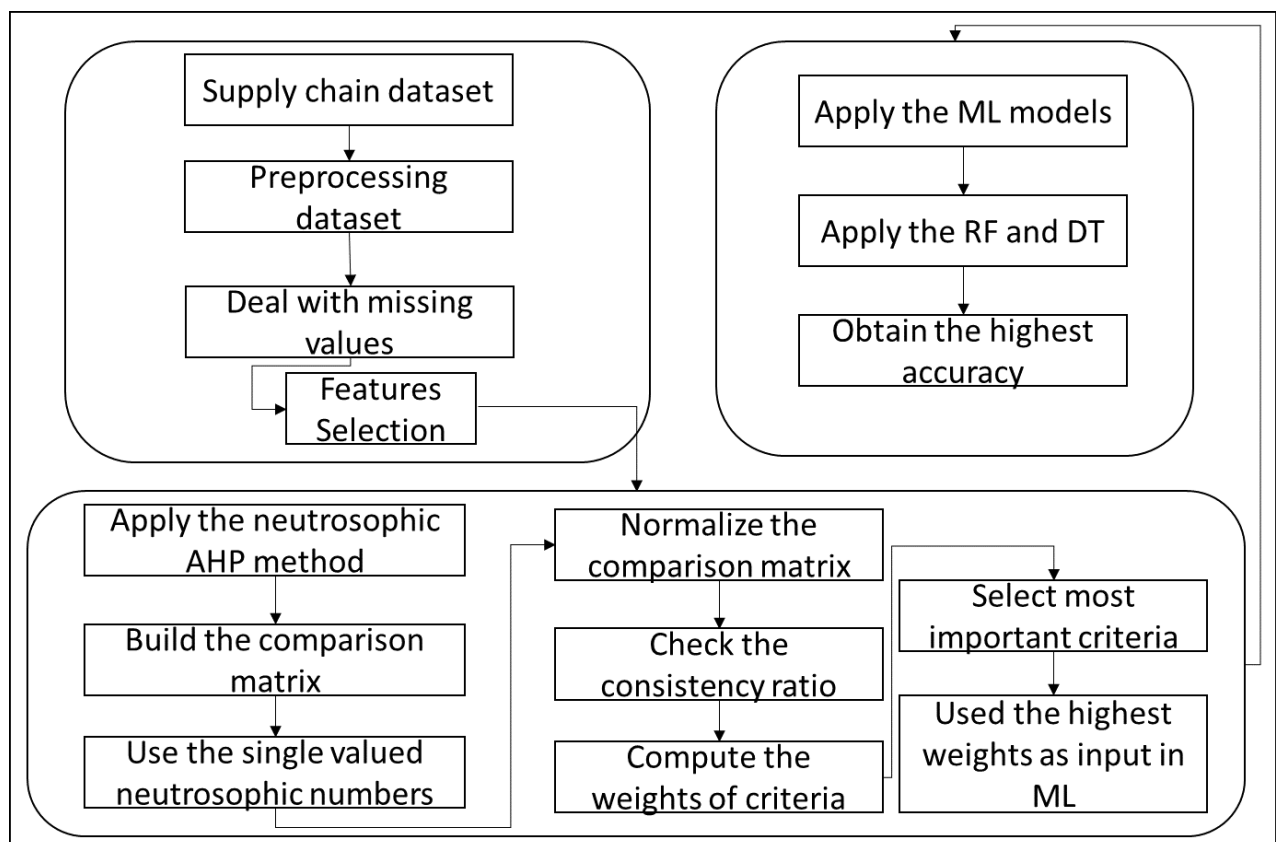


Figure 3: The steps of the neutrosophic and ML models.

### 2.1 Feature Selection

One of the fundamental aspects of choosing features is the attribute measure or assessment criteria. The basic idea of the supervised choice of features, which is often used for classification problems, is the degree to which a feature is relevant to, or correlated with the category label. When a dataset has several characteristics that may be useful, it can be narrowed down to only those characteristics using a process known as choosing features. It helps reduce the size of the data processing level by eliminating superfluous details. Learning algorithms may be preprocessed using an attribute choice approach, and effective element choice can have a positive impact on accuracy, speed, and clarity. Dimensionality reduction may be achieved in a few different methods, two of which are choosing features and extraction of criteria. In contrast to the feature choice procedure, the feature extraction process often involves transforming the original data to elements with good pattern identification capacity. In this paper, we used the neutrosophic model as a feature section by ranking the features by their weights and selecting the most important features[25-30]. This paper used the neutrosophic set as a feature selection. The single-valued neutrosophic set (SVNS) can be defined as:

$$T: Y \rightarrow [0, 1], I: Y \rightarrow [0, 1], F: Y \rightarrow [0, 1]$$

The elements of SVNS can be defined as:

$$T_g(y) = \begin{cases} T_g^L(x), & \text{if } g_1^t \leq y < g_2^t \\ w_c, & \text{if } g_2^t \leq y < g_3^t \\ T_g^R(x), & \text{if } g_3^t \leq y < g_4^t \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$I_g(y) = \begin{cases} T_g^L(x), & \text{if } g_1^i \leq y < g_2^i \\ w_c, & \text{if } g_2^i \leq y < g_3^i \\ T_g^R(x), & \text{if } g_3^i \leq y < g_4^i \\ 1 & \text{otherwise} \end{cases} \quad (2)$$

$$F_g(y) = \begin{cases} T_g^L(x), & \text{if } g_1^f \leq y < g_2^f \\ w_c, & \text{if } g_2^f \leq y < g_3^f \\ T_g^R(x), & \text{if } g_3^f \leq y < g_4^f \\ 1 & \text{otherwise} \end{cases} \quad (3)$$

The bipolar neutrosophic set can be defined as:

$$g = (y; T_g^+(y), T_g^-(y), I_g^+(y), I_g^-(y), F_g^+(y), F_g^-(y))$$

$$\left( \begin{matrix} T_g^+(y): \mathbb{R} \rightarrow [0, 1], T_g^-(y): \mathbb{R} \rightarrow [-1, 0] \\ I_g^+(y): \mathbb{R} \rightarrow [0, 1], I_g^-(y): \mathbb{R} \rightarrow [-1, 0] \\ F_g^+(y): \mathbb{R} \rightarrow [0, 1], F_g^-(y): \mathbb{R} \rightarrow [-1, 0] \end{matrix} \right) \quad (4)$$

The single-valued trapezoidal bipolar neutrosophic can be defined as

$$T_g^+(y) = \begin{cases} \frac{y-g_1}{g_2-g_1} w_g, & \text{if } g_1 \leq y < g_2 \\ w_g, & \text{if } g_2 \leq y < g_3 \\ \frac{g_4-y}{g_4-g_3} w_g, & \text{if } g_3 \leq y < g_4 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

$$T_g^-(y) = \begin{cases} \frac{g_1-y}{g_2-g_1} w_g, & \text{if } g_1 \leq y < g_2 \\ w_g, & \text{if } g_2 \leq y < g_3 \\ \frac{y-g_4}{g_4-g_3} w_g, & \text{if } g_3 \leq y < g_4 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

$$I_g^-(y) = \begin{cases} \frac{(g_2-y)+u_g(y-g_1)}{g_2-g_1} w_g, & \text{if } g_1 \leq y < g_2 \\ u_g, & \text{if } g_2 \leq y < g_3 \\ \frac{(y-g_3)+u_g(g_4-y)}{g_4-g_3} w_g, & \text{if } g_3 \leq y < g_4 \\ \mathbf{1} & \text{otherwise} \end{cases} \quad (7)$$

$$I_g^-(y) = \begin{cases} \frac{(y-g_1)+u_g(g_1-y)}{g_2-g_1} w_g, & \text{if } g_1 \leq y < g_2 \\ u_g, & \text{if } g_2 \leq y < g_3 \\ \frac{(g_4-y)+u_g(y-g_3)}{g_4-g_3} w_g, & \text{if } g_3 \leq y < g_4 \\ \mathbf{-1} & \text{otherwise} \end{cases} \quad (8)$$

$$F_g^-(y) = \begin{cases} \frac{(g_2-y)+x_g(y-g_1)}{g_2-g_1} w_g, & \text{if } g_1 \leq y < g_2 \\ x_g, & \text{if } g_2 \leq y < g_3 \\ \frac{(y-g_3)+x_g(g_4-y)}{g_4-g_3} w_g, & \text{if } g_3 \leq y < g_4 \\ \mathbf{1} & \text{otherwise} \end{cases} \quad (9)$$

$$F_g^-(y) = \begin{cases} \frac{(y-g_1)+x_g(g_1-y)}{g_2-g_1} w_g, & \text{if } g_1 \leq y < g_2 \\ x_g, & \text{if } g_2 \leq y < g_3 \\ \frac{(g_4-y)+x_g(y-g_3)}{g_4-g_3} w_g, & \text{if } g_3 \leq y < g_4 \\ \mathbf{-1} & \text{otherwise} \end{cases} \quad (10)$$

## 2.2 Random Forest

In terms of machine learning, RF is an ensemble approach that includes building several DTs by bootstrap aggregation (bagging). When an input is given to RF, it is propagated to all of the DTs that make it up. Every tree makes its prediction about which category it belongs to and "votes" for that category. The final RF forecast will be determined by the votes cast. The variation caused by little data is reduced, and the reliability of forecasts is enhanced because the aggregated vote of several DTs is naturally less noisy and less vulnerable to extremes than a single DT result [31-37]. As RF already has an attribute choice structure, it can process a large number of input parameters without requiring the elimination of any parameters as a means of achieving decreased dimensionality. The randomization test measures the rise in error in forecasting if the values of the parameter of interest are permuted throughout the out-of-bag data, allowing for the calculation of factor significance scores for RF. Every tree in the ensemble is given a score, which is the mean of all the scores multiplied by the standard deviation.

## 2.3 Decision Tree

DT is a tree-like framework, as suggested by its name, with leaves representing the names of results and branches representing combinations of input elements that led to those results. A binary DT uses the optimal feature split based on selected split criteria to divide the data set (parent cluster) into two parts (child nodes). The resultant two groups, now acting as parents, are further subdivided into two sets. As long as there are sightings to classify, the binary split will keep going. No inferences about the true distribution of the predictive variables are made by the method, making it nonparametric.

## 3. Application

This section introduced the dataset and results of application and machine learning models.

### 3.1 Dataset

This paper used the dataset of the supply chain from Kaggle. The dataset has 180519 rows and 53 columns. We performed some statistical analysis on the dataset like mean, count, max, min, and standard deviation as shown in Table 1.

Table 1: Statistics analysis on the dataset.

	count	mean	std	min	25%	50%	75%	max
<b>FSC21</b>	180519	0	0	0	0	0	0	0
<b>FSC20</b>	180519	141.2326	139.7325	9.99	50	59.99	199.99	1999.99
<b>FSC19</b>	0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
<b>FSC18</b>	180519	31.85145	15.64006	2	18	29	45	76
<b>FSC17</b>	180519	692.5098	336.4468	19	403	627	1004	1363
<b>FSC16</b>	24840	55426.13	31919.28	1040	23464	59405	90008	99301
<b>FSC15</b>	180519	21.97499	104.4335	-4274.98	7	31.52	64.8	911.8
<b>FSC14</b>	180519	183.1076	120.0437	7.49	104.38	163.99	247.4	1939.99
<b>FSC13</b>	180519	203.7721	132.2731	9.99	119.98	199.92	299.95	1999.99
<b>FSC12</b>	180519	2.127638	1.453451	1	1	1	3	5
...	...	...	...	...	...	...	...	...
<b>FSC10</b>	180519	29.71996	9.813646	-33.9376	18.26543	33.14486	39.27962	48.78193
<b>FSC9</b>	180519	5.44346	1.629246	2	4	5	7	12
<b>FSC8</b>	180516	35921.13	37542.46	603	725	19380	78207	99205
<b>FSC7</b>	180519	6691.379	4162.918	1	3258.5	6457	9779	20757
<b>FSC6</b>	180519	31.85145	15.64006	2	18	29	45	76
<b>FSC5</b>	180519	0.548291	0.497664	0	0	1	1	1
<b>FSC4</b>	180519	183.1076	120.0437	7.49	104.38	163.99	247.4	1939.99
<b>FSC3</b>	180519	21.97499	104.4335	-4274.98	7	31.52	64.8	911.8
<b>FSC2</b>	180519	2.931847	1.374449	0	2	4	4	4
<b>FSC1</b>	180519	3.497654	1.623722	0	2	3	5	6

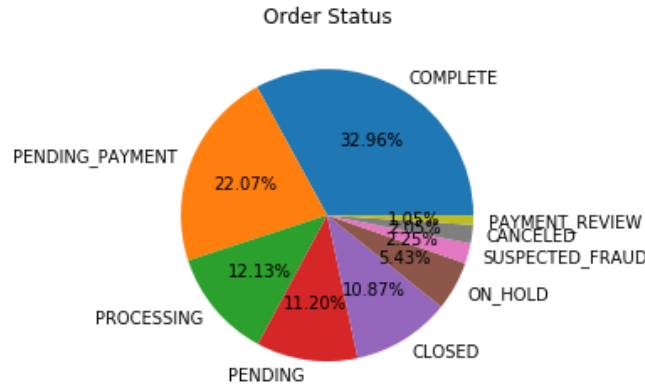


Figure 4: The size of elements on the dataset.

We applied some data analysis and visualization charts to the dataset. Figure 4 shows the size of the elements of the dataset. The complete has the highest size followed by the pending payment and processing element. Figure 5 shows the highest countries with the pending assignment.

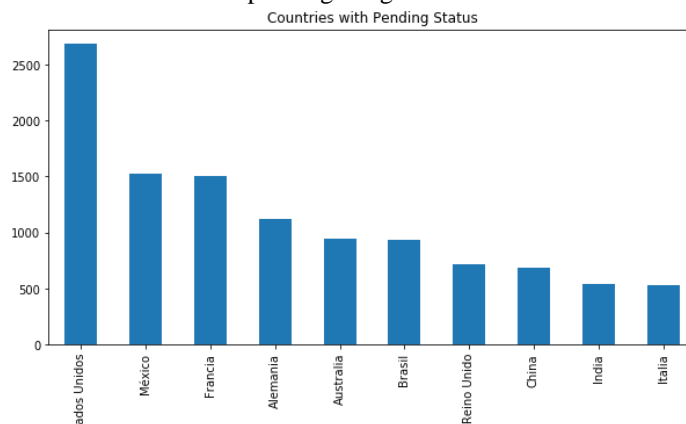


Figure 5: The countries with pending assignments.

Figure 6 shows the heatmap between elements of the dataset. The heatmap matrix shows the correlation between variables in the dataset and the highest correlation is entered as input into machine learning models. So we applied the neutrosophic sets as a feature selection to select the highest important criteria.

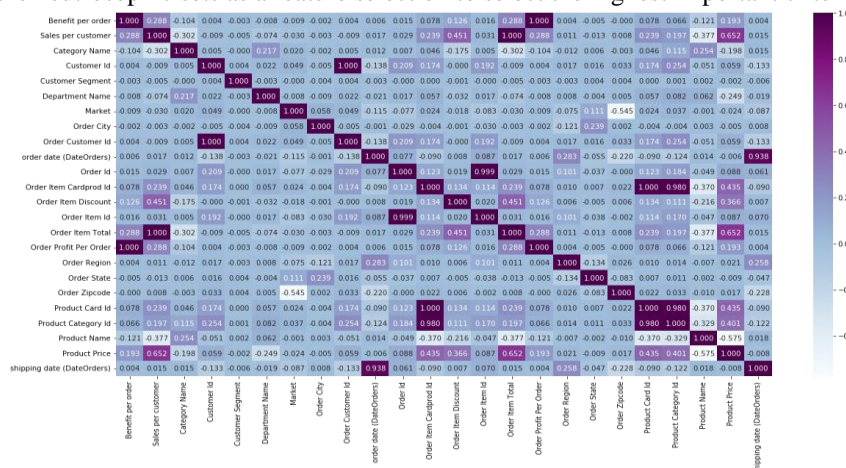


Figure 6: The heatmap of the dataset.

3.2 Results

We applied the neutrosophic AHP method as a feature selection method to select the best criteria. The AHP method was applied to the 15 criteria to compute the best important criteria. Table 2 shows the single-valued comparison matrix between 15 factors. Then applied the steps of the AHP method by using neutrosophic sets. Then normalize the comparison matrix and compute the weights of the criteria. Figure 7 shows the importance of the criteria. Then select the best importance criteria to enter as an input to machine learning models.

Table 2: The single-valued neutrosophic comparison matrix

FSC <sub>1</sub>	(0.9, 0.1, 0.1)	(0.8, 0.15, 0.2)	(0.7, 0.25, 0.3)	(0.6, 0.35, 0.4)	(0.5, 0.5, 0.5)	(0.4, 0.65, 0.6)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)
FSC <sub>2</sub>	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.7, 0.25, 0.3)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)	(0.2, 0.85, 0.8)
FSC <sub>3</sub>	(0.6, 0.35, 0.4)	(0.7, 0.25, 0.3)	(0.4, 0.65, 0.6)	(0.6, 0.35, 0.4)	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.6, 0.35, 0.4)	(0.4, 0.65, 0.6)
FSC <sub>4</sub>	(0.9, 0.1, 0.1)	(0.8, 0.15, 0.2)	(0.7, 0.25, 0.3)	(0.6, 0.35, 0.4)	(0.5, 0.5, 0.5)	(0.4, 0.65, 0.6)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)
FSC <sub>5</sub>	(0.6, 0.35, 0.4)	(0.7, 0.25, 0.3)	(0.4, 0.65, 0.6)	(0.6, 0.35, 0.4)	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.6, 0.35, 0.4)	(0.4, 0.65, 0.6)
FSC <sub>6</sub>	(0.8, 0.15, 0.2)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.4, 0.65, 0.6)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)
FSC <sub>7</sub>	(0.1, 0.9, 0.9)	(0.8, 0.15, 0.2)	(0.7, 0.25, 0.3)	(0.6, 0.35, 0.4)	(0.5, 0.5, 0.5)	(0.4, 0.65, 0.6)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)
FSC <sub>8</sub>	(0.1, 0.9, 0.9)	(0.9, 0.1, 0.1)	(0.8, 0.15, 0.2)	(0.7, 0.25, 0.3)	(0.6, 0.35, 0.4)	(0.5, 0.5, 0.5)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)
FSC <sub>9</sub>	(0.8, 0.15, 0.2)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.4, 0.65, 0.6)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)
FSC <sub>10</sub>	(0.8, 0.15, 0.2)	(0.9, 0.1, 0.1)	(0.8, 0.15, 0.2)	(0.7, 0.25, 0.3)	(0.6, 0.35, 0.4)	(0.5, 0.5, 0.5)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)
FSC <sub>11</sub>	(0.6, 0.35, 0.4)	(0.8, 0.15, 0.2)	(0.8, 0.15, 0.2)	(0.6, 0.35, 0.4)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)
FSC <sub>12</sub>	(0.9, 0.1, 0.1)	(0.8, 0.15, 0.2)	(0.7, 0.25, 0.3)	(0.6, 0.35, 0.4)	(0.5, 0.5, 0.5)	(0.4, 0.65, 0.6)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)
FSC <sub>13</sub>	(0.6, 0.35, 0.4)	(0.7, 0.25, 0.3)	(0.4, 0.65, 0.6)	(0.6, 0.35, 0.4)	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.6, 0.35, 0.4)	(0.4, 0.65, 0.6)
FSC <sub>14</sub>	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.7, 0.25, 0.3)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)	(0.2, 0.85, 0.8)
FSC <sub>15</sub>	(0.9, 0.1, 0.1)	(0.8, 0.15, 0.2)	(0.7, 0.25, 0.3)	(0.6, 0.35, 0.4)	(0.5, 0.5, 0.5)	(0.4, 0.65, 0.6)	(0.4, 0.65, 0.6)	(0.3, 0.75, 0.7)

	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.7, 0.25, 0.3)	(0.7, 0.25, 0.3)	(0.7, 0.25, 0.3)	(0.6, 0.35, 0.4)	(0.6, 0.35, 0.4)	1
	(0.1, 0.9, 0.9)	(0.7, 0.25, 0.3)	(0.6, 0.35, 0.4)	(0.5, 0.5, 0.5)	(0.4, 0.65, 0.6)	1	1/(0.6, 0.35, 0.4)	(0.1, 0.9, 0.9)
	(0.3, 0.75, 0.7)	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.6, 0.35, 0.4)	1	1/(0.4, 0.65, 0.6)	1/(0.7, 0.25, 0.3)	(0.3, 0.75, 0.7)
	(0.2, 0.85, 0.8)	(0.1, 0.9, 0.9)	(0.7, 0.25, 0.3)	1	1/(0.6, 0.35, 0.4)	1/(0.5, 0.5, 0.5)	1/(0.7, 0.25, 0.3)	(0.2, 0.85, 0.8)
	(0.7, 0.25, 0.3)	(0.7, 0.25, 0.3)	1	1/(0.7, 0.25, 0.3)	1/(0.1, 0.9, 0.9)	1/(0.6, 0.35, 0.4)	1/(0.7, 0.25, 0.3)	(0.7, 0.25, 0.3)
	(0.8, 0.15, 0.2)	1	1/(0.7, 0.25, 0.3)	1/(0.1, 0.9, 0.9)	1/(0.2, 0.85, 0.8)	1/(0.7, 0.25, 0.3)	1/(0.1, 0.9, 0.9)	(0.8, 0.15, 0.2)
1	1/(0.8, 0.15, 0.2)	1/(0.7, 0.25, 0.3)	1/(0.2, 0.85, 0.8)	1/(0.3, 0.75, 0.7)	1/(0.3, 0.75, 0.7)	1/(0.1, 0.9, 0.9)	1/(0.2, 0.85, 0.8)	1
	1/(0.6, 0.35, 0.4)	1/(0.8, 0.15, 0.2)	1/(0.1, 0.9, 0.9)	1/(0.3, 0.75, 0.7)	1/(0.4, 0.65, 0.6)	1/(0.2, 0.85, 0.8)	1/(0.3, 0.75, 0.7)	1/(0.6, 0.35, 0.4)
	1/(0.8, 0.15, 0.2)	1/(0.4, 0.65, 0.6)	1/(0.2, 0.85, 0.8)	1/(0.4, 0.65, 0.6)	1/(0.6, 0.35, 0.4)	1/(0.3, 0.75, 0.7)	1/(0.4, 0.65, 0.6)	1/(0.8, 0.15, 0.2)
	1/(0.6, 0.35, 0.4)	1/(0.5, 0.5, 0.5)	1/(0.3, 0.75, 0.7)	1/(0.4, 0.65, 0.6)	1/(0.1, 0.9, 0.9)	1/(0.4, 0.65, 0.6)	1/(0.4, 0.65, 0.6)	1/(0.6, 0.35, 0.4)
	1/(0.1, 0.9, 0.9)	1/(0.6, 0.35, 0.4)	1/(0.4, 0.65, 0.6)	1/(0.5, 0.5, 0.5)	1/(0.2, 0.85, 0.8)	1/(0.7, 0.25, 0.3)	1/(0.5, 0.5, 0.5)	1/(0.1, 0.9, 0.9)
	1/(0.2, 0.85, 0.8)	1/(0.7, 0.25, 0.3)	1/(0.6, 0.35, 0.4)	1/(0.6, 0.35, 0.4)	1/(0.1, 0.9, 0.9)	1/(0.1, 0.9, 0.9)	1/(0.6, 0.35, 0.4)	1/(0.2, 0.85, 0.8)
	1/(0.3, 0.75, 0.7)	1/(0.8, 0.15, 0.2)	1/(0.8, 0.15, 0.2)	1/(0.7, 0.25, 0.3)	1/(0.4, 0.65, 0.6)	1/(0.2, 0.85, 0.8)	1/(0.7, 0.25, 0.3)	1/(0.3, 0.75, 0.7)
	1/(0.4, 0.65, 0.6)	1/(0.9, 0.1, 0.1)	1/(0.8, 0.15, 0.2)	1/(0.8, 0.15, 0.2)	1/(0.7, 0.25, 0.3)	1/(0.3, 0.75, 0.7)	1/(0.8, 0.15, 0.2)	1/(0.4, 0.65, 0.6)
FSC <sub>9</sub>	1/(0.8, 0.15, 0.2)	1/(0.8, 0.15, 0.2)	1/(0.6, 0.35, 0.4)	1/(0.9, 0.1, 0.1)	1/(0.6, 0.35, 0.4)	1/(0.4, 0.65, 0.6)	1/(0.9, 0.1, 0.1)	1/(0.8, 0.15, 0.2)

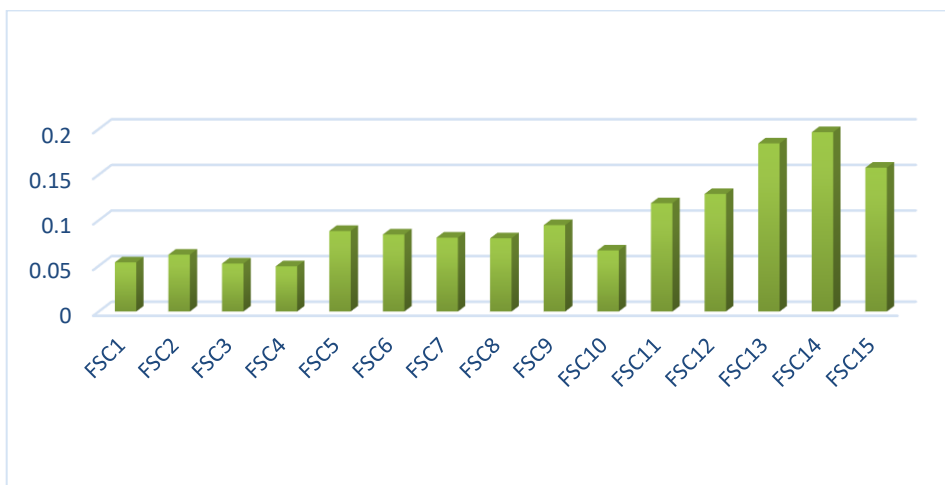


Figure 8: The importance of 15 factors of the dataset.

Then apply the random forest and decision tree models to a dataset. The accuracy of random forest and machine learning models is shown in Figure 9. The random forest is the highest accuracy followed by the decision tree.

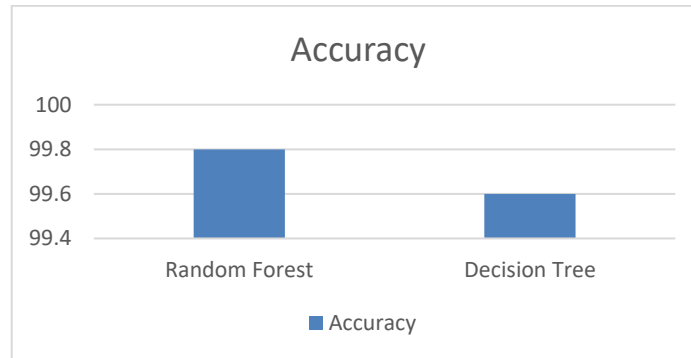


Figure 9: The accuracy of the two machine learning models.

#### 4. Conclusions and Future Works

The construction industry is increasingly adopting machine learning (ML) to automate processes. ML enables the generation of accurate solutions by teaching machines to emulate human thought processes, even with large volumes of data. Its applications in supply chain management (SCM) can enhance accuracy in logistics, operations, planning, and workforce management. Neutrosophic logic, when applied to SCM, offers advantages in addressing uncertainties, vagueness, and imprecise information. Key conclusions regarding neutrosophic logic in SCM include improved decision-making, enhanced risk management, flexible modeling and analysis, customer-centric approach, and optimization and efficiency. To fully leverage ML in SCM, future directions include exploring a wider variety of ML algorithms, enhancing robustness, and addressing interpretability concerns. Research should focus on testing the interpretability of ML algorithms in dynamic settings and persuading end-users to choose suitable ML methods. Further research is needed to explore the application of ML algorithms in SCM, enhance robustness, and address interpretability concerns.

Future works for the utilization of neutrosophic logic in SCM can focus on advanced modeling techniques, integration with emerging technologies, supply chain collaboration, decision support systems, sustainability and resilience, and industry-specific applications. By deepening the understanding and practical implementation of neutrosophic logic in SCM, researchers and practitioners can unlock its potential to optimize supply chain operations, enhance decision-making, and promote sustainability and resilience.

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