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Classification of Industrial and Commercial Facilities Using Machine Learning Techniques

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ABSTRACT

The performance of machine learning algorithms for the automatic classification of industrial and commercial facilities were examined within the scope of this project. A dataset containing a total of 47,683 data points, including 27,691 warehouses, 6,441 retail stores, and 13,551 factories, was used in this study. To classify these facilities as "factory," "warehouse," or "retail," ANN, RF, and kNN machine learning models were applied and compared. The ANN achieved the highest classification accuracy with 76.9%. This was followed by the RF algorithm with 73.9% and the kNN algorithm with 63.9%. The high performance demonstrated by the ANN indicates that it could be a powerful tool for automatic facility classification in industrial and commercial sectors. This classification can provide significant contributions such as increasing operational efficiency of businesses, more effectively guiding marketing strategies, and better management of resources. Future studies can expand research in this field by further increasing model accuracy and testing in various application scenarios.

1. Introduction

Artificial intelligence-supported machine learning algorithms hold a significant place in the logistics sector. These algorithms can help businesses optimize their logistics processes by analyzing data. The use of AI-supported machine learning algorithms can provide substantial benefits, particularly in areas such as supply chain management, warehouse management, and transportation planning. The applications of AI-supported machine learning algorithms in the logistics field are diverse. These include demand forecasting, production planning, inventory optimization, and fault prediction [1-3]. With the use of these algorithms, logistics companies can better meet customer demands, improve delivery processes, and reduce costs.

Warehouse management is a crucial component of the logistics process and plays a significant role in the success of businesses. Efficient warehouse management can increase efficiency in the supply chain, reduce inventory costs, and enhance customer satisfaction. Artificial intelligence-supported machine learning algorithms can offer various benefits in warehouse management. This study focuses on the use of machine learning algorithms in warehouse management and demonstrates their ability to classify facilities as factory, retail, and warehouse. Among the contributions our study provides to the literature are showcasing the role of artificial intelligence in increasing the efficiency of warehouse operations, optimizing inventory management, and making warehouse management systems smarter and more flexible. It also provides insights into the practical applications of classification algorithms.

Barakat et al., focused on the importance of fault detection and diagnosis in the field of machine monitoring. Their developed method combines advanced signal processing techniques and artificial neural networks for the systematic detection and diagnosis of faults in industrial systems. Particularly, this method, designed as an adaptive intelligent technique, integrates discrete wavelet transform and training techniques using Gauss neurons [2].

In another study by Gomes et al., they emphasized the importance of production instruction planning in manufacturing facilities and highlighted it as a key to an effective production process. In situations where storage space is limited and contractual quantities are of great importance, it plays a significant role in preventing adverse situations such as delayed production and early

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completion. The developed Ambient Intelligence decision support system aims to increase production quantity and efficiency in large organizations by integrating technologies such as ambient intelligence, optimization options, and machine learning. They developed this system to assist in defining standard operating procedures and aimed to optimize production planning and control processes [3].

Cho et al., presented an approach for the effective and efficient use of advanced Internet of Things (IoT)-based technologies in overall factory management. This study involves the development of a hybrid machine learning approach, which combines unsupervised and semi-supervised learning to create efficient maintenance strategies [4].

In their study, Terziyan et al., highlighted a trend related to Industry 4.0 and smart factories, emphasizing that the integration of artificial intelligence (AI) should play a crucial role in real-time decision-making processes. The Pi-Mind technology provides transparent, proactive, and autonomous decision-making capabilities by balancing human-expert-driven decision-making with AI-driven decision-making. This technology aims to enhance decision rationality in the industry by facilitating human influence in smart manufacturing processes while also leveraging traditional and intuitive human cognitive abilities [5].

Kolner aimed to develop a predictive model using data from a transportation control tower to forecast the on-time arrival rate of trucks at stores and help explain the variability in their on-time arrivals. The study demonstrates that the Random Forest model is the most suitable for detecting on-time arrivals. The Random Forest classifier achieves an F1 score of 86% [6].

The aim of the study by Valatsos et al was to predict the time intervals from a central warehouse to various locations across Europe for an international freight transportation company. They performed these predictions using five well-known ensemble learning techniques suitable for regression problems: Bagging, Random Forest, Gradient Boosting, Natural Gradient Boosting, and Extreme Gradient Boosting. They report that Random Forest and Natural Gradient Boosting provide the best prediction performance for most forecasting scenarios [7].

Tsolaki et al., reviewed and identified the latest technologies related to current trends in freight transportation, supply chain, and logistics, focusing on topics such as arrival time prediction, demand forecasting, industrial process optimization, traffic flow, location prediction, vehicle routing problems, and anomaly detection in transportation data. They categorize relevant studies according to machine learning methodologies, presenting the evolution of these methods over time and their connections to various applications in specific fields [1]. Based on a dataset of 42,683 data points, the study sought to test the hypothesis that machine learning techniques, including Artificial Neural Networks (ANN), Random Forests (RF), and k-Nearest Neighbors (kNN), can efficiently classify warehouses, retail stores, and factories. To evaluate the precision and dependability of each method in distinguishing between these facility kinds, performance metrics and confusion matrices were thoroughly examined. This study emphasizes how machine learning may revolutionize supply chain management, resource allocation, and industrial planning. In order to improve classification accuracy and application scope, future research should concentrate on adding more facility types to the data, integrating real-time data for dynamic insights, and investigating cutting-edge machine learning algorithms.

2. Material and Methods

The study involved conducting classification tasks on a dataset comprising 42,683 data, employing three distinct algorithms: Artificial Neural Network (ANN), Random Forest (RF), and k-Nearest Neighbors (kNN). Specifically, the objective of the classification process was to differentiate between diverse types of facilities, namely warehouses, retail stores, and factories. To evaluate the effectiveness of each algorithm, performance metrics results, as well as confusion matrix results were meticulously analyzed and compared. These metrics provided valuable insights into the accuracy and reliability of the classification models generated by the respective algorithms. Additionally, the methodology adopted in the study, outlining the step-by-step procedures followed for data preprocessing, algorithm implementation, and result analysis, is visually presented in Figure 1 for clarity and reference purposes.

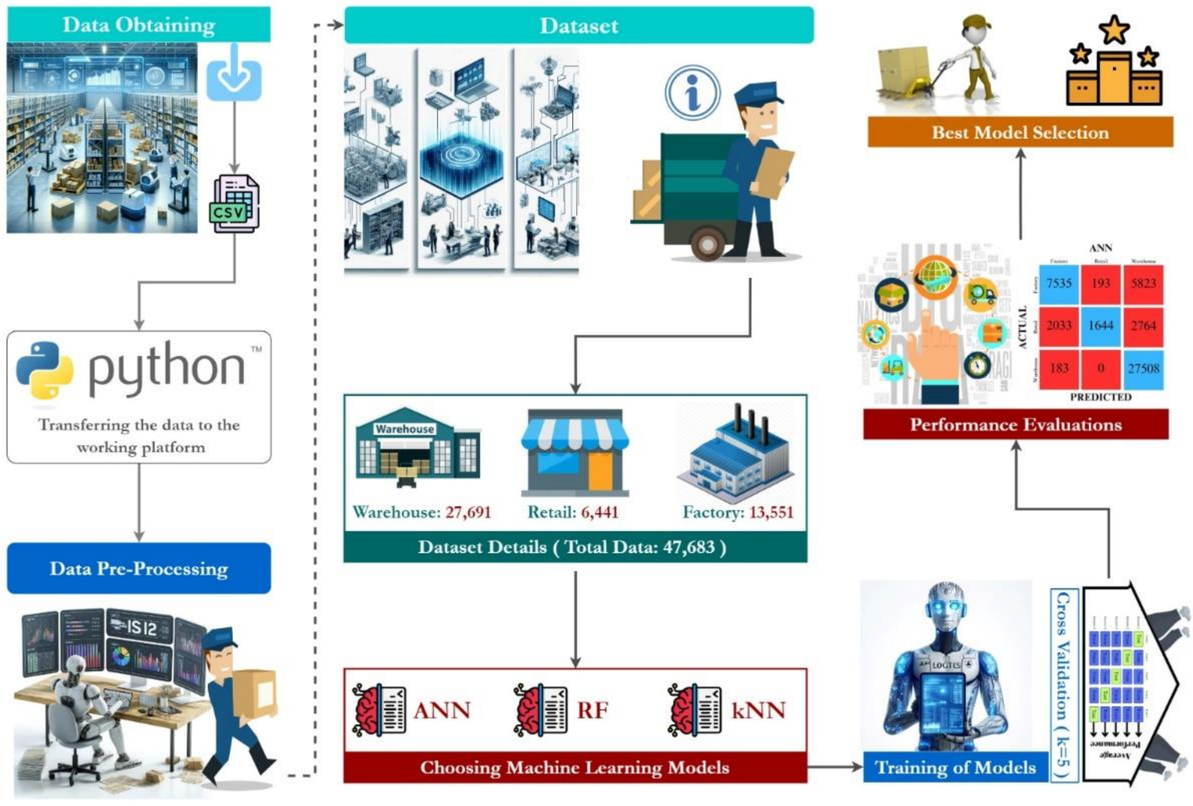


Figure 1. The Path Followed in The Study

2.1. Dataset

The dataset used in the study, titled "A dataset of logistics sites in England and Wales: Location, size, type and loading bays" by De Saxe et al., [8] , represents logistics fields in England and Wales. Here, the term "logistics site" broadly encompasses any area where heavy vehicles need to stop for loading or unloading goods or materials, particularly in a designated loading area.

The dataset comprises five features, with the "category" feature being the focus of classification. It consists of a total of 47,683 data, categorizing into 27,691 warehouses, 6,441 retail sites, and 13,551 factories [9]. A description of the features belonging to the dataset is provided in Table 1, as detailed in the studies by De Saxe et al., [8, 9].

Table 1. Information About the Dataset

Name	Description	Data Type	Units
Category	Keyword defining type of site. Values are ‘warehouse’, ‘factory’, ‘retail’	Discrete	-
Latitude	Latitude coordinate of the site	Float	Degrees (°)
Longitude	Longitude coordinate of the site	Float	Degrees (°)
Sqm	The floor area of the site as used for valuation purposes	Float	Square meters (m2)
Bays	The modelled number of loading bays at the site based on a sample of sites with a known number of loading bays.	Integer	-

2.2. Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are advanced computer algorithms that attempt to mimic the information processing of the human brain. Essentially, they have the ability to recognize patterns and relationships within large amounts of data. ANNs are used in various tasks such as data classification, regression analysis, pattern recognition, and even time series forecasting [10, 11]. The fundamental purpose of ANNs is to learn patterns in the dataset and adjust the model's output to match real-world data [12, 13]. The architecture of an ANN is illustrated in Figure 2. The artificial neural network (ANN) was configured with parameters including a hidden neuron layer of 100, ReLU activation function, Adam solver, regularization strength set to 0.0001, and a maximum of 200 iterations.

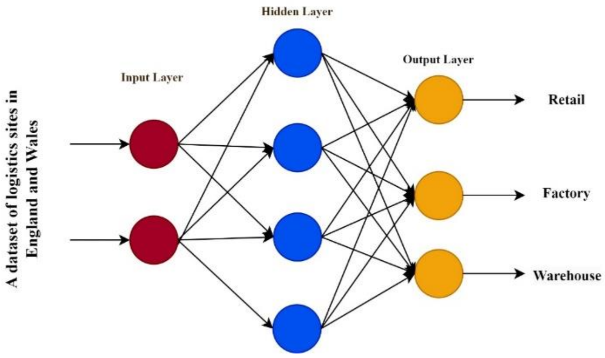


Figure 2. The Representation of The ANN Architecture

2.3. Random Forest (RF)

Random Forest is a powerful machine learning algorithm commonly used for both classification and regression tasks. It is an ensemble method that combines multiple decision trees to form a robust model [14, 15]. Ensemble methods aim to improve the performance of a single model by aggregating the predictions of multiple models. Random Forest enhances the stability and accuracy of the model while reducing the risk of overfitting [16, 17]. The representation of a Random Forest model is provided in Figure 3. The random forest model was constructed using 10 decision trees.

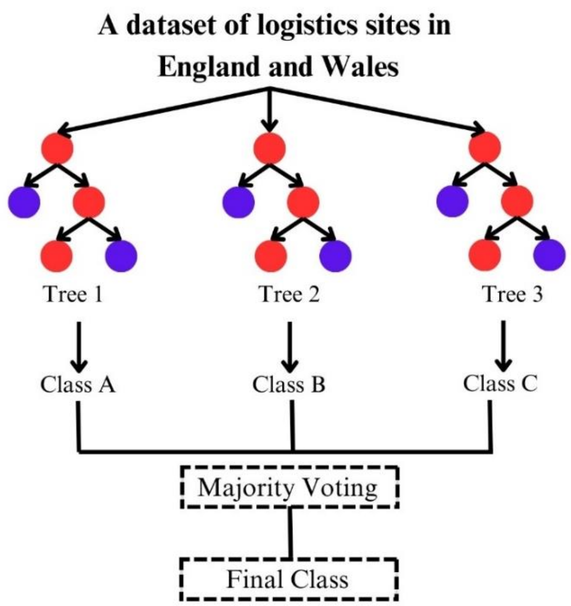


Figure 3. The Representation of The Random Forest Architecture

2.4. k Nearest Neighbor (kNN)

kNN is trained with a pre-labelled dataset and used to predict the class or value of a new data point. Firstly, kNN is trained with a labelled dataset. Then, when a new data point for prediction is presented, the distance between the new data point and each data point in the training set is calculated [18, 19]. The closest neighbors up to the selected value of K identified. Finally, based on the nearest K neighbors, the class or value of the new data point is predicted [20-22]. The architecture of kNN is illustrated in Figure 4. The k-nearest neighbors (kNN) algorithm used 10 neighbors with the Euclidean distance metric and uniform weighting.

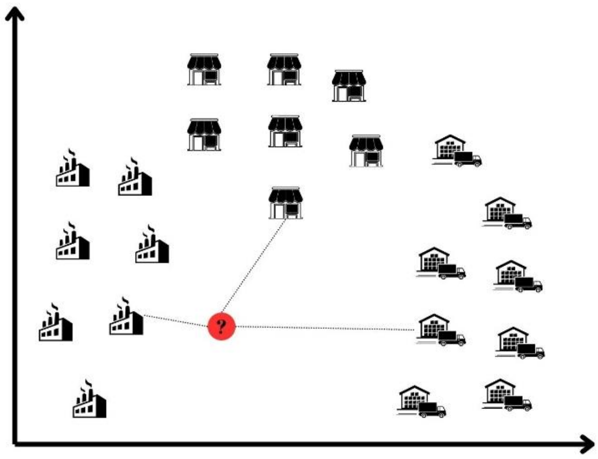


Figure 4. The Representation of The Knn Architecture

2.5. Cross Validation

Cross-validation is a statistical resampling method used to evaluate the performance of machine learning models more objectively and accurately. It works by splitting the dataset into different sections and using these sections for training and testing purposes. This enables obtaining a more reliable result about the overall performance of the model [23, 24]. The cross-validation (k=5) method is illustrated in Figure 5.

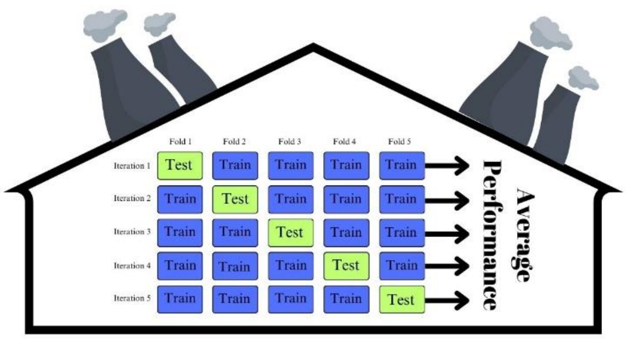
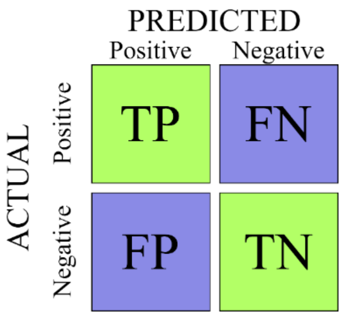


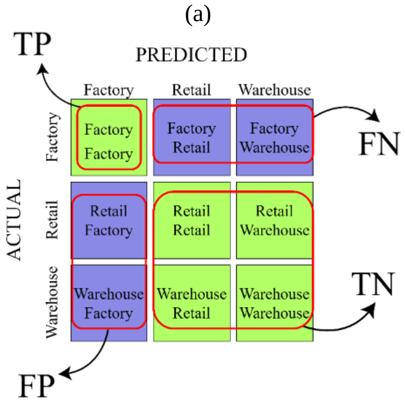
Figure 5. Cross Validation Method

2.6. Confusion Matrix

The confusion matrix is a performance evaluation tool used in classification problems. This table provides detailed information about the accuracy of the model's predictions. Additionally, the confusion matrix aids in comparing different machine learning models and provides insights into which scenarios require more careful consideration [25-27].



(a)



(b)

Figure 6. Two-class and multi-class confusion matrix (a) Two Class, (b) Multi Class

True Positive (TP): The number of examples that are truly factories and are predicted as factories.

False Positive (FP): The number of examples that are actually warehouses but are predicted as factories. (Type 1 mistake)

False Negative (FN): The number of examples that are actually factories but are predicted as warehouses. (Type 2 mistake)

True Negative (TN): The number of examples that are truly warehouses and are predicted as warehouses.

2.7. Performance Metrics

Performance metrics are measurements used to evaluate how well a model performs in fields such as artificial intelligence and machine learning. These metrics are used to determine how close the model's predictions are to the actual values and assist in quantitatively assessing the model's success [28-31]. The description and formulas of performance metrics are provided in Table 2.

Table 2. Performance Metrics Description and Formulas

Metrics	Description	Formula
Accuracy	Refers to the proportion of correctly predicted samples.	$\frac{\sum_{i=1}^{1} \frac{tp_i+tn_i}{tp_i+fn_i+fp_i+tn_i}}{l}$ (1)
Precision	It refers to the proportion of positively predicted samples that are actually positive.	$\frac{\sum_{i=1}^{1} \frac{tp_i}{tp_i+fp_i}}{l}$ (2)
Recall	It refers to the proportion of truly positive samples that are correctly predicted to be positive.	$\frac{\sum_{i=1}^{1} \frac{tp_i}{tp_i+fn_i}}{l}$ (3)
F1-Score	It is used to measure the balance between sensitivity and responsiveness. The F1 score takes the harmonic average of these two metrics.	$2 * \frac{\frac{\sum_{i=1}^{1} \frac{tp_i}{tp_i+fp_i}}{l} * \frac{\sum_{i=1}^{1} \frac{tp_i}{tp_i+fn_i}}{l}}{\frac{\sum_{i=1}^{1} \frac{tp_i}{tp_i+fp_i}}{l} + \frac{\sum_{i=1}^{1} \frac{tp_i}{tp_i+fn_i}}{l}}$ (4)

3. Experimental Results

In this study, a dataset named "A dataset of logistics sites in England and Wales: Location, size, type and loading bays" containing features such as the location, size, type, and loading platforms of logistics sites in England and Wales was used. The classification process was conducted using ANN, RF, and kNN algorithms. The performance of these algorithms was evaluated on a total of 47,683 data. The obtained performance metrics were used to measure the classification success of each algorithm. The results of the performance metrics are provided in Table 3. Additionally, the confusion matrix results for each algorithm are illustrated in Figure 7.

Table 3. Performance metrics results for all models

Models	Accuracy	Precision	Recall	F-1 Score
ANN	76.9%	78.3%	76.9%	73.8%
RF	73.9%	72.5%	73.9%	72.5%
kNN	63.9%	60.7%	63.6%	61.8%

When analyzing Table 2, it observed that ANN demonstrates the highest accuracy rate (76.9%), while Random Forests (RF) rank second with an accuracy of 73.9%. The kNN algorithm exhibits the lowest performance with an accuracy rate of 63.9%. ANN also has a higher precision value (78.3), indicating that this algorithm produces fewer false positive results in identifying and classifying logistic facility types. The high-performance metrics of ANN surpassing other algorithms suggest its superiority in classifying logistic facility types and producing more reliable results. While RF performs effectively, the lower values of the kNN algorithm indicate that it should be used more cautiously in specific scenarios.

While evaluating the results provided in Figure 7, the most successful ANN algorithm correctly classifies 36,487 out of 47,683 data samples while misclassifying 10,996 examples. The RF algorithm achieves 35,220 correct classifications out of 47,683 data points, with 12,463 misclassifications. The kNN algorithm, which has the lowest classification accuracy, correctly classifies 30,346 out of 47,683 data samples but misclassifies 17,337 examples.

Looking at the confusion matrix results, it is evident that there are many instances where data points are predicted as warehouses. Additionally, the confusion between warehouses and retail sites is observed to be quite low. It is observed that factories are confused with both retail and warehouse categories.

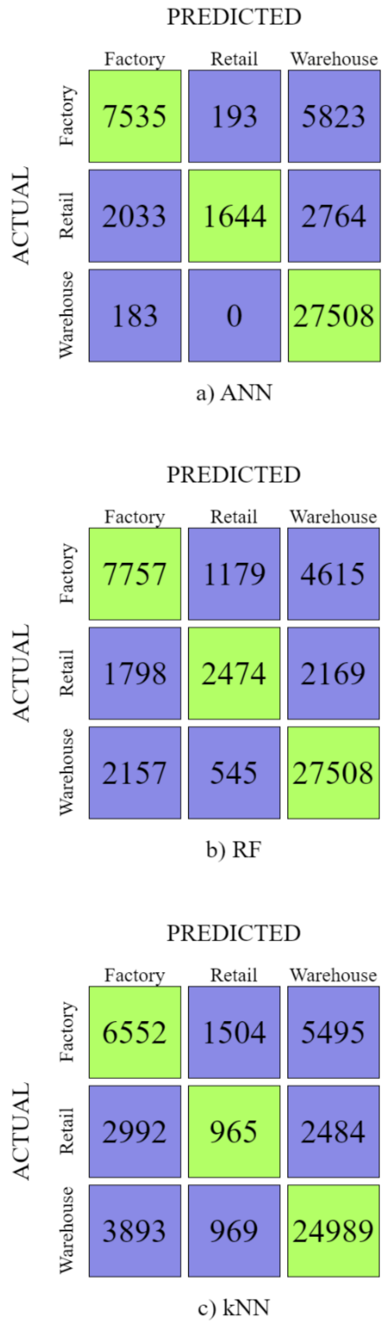


Figure 7. Confusion Matrix Results for All Models

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4. Discussion and Conclusions

Machine learning algorithms play a significant role in classifying different types of facilities, such as factories, warehouses, and retail stores. In this study, a classification process was conducted using four distinct features of these facilities. A total of 47,683 data points were classified using three different algorithms: Artificial Neural Networks (ANN), Random Forests (RF), and k-Nearest Neighbors (kNN). Among these, the most successful algorithm was ANN, achieving a classification accuracy of 76.9%, while kNN had the lowest accuracy at 63.9%. This study provides valuable insights into methods and algorithms for automatically identifying different types of facilities, and it can serve as a reference source to guide future research efforts in this area.

Classifying business types such as warehouses, retail outlets, and factories can significantly support industrial planning processes. Machine learning algorithms can assist in making critical industrial decisions related to infrastructure investments, supply chain management, and production strategies. For example, these algorithms can be used to determine the optimal placement of a new industrial facility or to optimize the operations of an existing one. By leveraging the predictive power of machine learning, stakeholders can enhance their decision-making processes, leading to more efficient and effective industrial planning.

The broader implications of our findings are substantial. Improved classification accuracy can lead to better resource allocation, enhanced infrastructure planning, and optimized supply chain management, resulting in significant cost savings and operational efficiencies for businesses and policymakers. The adoption of machine learning-based classification methods can transform industrial operations, making them smarter and more responsive to changing conditions.

Future studies will focus on various areas to enhance the efficiency and effectiveness of existing systems. One key area of improvement is data enrichment. By incorporating additional facility types and operational data, the accuracy and scope of the model can be significantly increased. This could involve integrating more granular data on facility operations, such as production volumes, storage capacities, and distribution networks. Furthermore, exploring the use of advanced machine learning techniques, such as deep learning and ensemble methods, could lead to even better classification performance.

Another avenue for future research is the integration of real-time data. By using real-time sensor data, machine learning models can be continuously updated and refined, allowing for dynamic and adaptive industrial planning. This could be particularly useful in scenarios where rapid changes in demand or supply require quick adjustments to industrial operations.

Moreover, interdisciplinary collaboration can play a crucial role in enhancing these classification systems. By working with experts in industrial engineering, logistics, and supply chain management, researchers can develop more comprehensive models that take into account the complex interplay of various factors influencing industrial facility classification.

In conclusion, the application of machine learning algorithms to the classification of industrial facilities offers significant potential for improving industrial planning processes. As future studies expand the scope and accuracy of these models through data enrichment, real-time data integration, and interdisciplinary collaboration, the benefits of these technologies will become even more pronounced, paving the way for smarter, more efficient industrial operations.

Data Availability

Contacting the corresponding author Christopher de Saxe or accessing the study's dataset through the Data in Brief; https://doi.org/10.1016/j.dib.2024.110399

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Declaration of Competing Interest

It is declared that neither the authors have any known competing financial interests nor personal relationships that might influence the work reported here.

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