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Container Classification: A Hybrid AHP-CNN Approach for Efficient Logistics Management

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ABSTRACT

This research presents a groundbreaking approach that integrates artificial intelligence (AI) and big data for container classification, utilizing the Analytic Hierarchy Process (AHP) and Convolutional Neural Network (CNN). The study aims to address the challenges associated with prioritizing containers based on weight, destination, special requirements, financial considerations, and additional criteria.
The multi-criteria AHP method is employed to determine the relative importance of each criterion, providing weighted inputs for the subsequent CNN classification. The hybrid AHP-CNN model is strategically designed to optimize container classification, minimizing reshuffling movements within container yards, and facilitating efficient prioritization.
Through a comprehensive simulation, the effectiveness and adaptability of the proposed model are showcased. The study includes a sensitivity analysis, evaluating the accuracy of the model across various weight scenarios. The results demonstrate the robustness of the hybrid model, achieving a high level of accuracy in container classification. Notably, in three distinct scenarios, the model exhibited accuracy rates of 89.00%, 88.84%, and 91.05%, respectively.

1. Introduction.

Efficient container classification within terminal operations serves as a cornerstone for enhancing the overall performance and productivity of container handling facilities. As terminal operations grapple with dynamism, diverse container attributes, and evolving logistical demands, the need for a systematic and adaptable classification methodology becomes increasingly imperative. Traditional manual categorization methods, often falling short in addressing the intricacies of contemporary terminals, pave the way for transformative solutions.

Consider the significant growth in global container traffic, exemplified by industry reports estimating nearly 11 billion metric tons of seaborne trade in 2021 and projecting almost 33 million twenty-foot equivalent units (TEU) of cargo to be transported across the Pacific Ocean in 2022. Against this backdrop, our research pioneers a groundbreaking approach that seamlessly integrates artificial intelligence (AI) and big data into container classification, harnessing the power of the Analytic Hierarchy Process (AHP) and Convolutional Neural Network (CNN). The primary objective is to tackle the multifaceted challenges associated with prioritizing containers based on critical factors such as weight, destination, special requirements, and financial considerations.

Beyond theoretical discourse, the true impact of this research resonates in the day-to-day operations of container terminals. By ensuring the precise allocation of each container to its optimal location, our methodology serves as a strategic tool to optimize space utilization, streamline workflows, and reduce operational bottlenecks and handling costs. In an era witnessing an unprecedented surge in global container traffic, the accuracy and efficiency of container classification methodologies emerge as integral components, making this research indispensable for the seamless functioning of the logistics industry.

To quantify the impact of our approach, we conducted a comprehensive simulation, meticulously evaluating the effec-

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tiveness and adaptability of the proposed model. The study includes a sensitivity analysis, scrutinizing the accuracy of the model across various weight scenarios. Notably, the results demonstrate the robustness of the hybrid AHP-CNN model, achieving a high level of accuracy in container classification. The model exhibited impressive accuracy rates of values 89.00%, 88.84%, and 91.05% in three distinct scenarios, respectively, underscoring its potential transformative influence on container management practices.

The structure of this paper unfolds as follows: Section 2 provides a recent review of studies focused on data classification using neural network processes, laying the groundwork for our innovative approach. Section 3 defines our proposed methodology, offering comprehensive details on the integrated methods applied to container classification. The efficacy of our work is evaluated in Section 4, shedding light on its effectiveness. Lastly, Section 5 concludes the paper by emphasizing the transformative potential of advanced technologies in container management and their capacity to address industry challenges.

2. Literature Review.

Recent studies in container logistics and management have delved into innovative approaches, notably exploring advanced technologies, particularly the Convolutional Neural Networks (CNNs). Our literature review strategically draws insights from a spectrum of CNN applications, highlighting their direct relevance to our proposed container management methodology.

The effectiveness of CNN processes is underscored by global data classification methodologies as exemplified by Han et al. (2018), Sun et al. (2019), and Varone et al. (2024). Despite contextual variations, these studies collectively emphasize the powerful applications of CNNs across diverse domains, suggesting a pivotal role in the realm of container logistics. The adaptability of CNN is prominently showcased in studies like Li et al. (2021) and Li et al. (2019), illustrating the versatility of CNN processes beyond specific domains. This adaptability becomes a key factor in considering CNN as a foundational technology for our proposed container classification methodology. In container logistics, the integration of advanced technologies, artificial intelligence (AI), and data science through CNNs for generic data classification aligns seamlessly with our innovative approach. This alignment is exemplified by the works of Liang et al. (2024) and former Carlo et al. (2014), providing a strong foundation for our proposed methodology. Achouch et al.'s (2023) application of machine learning, specifically LSTM neural networks, for predictive maintenance aligns directly with our objective of leveraging advanced technologies to enhance the efficiency of container logistics. This alignment emphasizes the broader spectrum of machine learning techniques beyond CNNs in our exploration. Aziz and Aznaoui's (2020) efficient routing approach, utilizing a combined AHP-TOPSIS model, strategically aligns with our innovative methodologies, particularly the combination of the Analytic Hierarchy Process (AHP) and Convolutional Neural Network (CNN). This alignment points to the synergy between traditional decision-making models and advanced neural network technologies in our proposed hybrid model. Aziz, Raghay, and Aznaoui's (2019) focus on an enhanced multipath routing protocol using Electre Tri corresponds directly to our aim of optimizing container classification through a hybrid AHP-CNN model. This alignment signifies the potential effectiveness of combining multi-criteria decision-making methods with advanced neural networks. Carlo, Vis, and Roodbergen's (2014) overview of transport operations in container terminals offers valuable insights into optimizing container logistics, providing a foundational understanding of our proposed methodology. Janiesch, Zschech, and Heinrich's (2021) comprehensive overview of machine learning (ML) and deep learning (DL) anticipates future research directions, aligning with our exploration of AI in container logistics. This alignment underscores the relevance of our study in the context of emerging trends in ML and DL. Le's (2020) Machine Learning-based model for predicting load-bearing capacity contributes practical insights relevant to our study's application in the initial research and design phase. This alignment highlights the transferability of machine learning models in diverse applications, including our proposed container classification. Lin et al.'s (2021) smart sorting screw system, leveraging deep learning and IoT technology for real-time defect detection in manufacturing, resonates with our focus on technological aspects of container logistics. While the application domain differs, the technological principles align, emphasizing the potential for similar technological advancements in our context. Kishore and Mukherjee's (2021) evaluation of deep learning networks, demonstrating superior classification performance, aligns with our exploration of network architectures and their performance. This alignment emphasizes the importance of selecting robust network architectures for effective container classification. The work by M. R. V., B. V., and N. S. (2023), focusing on optimizing wire electric discharge machining (WEDM) parameters with PSO and CNN, aligns strategically with our exploration of neural network architectures. This alignment showcases the potential of optimization techniques combined with CNNs for effective parameter tuning, a concept relevant to our proposed container classification model.

While the reviewed works predominantly focus on various applications, our study stands out by introducing a novel hybrid model for container classification. This model, combining AHP for generating criteria weights with the CNN model, marks a substantial contribution to the field of container management, offering a fresh perspective on leveraging advanced technologies for more efficient and accurate container classification.

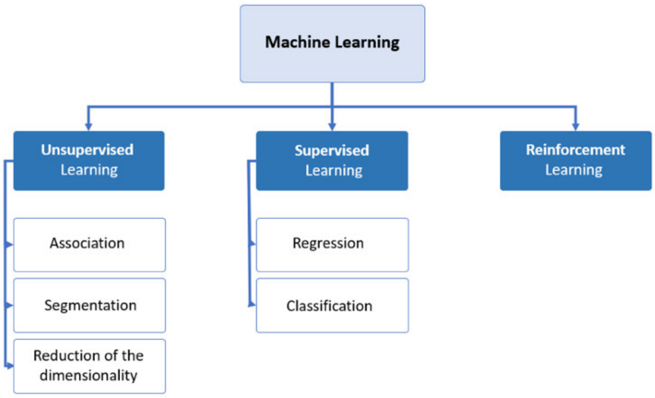
3. Transformative Methodology: Deep Learning and Hybrid Models for Container Classification.

In the dynamic landscape of container logistics and management, recent strides have been made in exploring avant-garde approaches harnessing advanced technologies. This section delves into a literature review that draws insights from various neural network applications, with a specific emphasis on Convolutional Neural Network (CNN) processes and their applicability to our innovative methodology in container management.

Our choice of a hybrid model integrating the Analytic Hierarchy Process (AHP) and Convolutional Neural Network (CNN) is rooted in the need for a comprehensive and adaptive container classification methodology. Traditional categorization methods may fall short in addressing the intricacies of modern terminals, necessitating the incorporation of cutting-edge technologies. The CNN's prowess in feature extraction and pattern recognition aligns seamlessly with the nuanced requirements of container data analysis. Meanwhile, the AHP brings a structured and systematic approach to prioritize decision criteria, providing valuable input weights for the CNN. This unique amalgamation not only enhances the precision of container classification but also optimizes space utilization, streamlines workflows, and reduces operational bottlenecks and handling costs. The adaptability of CNN is exemplified in various studies, such as the work of Li et al. (2021), where deep learning was adeptly employed to distinguish between different container classes. Similarly, Li et al. (2019) demonstrated the versatility of CNN processes in classification tasks, transcending specific domains. In the context of container logistics, the amalgamation of advanced technologies, artificial intelligence (AI), and data science holds significant promise for overcoming industry challenges. The application of CNN for generic data classification, as showcased in Han et al. (2018) and Carlo et al. (2014), where instances are converted into suitable image format matrices, aligns seamlessly with the innovative approach we propose for container classification.

While existing works predominantly focus on varied applications, our study introduces a groundbreaking hybrid model for container classification. This model harmoniously integrates the Analytic Hierarchy Process (AHP) for generating criteria weights with the CNN model. This unique amalgamation provides a robust tool for optimizing container logistics, constituting a substantial contribution to the field of container management. It offers a fresh perspective on leveraging advanced technologies to achieve a more efficient and accurate container classification. Furthermore, we categorize container classification methods into three distinct learning categories: supervised, unsupervised, and reinforcement learning. Supervised learning, with its emphasis on precise categorization based on labeled data, aligns seamlessly with our criteria of Weight, Destination, Special Requirements, and Financial Considerations. In contrast, unsupervised learning explores autonomous mechanisms, unveiling patterns and relationships within container data without explicit supervision. This autonomy proves beneficial in enhancing resource allocation and decision-making in the realm of container management. The introduction of reinforcement learning, with its focus on dynamic decision-making, underscores the adaptability of the system to evolving conditions, learning optimal strategies for container handling over time. A comparative study presented in Table 1 between these techniques provides valuable insights into their respective strengths and applications (Lin et al., 2021).

Figure 1: Machine learning classi?cations.



Source: Nacchia et al. (2021).

Table 1: Comparison of supervised learning via unsupervised learning.

Approach	Method	Strengths	Weaknesses
Supervised-based classifier	Classification network: CNN	Fast training and inference	1. Requires numerous abnormal and normal images for training 2. Hard to collect abnormal images in practical situations 3. Tedious manual annotation work
	Semantic network: U-Net, FCN	Fast training and inference; high performance of defect localization	
	Object detection network: YOLO, Faster R-CNN	Identify the defect with the bounding boxes	
Unsupervised-based classifier	Convolutional Autoencoder; Adversarial Autoencoder	Model training without annotation; requires only positive datasets for model training	1. Imprecise defect localization with poor reconstruction 2. A large amount of clean normal data are needed to obtain useful results

Source: Lin et al. (2021).

Artificial Neural Networks (ANNs) stand as essential for the efficient classification of containers based on Weight, Destination, Special Requirements, and Financial Considerations. Operating on a set of inputs, ANNs produce a singular output through an activation function, depicted in Figure 2. Whether linear or non-linear, this output activates neurons based on a defined limit (Haykin, S., 1999). The architecture of the ANN model is tripartite: input layers representing variables, hidden layers functioning as a functional layer, and output layers illustrating network outcomes. Computational neurons within these layers establish connections and compute the weighting parameters of the model. While ANNs can encompass multiple hidden layers, for simplicity, we focus on a single hidden-layer neural network. The ANN model employs a generalized non-linear function, expressed as follows (Le, 2020):

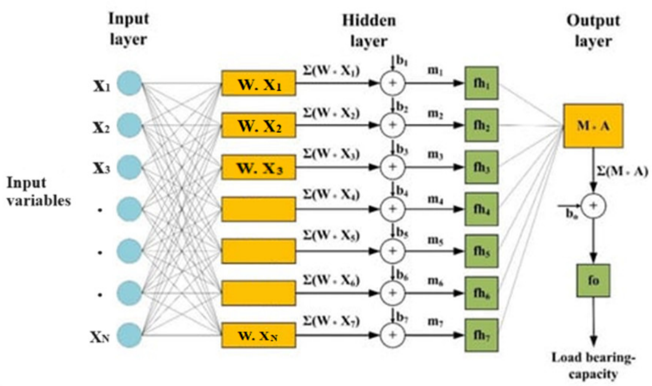
$$Y = fo.(M.(fh_i(b_i + w_i.x_i) + b_0) \qquad (1)$$

Where:

1. x_i are the input variables and Y is the predicted variable.
2. w_i , fh_i, b are the weights, the activation function, and the bias vector of the hidden layer, respectively
3. M, fo, b_o are the weight matrix, activation function, and bias vector of the output layer, respectively.

Inspired by the learning process of the human brain, neural networks form a multi-layered system, illustrated in Figure 3 (Svennevik et al. (2021))

Figure 2: Illustration of the ANN model involving one hidden.



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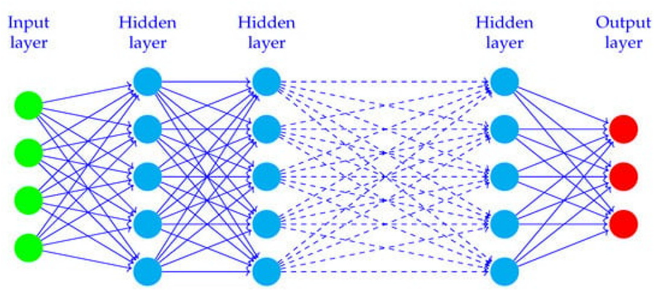
Source: Asteris et al. (2022).

Figure 3: The ANN layers.



Source: Svennevik et al. (2021).

3.1. Convolutional Neural Network (CNN) Architecture: Unraveling the Layers of Precision.

In the intricate architecture of a Convolutional Neural Network (CNN), comprising three pivotal layers – Convolution, Pooling, and Fully Connected – each layer assumes a critical role in the nuanced classification process.

Convolution Layer: The inaugural layer, the Convolution Layer, serves as the vanguard in feature extraction from container data. Operating as a mathematical filter on the image matrix, it discerns intricate patterns and features within the data.

Pooling Layer: Positioned as an intermediary stratum, the Pooling Layer undertakes the vital task of diminishing the complexity of image parameters. This proves especially advantageous when grappling with extensive container data. Various spatial pooling techniques, including Max pooling, Average pooling, and Sum pooling, contribute to effective dimensionality reduction.

Fully Connected Layer (FC): Concluding the trio, the Fully Connected Layer transforms the input matrix into a vector and assembles the model through feature amalgamation. Its primary mission is to categorize outputs deploying activation functions such as Sigmoid or SoftMax. The precision of the CNN's classification undergoes validation through the following equation:

$$A_c^i = \frac{C_{acc}^i + C_{rej}^i}{C_{acc}^i + C_{rej}^i + F_A^i + F_R^i} \tag{2}$$

Where :

- C_{acc}^i: Containers correctly classified in category i as matching the specified criteria (accepted for classification).
- C_{rej}^i: Containers correctly classified in category i as not matching the specified criteria (rejected from classification).
- F_A^i: Containers incorrectly classified in category i as matching the specified criteria (falsely accepted).
- F_R^i: Containers incorrectly classified in category i as not matching the specified criteria (falsely rejected).

For imbalanced datasets, the F-measure (F_m) is calculated:

$$F_m = \frac{2\,.P_r.\;R_c}{P_r + R_c} \tag{3}$$

Where :

- P_r: Precision of the classifier.
- R_c: Recall, assessing the classifier's completeness.

Evaluation of containers categorized as not meeting specific criteria is determined by:

$$P_r = \frac{C_{acc}^i}{C_{rej}^i + F_A^i} \tag{4}$$

Additionally, the completeness of the classifier can be further assessed through Recall R_c:

$$R_c = \frac{C_{acc}^i}{C_{acc}^i + F_R^i} \tag{5}$$

For container classification, the evaluation of containers categorized as not meeting specific criteria is determined by the formula:

$$P_r = \frac{C_{rej}^i}{C_{rej}^i + F_A^i} \tag{6}$$

3.2. The Analytic Hierarchy Process (AHP): Navigating Multi-Criteria Decision Making.

The Analytic Hierarchy Process (AHP) stands as a venerable method in the realm of multi-criteria decision-making, garnering extensive use for prioritizing decision alternatives, as underscored by Aziz et al. (2019) and Achki et al. (2017). Renowned for its robustness, AHP emerges as a valuable instrument for determining the weights of criteria, offering relevance in the calculation of importance values for criteria weights within our distinct context.

The AHP process unfolds through a systematic series of key steps:

Decomposition of Decision Problem:

Identify and dissect the decision problem into its fundamental criteria, establishing a comprehensive framework for evaluation.

Assigning Importance Values:

Attribute distinct importance values to each criterion, typically utilizing the Saaty scale (Table 2). This provides a quantifiable measure, elucidating the relative significance of each criterion.

Determining Relative Importance:

Calculate the relative importance of factors by computing eigenvectors corresponding to maximal eigenvalues. This step enhances the nuanced understanding of each criterion's influence on the decision-making process.

Consistency Verification:

Ensure the study's consistency through the evaluation of two critical factors: the Consistency Index (CI) and the Consistency Ratio (CR), following the framework proposed by Aziz and Aznaoui (2020).

$$CI = \frac{\mu_{max}}{n-1} \tag{7}$$

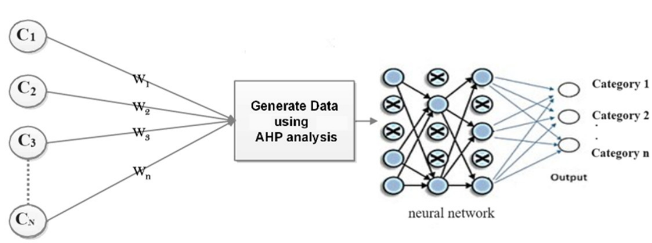
$$CR = \frac{CI}{RCI} \tag{8}$$

Where:

- μ_{max} is the maximal eigenvalue.
- n is the number of criteria.
- RI is the Random Index for a given n.

The Random Consistency Index (RCI), as introduced by Aziz et al. (2018), represents random values of CI based on the number of criteria \(n\), with specified values presented in Table 3. This index serves as a pivotal instrument in evaluating the consistency of the decision-making process within the AHP framework.

Figure 4: The neural network process.



Source: Author.

Table 2: Criteria importance meaning.

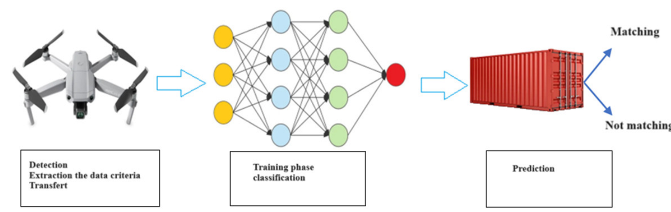
Relative importance	Meaning
1	Equal
3	Weak
5	Strong
7	Demonstrated over the others
9	Absolute

Source: Author.

3.3. Integrating AHP and CNN: A Holistic Container Classification Approach.

The articulated steps collectively form the bedrock for applying the Analytic Hierarchy Process (AHP) in determining the crucial values of criteria weights within our decision-making framework. The derived weights, calculated through the AHP methodology, hold pivotal significance, underscoring the importance of each criterion in our decision framework. Notably, these calculated weights serve as fundamental inputs for the Convolutional Neural Network (CNN).

Figure 5: The proposed hybrid-model.



Source: Author.

Figure 5 visually encapsulates our conceptual model, delineating a structured approach manifesting in two primary phases. In the initial phase, the emphasis lies on the meticulous generation of weights through the AHP process. These weights assume a critical role in empowering the CNN to conduct the subsequent classification of containers with precision. The symbiotic relationship between AHP and CNN in these two phases stands as the nucleus of our proposed methodology, ensuring a holistic, robust, and effective approach to container classification.

Table 3: RCI Values.

Criteria Number	(RCI)
1	0
2	0
3	0.5799
4	0.8921
5	1.1159
6	1.2358
7	1.3322
8	1.3952
9	1.4537
10	1.4882
11	1.5117
12	1.5356
13	1.5571
14	1.5714
15	1.5861

Source: Author.

4. Container Classification: Simulation and Discussion.

In this simulated scenario, we replicate the criteria essential to container classification, encompassing Weight, Destination, Special Requirements, and Financial Considerations. Employing the multi-criteria Analytic Hierarchy Process (AHP), we determine the weight of each criterion to categorize a set of containers into two classes: those meeting and those not meeting the specified criteria.

The simulation is conducted on a meticulously curated dataset that mirrors real-world container attributes and scenarios. The dataset comprises a diverse range of containers, considering variations in weight capacities, destinations, special requirements (including those for hazardous materials or refrigeration), and financial considerations (encompassing ownership status and lease terms). This diversity ensures that the model is robust and adaptable to the complexities observed in actual container terminals.

In the application of AHP to our container classification methodology, we begin by establishing a decision matrix that outlines the importance of different criteria. As an illustrative example, the criteria include Weight (C_1), Destination (C_2), Special Requirements (C_3), Financial Considerations (C_4), Container Type (C_5), and Security Level (C_6). The decision matrix is as follows:

Table 4: Matrix of criteria importance.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6
C_1	1.00	0.33	0.20	0.11	0.14	3.00
C_2	3.00	1.00	0.33	0.14	0.33	3.00
C_3	5.00	3.00	1.00	0.20	0.20	3.00
C_4	9.00	7.00	5.00	1.00	3.00	7.00
C_5	7.00	3.00	5.00	0.33	1.00	9.00
C_6	0.33	0.33	0.33	0.33	0.11	1.00

Source: Author.

The matrix is normalized as shown in Table 5.

Table 5: Normalized matrix.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6
C_1	0.039	0.023	0.017	0.052	0.030	0.115
C_2	0.118	0.068	0.028	0.067	0.070	0.115
C_3	0.197	0.205	0.084	0.094	0.042	0.115
C_4	0.355	0.477	0.421	0.472	0.627	0.269
C_5	0.276	0.205	0.421	0.157	0.209	0.346
C_6	0.013	0.023	0.028	0.157	0.023	0.038

Source: Author.

Weights for the criteria are calculated as follows: C_1 = 0.046, C_2 = 0.078, and C_3 = 0.123, **C_4 =0.437**, C_5 =0.269, C_6 =0.047.

The Consistency Ratio (CR) value ensures the robustness of this process, and the weighted matrix is presented in Table 6.

Table 6: Weighted matrix.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6
C_1	0.001797	0.00106	0.000783	0.002396	0.001382	0.005299
C_2	0.009186	0.005294	0.00218	0.005216	0.005449	0.008952
C_3	0.024221	0.025205	0.010328	0.011557	0.005164	0.014139
C_4	0.155102	0.208404	0.183938	0.20622	0.27394	0.117528
C_5	0.074266	0.055161	0.113283	0.042246	0.056238	0.093102
C_6	0.000613	0.001084	0.00132	0.007401	0.001084	0.001791

Source: Author.

Utilizing AHP-generated weights, we compute inputs for the neural network by transforming the data into an image format. The correlation matrix (M), correlation vector (L), and reordering matrix (O) are calculated using provided formulas (Equations 9 and 10).

$\mu_{max} = 7.056, CI = 0.211, CR = 0.169.$

$$M_{j,k} = \frac{\sum_{c=1}^{N} (x_{c,j} - f_j)(x_{c,k} - f_k)}{\sqrt{\sum_{c=1}^{N} (x_{c,j} - f_j)^2}\sqrt{\sum_{c=1}^{N} (x_{c,j} - f_j)^2}} \quad (9)$$

where f_j is the means of the Category j and f_k represents the means of the category k.

$$L_{1,j} = \frac{\sum_{c=1}^{N} (x_{c,j} - f_j)(y_c - \overline{y})}{\sqrt{\sum_{c=1}^{N} (x_{c,j} - f_j)^2}\sqrt{\sum_{c=1}^{N} (y_c - \overline{y})^2}} \quad (10)$$

where $\overline{y}$ represents the mean of the label.

The Convolutional Neural Network (CNN) is employed to classify the group of containers. Figure 6 visually represents the results of the classification, demonstrating the diagnostic ability of the hybrid AHP-CNN model.

A sensitivity analysis is conducted, evaluating accuracy across three distinct scenarios, summarized in Table 7, with corresponding accuracy values in Table 8.

Table 7: The weights of cases.

scenarios	C_1	C_2	C_3	C_4	C_5	C_6
scenario 1	0.046	0.078	0.123	0.437	0.269	0.047
scenario 2	0.133	0.154	0.126	0.237	0.196	0.154
scenario 3	0.124	0.084	0.199	0.415	0.147	0.030

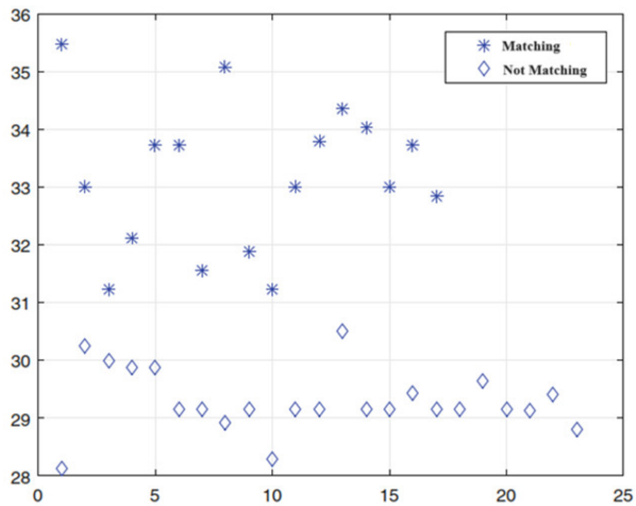
Source: Author.

Table 8: The accuracy of cases.

scenarios	Accuracy
scenario 1	89.00%
scenario 2	88.84%
scenario 3	91.05%

Source: Author.

Figure 6: Container Classification.



Source: Author.

This comprehensive simulation and discussion showcase the effectiveness and adaptability of the hybrid AHP-CNN model in the dynamic context of container classification.

5. Limitations.

While our research has unveiled a promising hybrid model integrating AHP and CNN for container classification, it is crucial to acknowledge the inherent limitations of our study. The dataset employed for simulation, although carefully selected, may not capture the full spectrum of real-world container logistics scenarios. The generalizability of our findings could be influenced by the specific characteristics of the dataset, potentially limiting the applicability of our proposed model to diverse operational contexts. Additionally, the simulation environment may not encompass all the complexities and uncertainties inherent in live container terminal operations. As with any computational model, our approach is contingent upon the accuracy and representativeness of the input data. Moreover, the proposed model's performance could be sensitive to variations in dataset size and composition. These limitations warrant cautious interpretation of our results and signal avenues for future research aimed at refining and expanding the scope of the hybrid AHP-CNN model in the dynamic landscape of container management.

Conclusions.

Container management, a pivotal facet of global trade, grapples with challenges demanding innovative solutions to enhance efficiency and streamline operations. In response to these challenges, this paper presents a pioneering approach that leverages artificial intelligence (AI) and big data for container classification. Building on the success of AI applications in diverse domains, our vision extends to applying AI for identifying, monitoring, and predicting container movements. The proposed model seamlessly integrates the Analytic Hierarchy Process (AHP) for determining criteria weights and the Convolutional Neural Network (CNN) for precise container classification. The AHP, a multi-criteria method, plays a crucial role in ranking the importance of criteria such as weight, destination, special requirements, and financial considerations. The resulting weights serve as inputs for the CNN classifier. This hybrid model is strategically designed to optimize container classification, facilitating efficient prioritization, and minimizing reshuffling movements within container yards. In an illustrative example, the AHP tool was employed to generate criteria weights, and the proposed hybrid AHP-CNN model demonstrated effectiveness in container classification. This study underscores the significance of the integrated model in delivering swift and accurate container classification, showcasing its potential to revolutionize container management practices.

As a future step, the proposed model can undergo sensitivity analysis and further evaluation to validate its accuracy across various scenarios. The fusion of AI and big data in container logistics holds promising prospects for addressing industry challenges, offering opportunities for heightened efficiency and operational optimization. This approach marks a transformative stride toward the future of container management, aligning with the evolving landscape of technology-driven solutions.

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