PACKAGING PLANNING PREDICTION USING MULTI-CLASS AND MULTI-OUTPUT ALGORITHMS

ÇOKLU SINIF VE ÇOKLU SONUÇ ALGORİTMALARI İLE PAKETLEME PLANLAMA TAHMİNİ

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Submitted to
Graduate School of Science and Engineering of Hacettepe University
as a Partial Fulfillment to the Requirements
for the Award of the Degree of Master of Science
in Computer Engineering

January 2024

ABSTRACT

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January 2024, 77 pages

In the rapidly evolving industrial landscape, Artificial Intelligence (AI) has emerged as a transformative force in various sectors, including manufacturing and supply chain management. Meanwhile, packaging planning is another area that is still open to development for AI. Effective packaging planning is a complicated task to be handled carefully throughout the entire planning process. To solve this problem, we propose a relation-based heterogeneous chain-based multi-output classification model for effective packaging planning in predicting the dimensions and types of packages for each shipment. While conventional regressor chain models typically employ only a single classifier within each chain, our model allows for the utilization of distinct classifiers within each chain. Our model is analyzed on a real-world dataset by employing different multi-output classification algorithms including Random Forest (RF), Decision Trees (DT), and K-Nearest Neighbors (KNN). Experimental results demonstrate that our homogeneous chain-based multi-output classification model, based solely on a DT, and our relation-based heterogeneous chain-based multi-output classification model outperform others, achieving the highest accuracy with an overall accuracy value of 0.98, as compared to traditional multi-output classification and chain regression models. Additionally, our heterogeneous chain-based multi-output classification model, utilizing different classifiers, has the second-highest overall accuracy result among all models and surpasses the overall accuracy achieved by traditional chain-based models.

Keywords: multi-output classification, chain of classifiers, packaging planning, artificial intelligence

ÖZET

ÇOKLU SINIF VE ÇOKLU SONUÇ ALGORİTMALARI İLE PAKETLEME PLANLAMA TAHMİNİ

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Ocak 2024, 77 sayfa

Hızla gelişen endüstriyel manzara içerisinde, yapay zeka, imalat ve tedarik zinciri yönetimi dahil olmak üzere çeşitli sektörlerde dönüştürücü bir güç olarak ortaya çıkmıştır. Aynı zamanda, paketleme planlama, yapay zeka için hala geliştirilmeye açık bir alan olan bir başka alandır. Etkili paketleme planlama, tüm planlama süreci boyunca dikkatlice ele alınması gereken karmaşık bir görevdir. Bu sorunu çözmek için, her sevkiyat için paketlerin boyutlarını ve tiplerini tahmin etmek için etkili bir paketleme planlama için geliştirilmiş bir ilişki tabanlı heterojen zincir tabanlı çoklu çıkışlı sınıflandırma modeli öneriyoruz. Geleneksel regresyon zinciri modelleri genellikle her zincir içinde yalnızca tek bir sınıflandırıcı kullanırken, modelimiz her zincir içinde farklı sınıflandırıcıların kullanılmasına izin verir. Modelimiz, gerçek bir veri kümesi üzerinde farklı çoklu çıkışlı sınıflandırma algoritmalarını, Random Forest (RF), Decision Tree (DT) ve K-Nearest Neighbors (KNN) dahil kullanarak analiz edilir. Deneysel sonuçlar, DT temelli homojen zincir tabanlı çoklu çıkışlı sınıflandırma modelimizin ve ilişki tabanlı heterojen zincir tabanlı çoklu çıkışlı sınıflandırma modelimizin, geleneksel çoklu çıkışlı sınıflandırma ve zincir regresyon modellerine göre 0.98 genel doğruluk değeri ile en iyi performansı elde ederek daha iyi bir sonuç verdiğini göstermektedir. Ayrıca, farklı sınıflandırıcılar kullanan

heterojen zincir tabanlı çok çıkışlı sınıflandırma modelimiz, tüm modellerde ikinci en iyi genel doğruluk sonucuna sahiptir ve geleneksel zincir tabanlı modellere göre daha yüksek bir genel doğruluk sonucuna sahiptir.

Keywords: çoklu çıkış sınıflandırma, sınıflandırıcı zincirler, paketleme planlama, yapay zeka

ACKNOWLEDGEMENTS

First and foremost, I am immensely thankful to my thesis advisor, Professor Suat Özdemir, for their unwavering support, invaluable guidance, and relentless encouragement throughout this research journey. Their expertise and insights have been instrumental in shaping this work. I want to express my sincere gratitude to Asst. Prof. Feyza Yıldırım Okay, for their unwavering support at every stage of my research. Their invaluable guidance and expertise significantly contributed to the success of my work. I appreciate Asst. Prof. Feyza Yıldırım Okay's dedication and insightful feedback, enriching my academic journey. Their mentorship has been an inspiring and essential part of this thesis, and I am genuinely thankful for the privilege of working with them.

I extend my heartfelt gratitude to my husband, Nurettin Yıldız, for being my constant source of support and encouragement throughout this academic journey. His unwavering belief in my abilities and his patience during challenging times have been my greatest motivators. Thank you for standing by me and being the driving force behind my success.

Lastly, I would like to express my sincere appreciation to my colleagues who generously shared their insights and expertise during the development of my thesis. Special thanks to Volkan Haskılıç, Ph.D., Miray Cansev Koyuncu, Emrah Öztürk, İbrahim Dil and Buğra Kaan Türkmenoğlu for their invaluable contributions and thoughtful discussions. Their guidance and constructive feedback played a pivotal role in shaping the direction of my research. I am grateful for the collaborative spirit and willingness to share knowledge that exists within our team. Your support has been instrumental in the progress of my work, and I am truly fortunate to have such knowledgeable and supportive colleagues. Thank you for being an essential part of my academic journey.

In closing, I extend my thanks to everyone who, directly or indirectly, contributed to the successful completion of this thesis. Your support has been invaluable, and I am deeply appreciative of your contributions.

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ABBREVIATIONS

AI	:	**A**rtificial **I**ntelligence
ANNs	:	**A**rtificial **N**eural **N**etworks
BCC	:	**B**ayesian **C**hain **C**lassifier
CC	:	**C**lassifier **C**hains
CT	:	**C**lassifier **T**rellis
DT	:	**D**ecision **T**ree
ECC	:	**E**nsemble **C**lassifier **C**hains
ECCRU	:	**E**nsemble **C**lassifier **C**hains **R**andom **U**ndersampling
ELM	:	**E**extreme **L**earning **M**achine
FB-AMC	:	**F**eature **B**ased **A**utomatic **M**odulation **C**lassification
KNN	:	**K**- **N**earest **N**eighboor
LS-SVM	:	**L**east **S**quare **S**upport **V**ector **M**achine
MLC	:	**M**ulti **L**abel **C**lassification
MMLC	:	**M**emory-based **M**ulti **L**abel **C**lassification
PS-SVM	:	**P**roximal **S**upport **S**upport **V**ector **M**achine
ReID	:	**Re** **I**dentification
RF	:	**R**andom **F**orest
SCM	:	**S**upply **C**hain **M**anagement
SPSS	:	**S**tatistical **P**ackage for the **S**ocial **S**ciences
SVM	:	**S**upport **V**ector **M**achine

1. INTRODUCTION

Firms engage in a shipment process where they initiate shipment requests to dispatch their products to clients or subcontractors. During the creation of these requests, detailed information is provided concerning the shipment's destination, recipient, and the specific contents, including its constituent parts. An integral stage within this procedural framework is the meticulous planning of packaging, a multifaceted process encompassing two pivotal dimensions: packing and packaging [1].

The first dimension, packing, centers on safeguarding the individual components through the utilization of materials such as cardboard or wooden boxes. Within a singular shipment, the deployment of one or more boxes, varying in dimensions and types, is a common practice. The primary objective is the protection of the enclosed parts against potential damage during transit. This aspect underscores the utilitarian and protective attributes of the packaging process. Conversely, the second dimension, packaging, assumes a more aesthetic and representative role in the overall process. Its primary objectives extend beyond mere protection, with an emphasis on visually appealing and attractive presentation. This often involves the use of larger carton boxes or robust wooden chest containers [2]. The packaging aspect is instrumental in creating a positive impression on clients and plays a crucial role in brand representation.

Together, the dynamic interplay of packing and packaging constitutes a comprehensive strategy for efficient and effective shipment handling. By understanding the nuanced requirements of each aspect, companies can optimize their logistics processes, enhance product presentation, and ultimately contribute to a positive and impactful customer experience. This intricate balance between functionality and aesthetics underscores the significance of packaging planning in the broader context of the shipment process.

Currently, packaging planning experts handle all processes of packaging; however, it is not a simple task. They need to coordinate with project managers and workers responsible for measuring the parts or products to be delivered. This step is crucial because the dimensions of these parts are not available in any system. Therefore, for each shipment, this process needs to be repeated. After measuring the parts, experts consult with project managers to understand the client's packaging expectations, as each client has specific standards. After these discussions, packaging planning experts create packing requirements and packaging specifications. Finally, workers place the parts in the designated packs and package them accordingly. In seeking to revolutionize the current manual processes involved in packaging planning, the overarching objective of this study is to introduce automation facilitated by Artificial Intelligence (AI). The intent is to streamline and enhance the packaging planning process, ultimately ensuring the efficient delivery of a meticulously crafted final product to end users. The central premise is to replace or augment the manual decision-making of experts with a sophisticated AI-driven system.

Within this automated framework, experts retain a crucial role by having the autonomy to interact with the AI-generated packaging suggestions. They are empowered to make decisions based on their expertise, with the options to either accept the proposed packaging, reject it entirely, or introduce modifications by adjusting the characteristics of the packages or internal components. This interactive and collaborative aspect ensures that human insights are integrated into the automated process, fostering a symbiotic relationship between human expertise and AI capabilities.

Furthermore, any modifications made by the experts are seamlessly incorporated back into the system as additional inputs. This iterative feedback loop not only refines the AI model but also serves as a valuable learning mechanism, enabling the system to adapt and improve its predictions over time. The integration of expert adjustments as model inputs enhances the precision of the system and provides insightful information to experts during subsequent, similar operations.

To improve the packaging planning process, we propose a relation-based heterogeneous chain-based multi-output classification model. Our proposed model is developed in three steps: homogeneous model, heterogeneous model, and finally, relation-based model. All three models are chain-based multi-output classification models. However, their differences arise from the base estimator and relation parameter for the chain structure. Although this process can be theoretically framed as an optimization problem, our primary focus is not on optimizing the process itself. Instead, our emphasis lies in leveraging historical data for predictive analysis, thereby reducing time losses in the packaging planning process. This strategic use of historical data enhances decision-making efficiency, allowing for faster and more informed packaging decisions.

This thesis explores how chain classification can improve the accuracy and efficiency of packaging planning by considering the sequential nature of decision-making in this domain. Each output does not have to show maximum performance with the same algorithm. In our heterogeneous model, we have the flexibility to use different classification algorithms for each output, and each output also becomes an input for the next classifier. We investigate how the predictions of one classifier can influence the performance of subsequent classifiers, ultimately leading to more informed and effective packaging solutions. For instance, we use a DT for predicting package numbers. The predicted package number then becomes the input for the second classifier RF tree. This process continues, with the composition of our initial inputs and the predicted values from each step becoming the new input for the next classifier. Ultimately, this chain of classifiers predicts the package length, package width, and so on.

Additionally, the evaluation extended to assess the utility of each output in a chain classification structure of a multi-output classifier influencing all subsequent outputs. For instance, when Output 1 influences Outputs 3 and 5, it might generate a positive impact, whereas neglecting Inputs for Outputs 2 and 4 could potentially result in higher accuracy values for these two outputs. Therefore, our model was intentionally designed to be relationship-based, allowing for a more versatile usage. We further evaluated its performance using our dataset to analyze the outcomes in this context.

Comparing with the previous example, initially, we predict the package type with our main inputs. Subsequently, incorporating the predicted package type, we predict the package number. Then, our main inputs include both the predicted package type and package number, and when predicting the package length, we use these two predictions as inputs.

When predicting the package width, the predicted package length becomes part of our main inputs. However, in our relation-based heterogeneous chain-based multi-output classification model, we decided to exclude the package number from this relationship. In this case, when predicting the package number, the predicted package type was used as an input, but when predicting the package length and width, the predicted package number was not included in the main inputs. In our dataset, we could achieve this for the package number, but in different datasets, the relationships in this model could be further deepened. For example, Output 1 could influence Outputs 2, 3, 4, 5, 6; Output 2 might only influence Output 6; Output 3 could influence Outputs 4, 5, 6; and Outputs 4, 5, 6 might not influence any other output.

In summary, this thesis represents a paradigm shift by introducing automation through AI in the packaging planning domain. By combining the strengths of human expertise and AI capabilities, our approach aims to enhance the effectiveness, accuracy, and responsiveness of the packaging planning process, ultimately contributing to an improved overall user experience.

1.1. Scope Of The Thesis

This thesis mainly focuses on improving chain-based multi-output classification. Traditional methods for multi-output classification mostly work in parallel. They use the same input for different outputs and predict them simultaneously. One step further from this method is chain-based multi-output classification. When the example research is investigated, two accepted methods, common chain regression and classifier chain, are commonly used. When we focused on the classifier chain because our problem is also a classification problem, we noticed that it is used for binary classification. So, we tried to use chain regression to solve our classification problem, and it works with classification algorithms. However, there is also another problem: this algorithm uses one classification algorithm to construct the chain model. Our approach aims to include heterogeneous classification algorithms in a chain and relation-based chains for comparison against homogeneous ones. In the literature review, other research related to our approach, such as classifier trellis and hybrid classifier chains, has also been explored.

1.2. Contributions

This thesis contributes to the literature by proposing a relation-based heterogeneous chain-based multi-output classification model for effective packaging planning by allowing the utilization of different classifiers within each chain. Unlike most previous works, we utilize a heterogeneous chain-based multi-output classification model and incorporate the relation parameter. The model is then evaluated as a relation-based heterogeneous chain-based multi-output classification model. Up to our knowledge, this is the first study that applies this approach to the packaging planning problem. Our simulation results show that chain-based models improve accuracy compared to traditional multi-output classification.

1.3. Organization

The structure of the thesis is outlined as follows:

- Chapter 1 introduces our motivation, contributions and the scope of the thesis.
- Chapter 2 introduces preliminaries.
- Chapter 3 examines the literature that focuses on packaging planning .
- Chapter 4 provides information about the dataset and explains the proposal model.
- Chapter 5 discusses the experimental results.
- Chapter 6 summarizes the paper by essential concluding remarks and presents future research directions.

2. BACKGROUND OVERVIEW

Packaging planning is a fundamental aspect of modern supply chain management, ensuring the safe and efficient transportation of goods from manufacturers to consumers. In addition, machine learning and AI have gained prominence across various industries, including supply chain management. AI-driven solutions offer the potential to optimize logistics, improve decision-making, and enhance overall efficiency. Within this landscape, one particular area of interest is the application of chain classification in the realm of packaging planning. The combination of chain classification and packaging planning represents a new approach for automating the packaging process.

In this context, each packaging property, such as the number of package, dimensions, and types, becomes an output variable. The prediction of one property relies not only on input data but also on the predictions of previous properties, reflecting the inherent dependencies in the packaging planning process.

The comparative analysis of outcomes emanating from classification models, specifically those pertaining to multi-output classification and chain-based methodologies, contributes to the scholarly discourse on machine learning paradigms. Furthermore, the investigation entails the deployment of foundational base estimators, including the RF, DT, and KNN models. The RF, as an ensemble method, amalgamates multiple DTs, fostering predictive robustness. In contrast, the DT, renowned for its interpretative prowess, elucidates decision pathways with clarity. Concurrently, the KNN model, characterized by its simplicity, navigates classification via proximity metrics. This analytical framework affords an exploration into the ramifications of diverse classification models anchored by distinct base estimators, thereby enriching our understanding of the methodological intricacies inherent in predictive modeling.

2.1. Random Forest Classification

RF Classification is an ensemble learning algorithm that constructs multiple DTs during training and aggregates their predictions to improve accuracy and robustness [3]. The

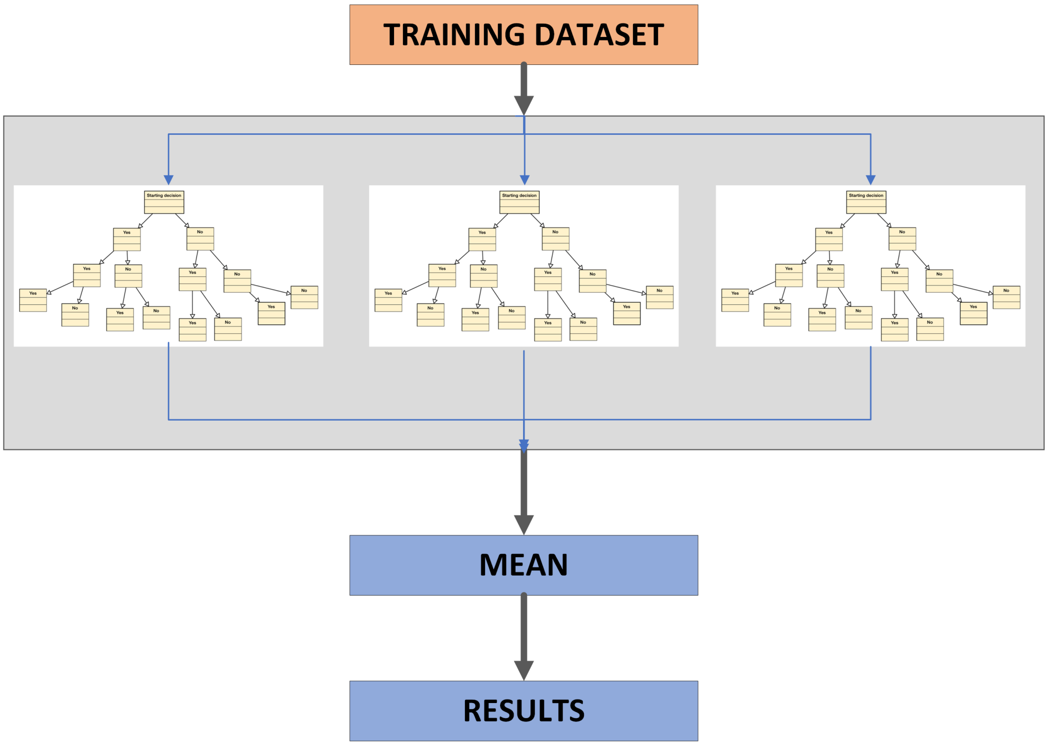

Figure 2.1 RF Classifier

algorithm introduces randomness through two main mechanisms: random subsampling (bagging) of the training data, where each tree is trained on a distinct subset with replacement, and random feature selection at each split to prevent overfitting. The final prediction for a given input is determined by a majority vote among the individual trees. Mathematically, let X represent the input features, Y the output class, and $h_i(X)$ the DT models. The RF prediction is given by $\hat{Y}(X) = \text{mode}\{h_i(X)\}$, where the mode represents the most frequently predicted class. The algorithm is trained by optimizing parameters of the individual trees, such as the number of trees N, tree depth, and the number of features considered at each split. RF excels in handling complex relationships in data, providing high accuracy and robustness across various applications. The RF classifier is visualized in the Figure 2.1.

2.2. Decision Tree Classification

DT Classification is a supervised machine learning algorithm that recursively partitions the dataset into subsets based on feature values to make sequential decisions and assign class labels to inputs [4]. The algorithm constructs a tree-like structure where each internal node

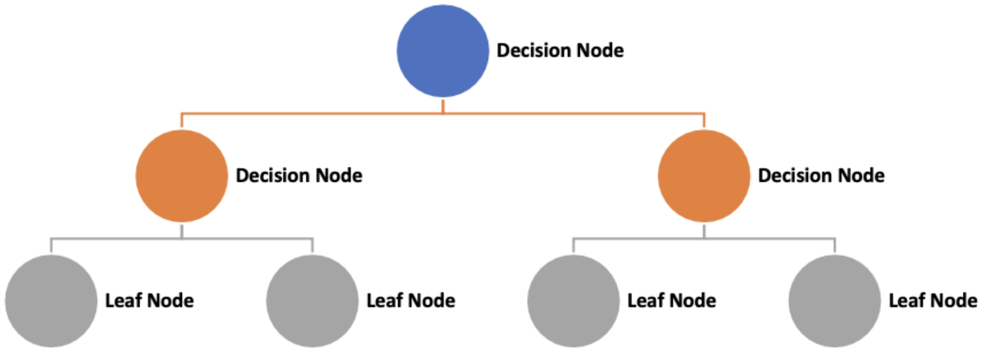

Figure 2.2 DT Classifier

represents a decision based on a specific feature, each branch corresponds to a possible outcome, and each leaf node indicates the predicted class. Decision-making at each node is guided by criteria such as Gini impurity or entropy, measuring the homogeneity of classes in a subset. The process continues until a stopping criterion, like maximum depth or minimum samples in a leaf, is met. Mathematically, the DT prediction for an input X is given by $\hat{Y}(X) = \text{Traverse}(X, \text{Tree})$, where Traverse is the function navigating the tree based on X's feature values. The algorithm is trained by determining optimal splits during the tree-building process. DT Classification is renowned for its interpretability, though it may be prone to overfitting on noisy data. The DT classifier is shown in the Figure 2.2.

2.3. K-Nearest Neighbor Classification

KNN classification is a supervised machine learning algorithm that classifies an input by considering the majority class among its KNN in the feature space. KNN classifier is depicted in the Figure 2.3.

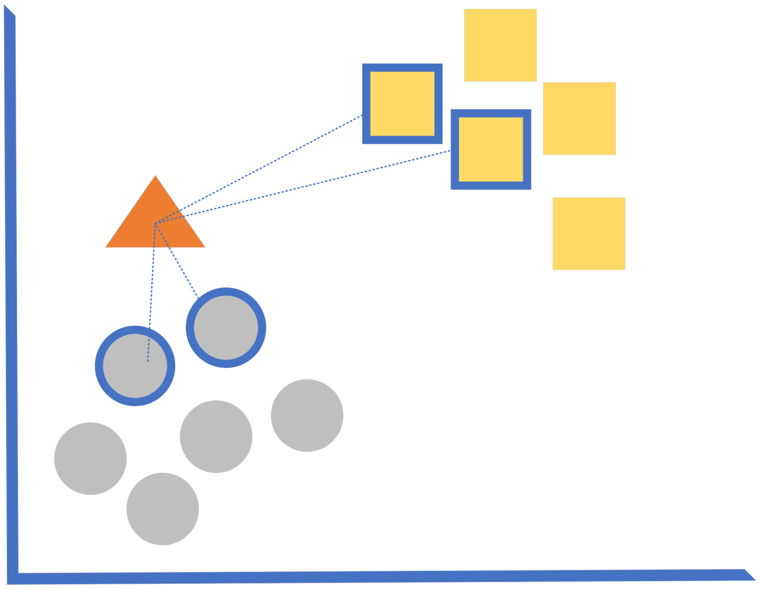

Figure 2.3 KNN Classifier

The algorithm operates on the assumption that similar instances in the feature space tend to belong to the same class. To make predictions, it calculates the distance between the input data point and all other points in the training set, typically using metrics like Euclidean distance. It then selects the K training instances with the smallest distances and assigns the class label that is most common among them. KNN is a non-parametric algorithm as it doesn't make assumptions about the underlying data distribution. The choice of K is crucial, influencing the algorithm's sensitivity to noise and model complexity. Mathematically, the KNN prediction for an input X is given by $\hat{Y}(X) = \text{MajorityVote}(\text{KNN}(X))$. The algorithm's simplicity makes it easy to understand, but it may be sensitive to outliers and high-dimensional spaces.

2.4. Multi-Output Classification

Multi-output classification is an advanced machine learning paradigm that extends traditional classification methods to scenarios where multiple output variables are predicted, and each output variable can have multiple classes or labels [5]. Classification algorithms mainly have four types, demonstrated in Figure 2.4.

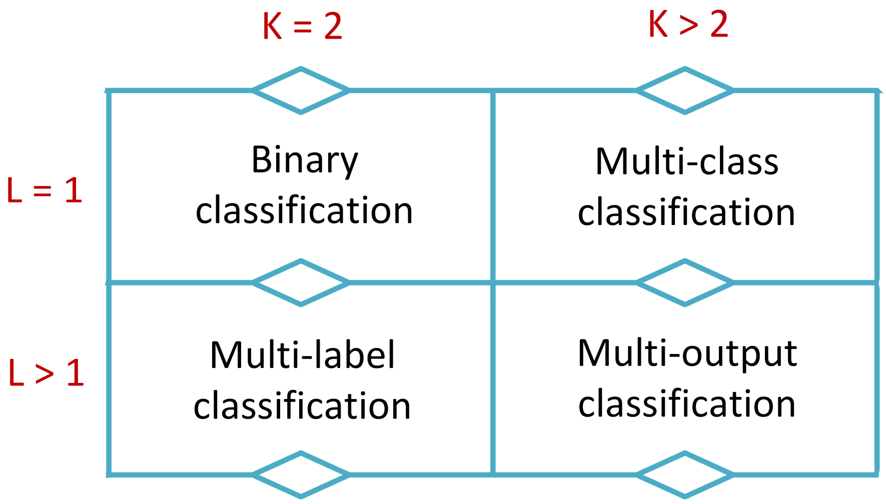

Figure 2.4 Classification Types (L is the number of labels and K is the number of values that can be assigned to each label variable)

Binary classification, with its straightforward two-class prediction, is often applied in scenarios where decisions need to be made between two exclusive outcomes. In contrast, multi-class classification becomes essential when the task involves distinguishing among more than two possible classes, allowing for a richer and more nuanced understanding of the data. Multi-class problems are common in image recognition, natural language processing, and many other fields where items can be grouped into multiple categories.

Multi-label classification broadens the scope further, accommodating instances where items may belong to several distinct categories simultaneously. This is particularly valuable in applications like content tagging, where a single document or image can cover multiple topics. The flexibility of multi-label classification makes it well-suited for tasks where the boundaries between classes are not rigid and where items may exhibit a variety of characteristics. The main structure of the multi-output classifier is shown in the Figure 2.5.

Moving beyond the traditional classification paradigms, multi-output classification extends the model's capabilities by predicting multiple types of outputs for each input. This is especially useful when the target variable includes both categorical and numerical elements. For example, predicting both the genre and box office revenue for movies allows for a more comprehensive understanding of the factors contributing to a film's success.

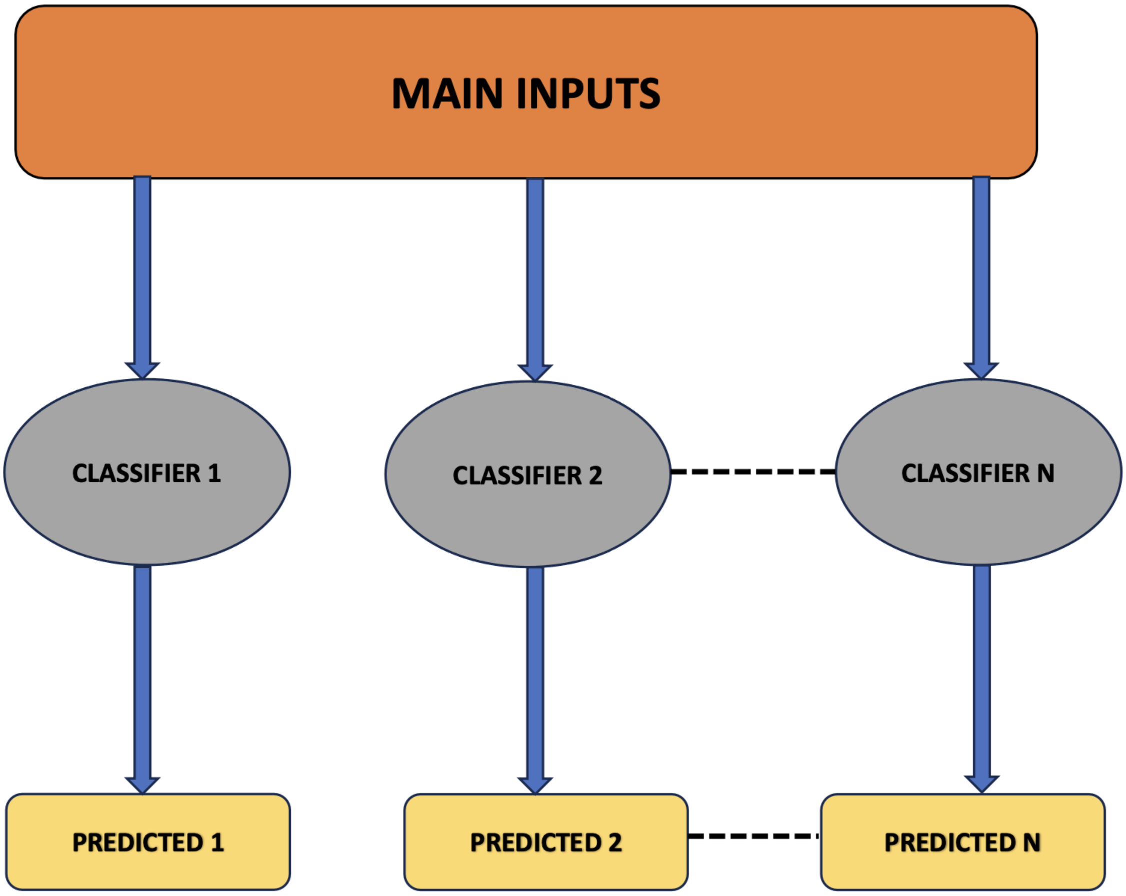

Figure 2.5 Multi-output Classifier

Ultimately, the choice of classification type depends on the nature of the data and the specific goals of the machine learning project. These classification approaches collectively provide a versatile toolkit, enabling practitioners to address a wide array of complex problems and extract meaningful insights from diverse datasets.

2.5. Chain Classification

Chain classification is a machine learning approach that extends traditional classification by considering the dependencies between multiple output variables [6]. Unlike independent classification tasks, where each output is predicted in isolation, chain classification recognizes that the prediction of one output variable can influence the prediction of subsequent variables [7]. This approach is particularly relevant when dealing with complex

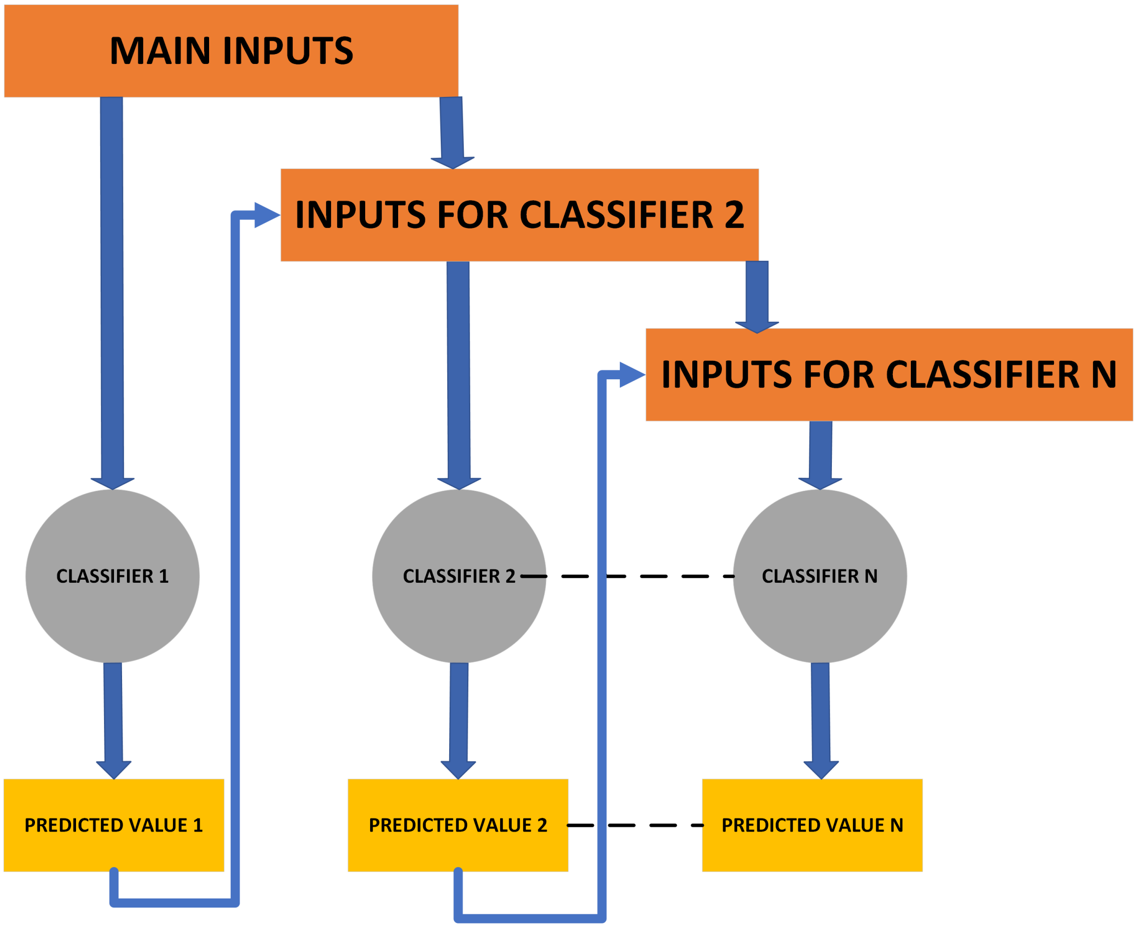

Figure 2.6 Classifier Chain

systems where outputs are interconnected. It can be beneficial if the predictions are accurate, but it can also negatively impact accuracy if the predictions are not accurate. The structure of the chain-based multi-output classifier is shown in the Figure 2.6.

In numerous real-world scenarios, data samples are linked to multiple labels, leading to multi-label classification. The Classifier Chains (CC) method is commonly used for such tasks, where the order of labels significantly influences performance. Jun et al. [8] introduced ranking methods according to the conditional entropy of labels. Unlike existing approaches, a single order is determined, eliminating the need to train more classifiers than CC. Experimental results on nine datasets demonstrate the effectiveness of the proposed methods, achieving superior performance based on eight evaluation measures.

2.6. Packaging Planning

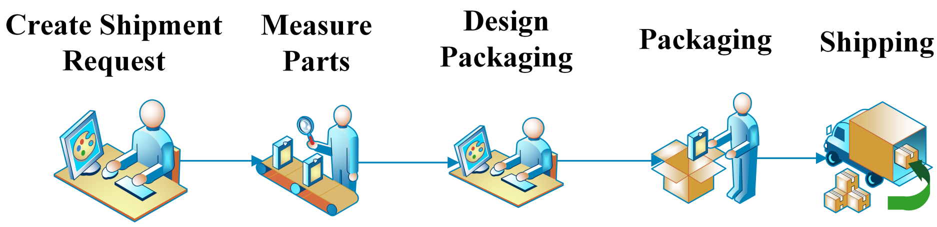

Figure 2.7 Packaging Planning Process

Packaging planning is a critical component of the logistics process in many industries[9]. It involves determining how products or components should be packed to ensure safe transportation to their destination [10]. Packaging planning encompasses various aspects, as shown in Figure 2.7. It begins when a shipment request arrives at the packaging department. The process then continues with measuring parts, selecting appropriate packaging materials, determining package dimensions, and optimizing the arrangement of items within packages during the design step. Finally, once the design is decided upon, workers place the parts in the appropriate package and load them onto a transportation vehicle for shipment. This process is essential to protect goods from damage during transit and to meet the specific requirements of clients or projects.

Packaging planning can indeed be seen as both an optimization problem and an AI problem. Packaging planning often involves optimizing various factors such as cost, space utilization, transportation efficiency, and material usage. Determining the best arrangement of products within a package, selecting appropriate packaging materials, and minimizing waste can all be framed as optimization problems. AI techniques can be applied to various aspects of packaging planning. For example, AI can be used for efficient packaging if dimensions are known or can predict the packing dimensions and type and packaging layouts based on historical data and constraints.

Packaging planning, nestled within the intricate domain of supply chain management, has witnessed a transformative evolution. The infusion of AI methods has elegantly permeated both realms, bestowing a newfound sophistication over the years. Pournader et al. [11]

provide a comprehensive examination of AI applications in supply chain management (SCM), analyzing 150 journal articles from 1998 to 2020. The study introduces an AI taxonomy with three research categories: sensing and interacting, learning, and decision making. The analysis reveals a growing interest in learning methods and emerging research in sensing and interacting. The paper underscores the importance of incorporating behavioral aspects in upcoming AI studies in SCM. The literature review aims to answer questions about the current state of AI applications in SCM, the investigated AI methods, future research possibilities, and the broader context of AI research trends in SCM.

The effective operation of a supply chain is essential for achieving business success, and precise inventory projections provide a competitive advantage. AI has become an extension of human capabilities, enhancing mental abilities. Contrary to the notion that AI will substitute humans, it serves to unlock strategic and creative capabilities. AI incorporates computational technologies for sensing, learning, reasoning, and acting. Through progress in technology, including mobile computing, internet data storage, cloud-based machine learning, and information processing algorithms, AI has been integrated into different industry domains, reducing costs, increasing revenue, and improving asset utilization. AI aids in accurate demand projection, optimizing RD and manufacturing, facilitating targeted promotions, and enhancing customer experiences. Leaders in the supply chain utilize AI for streamlined designs, continuous monitoring in real-time, flawless production processes, and accelerated innovation. The widespread adoption of AI across industries is reshaping business strategies, manufacturing footprints, and supply chain models, marking a significant global trend [12].

Each shipment consists of a variety of components, and addressing the resulting time loss often involves optimization techniques. Many researches in this field focus on minimizing the dimensions of individual parts to achieve more efficient packaging planning. However, our approach places a critical emphasis on dimensions, with optimization as a secondary objective. When clients have specific requirements for certain parts, we refrain from optimizing the packaging for those components.

3. RELATED WORK

Various views exist on the use of AI in supply chain and manufacturing processes; however, certain minor aspects within these extensive processes still offer opportunities for new experimental AI techniques. Fahle et al. [13] presented comprehensive research on the potential applications of AI in production and supply processes as a whole. According to the study, contemporary businesses place a significant emphasis on the study of AI, to the extent that it forms the basis for their Kaggle competitions. Although the use of AI is essential, it should be reserved for tasks that demand the outcomes of human intuition, excluding calculations, which need not be employed in domains where rule-based solutions can be developed. The details of the research demonstrate how AI may be used in logistics, quality control procedures, manufacturing process planning in factories, and maintenance predictions. Investigations in the field of logistics have shown that combining optimization and AI has applications for smart factories and logistics planning.

Many research studies were not identified when searches were conducted for studies that could automate the packaging process using AI, as suggested in the literature for designing this. Knoll et al. [1] focused on automating this procedure by incorporating machine learning into the package planning process. This study encompassed two key components: packaging planning itself and the subsequent shipping of these packages. Regression and supervised machine learning were employed for this stage, with clustering initially used to determine which parts should be placed in which packages. Then, RF regression technique is used to estimate how much the packages could be filled. Also, hyperparameters for these algorithms were determined by employing grid search. The research studies used the RF algorithm for predicting packaging, aligning with our approach. However, our unique contribution lies in the application of chain classification to predict packaging properties. These properties encompass aspects such as the number of packages to be used in a shipment, their dimensions, and types. These properties pertain to packing and ultimately determine the type of packaging.

Toorajipour et al. [14] conducted a comprehensive literature study on the ways AI can be integrated into procurement processes. The authors asserted that AI can address issues more quickly and accurately. Through the utilization of techniques such as neural networks, fuzzy logic, and agent-based systems, it was concluded that AI is primarily applied in the industrial sector of supply chain management. Artificial neural networks, fuzzy models, and general AI are commonly used within the supply chain.

Kuhnle et al. [15] provided valuable insights into how production systems can adapt through reinforcement learning and how machines can gain a deeper understanding when humans make decisions. According to the authors, attempts to utilize conventional optimization or heuristic research for demand forecasting have proven unsuccessful. Experimental results show that reinforcement learning can yield superior results in dynamic applications.

Another important application of AI usage in the manufacturing industry. According to a study conducted by Waschneck et al. [16], the process of self-organization and self-learning within production systems has commenced in the rapidly evolving environment due to Industry 4.0. The authors employed Deep Q Network and reinforcement learning to investigate production control planning. The system autonomously develops scheduling solutions without human intervention, with predefined rules, it can achieve expert-level performance in just 2 days of training. The system can also detect unsuitable issues during manufacturing.

Read et al. [17] proposed a new model called Classifier Trellis (CT). They inferred that the individual classifier has less accuracy than the dependent ones. Also, they discussed the challenges of modeling label dependence in multi-label classification. Their study highlights that complex methods do not always lead to better results. The experiments show no clear dominance among methods. An alternative, CT is introduced, performing well and being scalable. According to their model, each output does not affect the whole; a structure can be built, and necessary dependencies between them can be decided.

Dzeroski et al. [18] showed in their experiments that using heterogeneous models improves accuracy in contrast to selecting the best-predicted model. They evaluated various methods for constructing classifier ensembles using stacking and introduced two new stacking methods. One of these outperforms existing approaches and cross-validation. These methods are designed for strong, diverse classifiers. Their research also addressed discrepancies between their results and claims in previous literature due to differing experimental methodologies. Their study offered a clear view of the relative performance of stacking.

Durand et al. [19] addressed multilabel image classification challenges in everyday scenarios. It proposes a scalable approach to train a classifier with partial labels, reducing annotation costs. A new classification loss is introduced for partial labels, enabling the use of existing training settings. Curriculum learning strategies are explored for predicting missing labels. Experiments on large-scale datasets demonstrate improved performance. Future work aims to combine datasets for enhanced training data.

Kharbech et al. [20] compared four widely used classifiers—classification tree, KNN, Artificial Neural Networks (ANNs), and support vector machines— for feature-based automatic modulation classification (FB-AMC) in the context of cognitive radio systems. The evaluation takes place over multiple-input–multiple-output channels using statistical pattern recognition techniques. The study assesses classifiers based on both classification accuracy and computational complexity, revealing that artificial neural networks demonstrate the best performance-to-complexity tradeoff within the specified context. To ensure impartiality, each classifier undergoes optimization through model selection using 'k-fold cross-validation' as the model validation technique.

Balasubramanian et al. [21] addressed the challenge of conditional modeling $x \to y$ in machine learning, with a focus on cases involving high-dimensional vectors. While traditional methods struggle with overfitting when x is high-dimensional, the study explores the scenario of high-dimensional y, whether x is low or high dimensional. The baseline involves constructing independent models $x \to y_i \in \mathbb{R}$ for $i = 1, \ldots, k$, leveraging various single-output models. However, this approach neglects potential correlations between dimensions of y. The proposed method selects a subset L of y's dimensions, constructing two models: $x \to y_L$ and $y_L \to y$. The approach addresses subset selection, model

(1) and model (2) estimation, employing least-squares regression with group Lasso-based hierarchical regularization. The method assumes landmark variables in y and expresses remaining dimensions as a noisy linear combination. Practical applications include stock price prediction and image classification. Experimental results demonstrate the method's superiority in classification and regression for high-dimensional outputs. The study suggests future directions for analysis, including assessing improvements over competing methods and considering label vector patterns of missingness.

Har-Peled et al. [22] introduced the constraint classification framework for multiclass classification, encompassing winner-take-all, multilabel classification, and ranking. It presents a meta-algorithm utilizing a single linear classifier in high dimensions, discussing distribution-independent and margin-based generalization bounds. The empirical and theoretical evidence highlights the advantages of constraint classification over existing multiclass methods. Constraint classification contributes by providing a conceptual generalization covering various classification scenarios and reminding that the Kesler construction extends any binary classification algorithm to the multiclass setting. Experimental results demonstrate the superiority of the constraint approach. The paper simplifies the understanding of existing approaches and suggests real-world applications due to the intuitive nature of constraint classification.

Moral et al. [23] addressed the increased difficulty in multi-class classification problems as the number of classes grows. It introduces the concept of heterogeneity of decision boundaries, suggesting that the interaction between different decision boundaries contributes to the complexity of the task. The study analyzes various state-of-the-art approaches to multi-class classification, showing that an increase in heterogeneity generally leads to decreased performance, except for one-vs-one methods. The paper proposes decompositions that consider the heterogeneity, resulting in improved classification outcomes. The findings are demonstrated through synthetic datasets, a real dataset, and a nonlinear SVM classifier, showcasing the impact of decision boundary heterogeneity on classification performance. The identification and understanding of this phenomenon contribute to a more nuanced approach to solving multi-class classification problems.

Huang et al. [24] introduced a unified learning framework named Extreme Learning Machine (ELM), encompassing Least Square Support Vector Machine (LS-SVM), Proximal Support Vector Machine (PSVM), and other regularization algorithms. ELM operates regarding single-hidden-layer feedforward networks, including SVM, polynomial networks, and conventional feedforward neural networks. The key idea is that ELM simplifies LS-SVM and PSVM, eliminating the need for tuning the hidden layer. The study demonstrates that ELM serves as a unified platform for various feature mappings, applicable directly to regression and multiclass classification. ELM exhibits less stringent optimization constraints in comparison to LS-SVM and PSVM, achieving faster learning speeds and scalability, with theoretical capabilities to approximate any continuous function and classify disjoint regions. Simulation results confirm ELM's superior generalization performance over traditional SVM and LS-SVM, particularly in multiclass classification scenarios.

Jha et al. [25] introduced a statistical anomaly detection algorithm centered around Markov chains, primarily designed for intrusion detection systems. The method entails building a model of regular behavior using a collection of normal traces. Subsequently, this statistical model is employed to formulate a classifier capable of differentiating between normal and anomalous system activity. The paper outlines a broad framework for building classifiers from Markov chains and introduces three particular classifiers within this framework. Criteria for assessing the effectiveness of classifiers in the realm of intrusion detection are defined. The outcomes of the experiments demonstrate the efficacy of the proposed approach, and the classifiers can be readily integrated into intrusion detection systems. The paper concludes by suggesting various directions for future research in this domain.

Cheng et al. [26] delve into the realm of multilabel classification (MLC) and challenges the commonly held belief that optimal predictive performance requires explicit consideration of label dependence. It formalizes and analyzes MLC within a probabilistic setting, allowing for an examination from the perspectives of risk minimization and Bayes optimal prediction. The paper introduces a new MLC method, probabilistic classifier chains, which generalizes and outperforms an existing approach called classifier chains. The proposed probabilistic framework distinguishes between conditional and unconditional label dependence, providing insights into the nature of MLC and shedding light on the considerations of recent contributions in exploiting label dependence. The theoretical analysis emphasizes that the importance of label dependence depends on the type of dependence and the loss function to be minimized. The new method estimates the entire joint distribution of labels, allowing adaptation to various loss functions, albeit with increased computational complexity. The paper also offers a formal interpretation of the classifier chains algorithm as a greedy approximation of the most probable label combination, providing a theoretical foundation for this existing method.

Sucar et al. [27] proposed Bayesian chain classifiers (BCC) as a novel solution to challenges in multi-label classification problems, intending to overcome drawbacks observed in established methods like binary relevance and conventional chain classifiers. In multi-label classification, instances are assigned to multiple classes, and traditional methods face challenges in capturing interactions between classes or dealing with high computational complexity. BCC combines the advantages of classifier chains and Bayesian networks by inducing a Bayesian network to represent probabilistic dependencies between classes. The method constructs a chain classifier based on the learned Bayesian network, employing a tree structure initially and adopting a random class order that aligns with the tree in the first phase. The suggested method undergoes experimental assessment, comparing it against diverse strategies. This includes examining different training schemes, employing heuristics to determine the chain order, altering the number of classes in each classifier, exploring alternative base classifiers, and assessing single chains versus ensembles. The results demonstrate that BCC, despite having a straightforward tree structure and naive Bayes base classifier, outperforms multi-dimensional Bayesian network classifiers and chain classifiers. The study extends the analysis of BCC with several alternative strategies and emphasizes the benefits of considering dependencies among classes in multi-label classification. Future research directions include exploring more complicated dependency structures and identifying detached classes to enhance the chain process and overall performance.

Liu et al. [28] discussed the challenge of class imbalance in multi-label data and proposes

ECCRU, a method that couples the Ensemble of Classifier Chains (ECC) with random undersampling to address this issue. ECCRU variations, ECCRU2 and ECCRU3, are introduced to enhance the exploitation of majority examples within a fixed computational budget. Experimental results on 16 datasets demonstrate the effectiveness of these approaches.

Wang et al. [29] introduced an method for unsupervised person re-identification (ReID) by framing it as a multi-label classification problem. The method gradually assigns accurate labels to images by initially using a single then evolving to multi to label classification. To enhance training efficiency, a memory-based multi-label classification loss (MMCL) is proposed. The iterative label prediction and MMCL significantly improve ReID performance. Tests conducted on extensive datasets, including MS COCO, NUS-WIDE, and Open Images, illustrate the effectiveness of the proposed technique in unsupervised person ReID, while also showcasing state-of-the-art performance in a transfer learning setting.

Min [30] explores the application of artificial intelligence in supply chain management to improve decision-making processes and efficiency. Despite the possible advantages of AI, its use in SCM has been limited. The study identifies sub-fields of AI suitable for SCM, reviews past AI applications, and discusses practical applications and technical strengths. A hierarchical classification is developed to categorize existing AI literature based on SCM application areas, the scope of problems addressed, and methodology. The analysis reveals that AI applications in SCM are mostly focused on well-structured tactical and operational problems, with agent-based systems emerging as popular tools. Challenges and future research directions for integrating AI into SCM are discussed, emphasizing potential applications in SC integration, risk management, real-time pricing, reverse auctioning, game theory, expert systems, and hybrid meta-heuristics. Despite challenges, the paper anticipates a promising future for AI in SCM as the discipline matures.

Helo et al. [31] explore the transformative potential of AI in SCM, addressing the evolving landscape of global competition. It offers an overview of AI and SCM, analyzing emerging AI-based business models in various companies. The study defines the fundamentals of creating value for AI in the supply chain and presents an approach to designing business models for AI applications in SCM. Case studies of companies like Walmart, ABB, and Infinera illustrate how AI is leveraged in SCM for decision-making, automation, and optimization. The essential factors for achieving success in SCM, including information sharing and collaboration, are emphasized. While acknowledging AI's substantial potential, the study highlights the ongoing need for research on organizational and cultural factors influencing AI adoption in SCM.

Sharma et al. [32] examine AI trends in supply chain management, identifying key research clusters. It proposes a research framework for understanding current patterns in AI-SCM. Limitations include a focus on business journals. Future research suggestions include exploring AI in healthcare SCM, vertical sectors, legal aspects, fintech, marketing operations, sustainability, and organizational resistance.

Ali et al. [33] conducted a comprehensive analysis comparing the performance of RF and J48 DT models across twenty diverse datasets obtained from the UCI repository . The evaluation encompassed a range of critical classification parameters, including correctly and incorrectly classified instances, F-Measure, Precision, Accuracy, and Recall. The findings revealed that RF exhibited superior performance, particularly excelling in the realm of larger datasets characterized by a substantial number of instances. On the other hand, J48 DT demonstrated its effectiveness in handling smaller datasets. Noteworthy is the example drawn from a breast cancer dataset, where the study showcased RF's heightened accuracy as the number of instances increased. This observation underscores the efficacy of RF, particularly in scenarios involving larger datasets.

Singh et al. [34] evaluated the impact of data types (Text, Numeric, Text + Numeric) on RF and KNN classifiers. Both RF and KNN outperformed Naïve Bayes, with similar mean accuracy. Notably, changing attributes had no significant effect on RF, while KNN's accuracy improved with more attributes. RF had higher computational time, while KNN was faster. The study suggests that for versatile datasets, KNN and RF are optimal, each excelling in different scenarios, and the choice depends on specific application requirements.

Wozniak et al. [35] focus on the current research trend in pattern classification, specifically the utilization of multiple classifier systems (MCS) within Hybrid Intelligent Systems. The paper highlights the importance of combining classifiers to overcome limitations in traditional approaches. The survey addresses crucial issues like diversity and decision fusion methods in MCS. Transitioning to recommender systems, the paper explores their expanded applications and the advantages of hybrid recommender systems, citing diverse methods from various works. In summarizing research streams on multiple classifier systems, the paper underscores the significance of classifier diversity and combination methods. It also delves into potential future directions, such as merging raw data from different sources, integrating expert knowledge, and addressing issues related to data privacy and computational efficiency.

Komatsu et al. [36] introduce a novel approach for acoustic event detection (AED) using classifier chains based on the probabilistic chain rule. Utilizing a gated recurrent unit (GRU), the method iteratively detects multiple events, considering their interdependence during classification. Experimental results with a real-recording dataset show a significant 14.80% improvement over a baseline system with multiple binary classifiers. The proposed approach, employing GRU in classifier chains, outperforms existing methods, emphasizing the importance of the class order within the chain. Future directions include extending the method to weakly supervised training and evaluating its performance on datasets with a large number of classes, such as AudioSet.

4. PROPOSED METHOD

In this thesis, we propose a relation-based heterogeneous chain-based multi-output classification model which is an improved model of chain regression models. In our model, we integrate traditional multi-output classification models and chain regression models.

4.1. Dataset

In order to analyze our models, we use a real-world dataset for packaging planning. It comprises six input and six output variables given in Table 4.1 with their definitions. Inputs include shipment id, part id, part quantity, shipment type, and shipment scope, all of which are related to the shipment and its contents. Outputs comprise package type, package number, package length, package width, package height, and packaging type, which pertain to the outer packaging of the shipment.

Table 4.1 Dataset Definition

Variable	**Definition**
Shipment Id	Generated number for shipment request
Part Id	Identity number of part
Quantity	Quantity of part for the shipment
Client	Receiver of the shipment
Scope	Scope of the shipment
Shipment Type	Type of the shipment
Package Type Id	Identity number of package type
Package Number	Generated from one for each shipment
Package Length	Length of the package
Package Width	Width of the package
Package Height	Height of the package
Packaging Type	Outer part of the package for protection

Shipment Id is an integer value that represents a shipment and is generated for each shipment. Part Id is a definition number assigned to each part in the system; each part has a predefined id with an integer value. Quantity is also an integer value that defines the quantity of parts to be sent with a shipment. Client, like Part Id, is an integer value holding predefined information about the client. Scope and shipment type are also integer values, each with predefined definitions. Package Type (3) and Packaging Type (21) can have multiple values, and these values are also integer values that imply predefined definitions for themselves. The dimensions of the package are also represented by integer values, based on centimeters. Multiple options are available for length (23), width (21), and height (27).

Table 4.2 Dataset Explanation with Draft Data

Shipment Id	Client	Scope	Shipment Type	Part Id	Quantity	Package Type Id	Package Number	Package Length	Package Width	Package Height	Packaging Type
10001	14456	1	2	3425	2	1	1	600	220	85	10
10001	14456	1	2	7637	1	1	1	600	220	85	10
10001	14456	1	2	1267	1	3	2	30	20	15	10
10002	7464	2	1	2374	1	1	1	300	200	230	1

In Table 4.2, variables are explained with example data. However, this data is not the actual dataset; rather, it represents the main idea of our dataset. Shipment ID, client, scope, and shipment type form our outer circle for each shipment. These terms remain the same for every part and quantity within the same shipment. Based on these six input variables, our model attempts to predict the next six variables. For instance, according to the table, shipment 10001 will be sent to client 14456. We can assume that client 14456 represents a firm named A. The scope is 1, indicating sales transportation, and its type is 2, implying that it will be sent via sea. The first three rows share the same shipment information, suggesting that this shipment includes three parts. According to the rest of the parts, part number 3425 will be sent in two pieces, while the others will be sent in one piece. Parts 3425 and 7637 are placed in one package, and 1267 is put in a different package. We deduce this from their package types and package numbers. In this example, the package types are not the same; however, in some cases, even if the package types are the same, the package number can increase because some parts cannot fit in the same package. In this example, parts 3425 and 7637 are placed in a crate package with dimensions of 600 cm x 220 cm x 85 cm, and part 1267 is placed in an envelope package with dimensions of 30 cm x 20 cm x 15 cm. Finally, these packages are put into a predefined packaging type with ID 10, representing a larger belted wooden box with dimensions of 700 cm x 250 cm x 100 cm. In the final row, another shipment is seen that will be sent to client 7464, which we can identify as firm B. According to the shipment type, we can assume that it is a maintenance shipment, and it will be sent via air transportation. It includes only one part and one piece. The package type is 1, and it is a crate package. There is only one package, and its dimensions are 300 cm x 200 cm x 230 cm. Finally, this package is put into a predefined packaging type with dimensions of 350 cm x 250 cm x 250 cm, a belted wooden box.

Determining which part is placed in which package, the respective package properties and dimensions, and ultimately selecting the appropriate packaging type for these packages are the key aspects of this process. The data does not contain complete shipment information; it primarily includes the most commonly used package dimensions. Data regarding shipments with other package dimensions is not included. Therefore, instead of using regression, we opted for classification. The inputs provide information about which parts are being forwarded to a specific client within a shipment and the quantity of each part. Additionally, we have contextual details about the shipment, such as its scope and type. For instance, a shipment might be categorized as 'maintenance' or 'sales' and can be sent by road or sea.

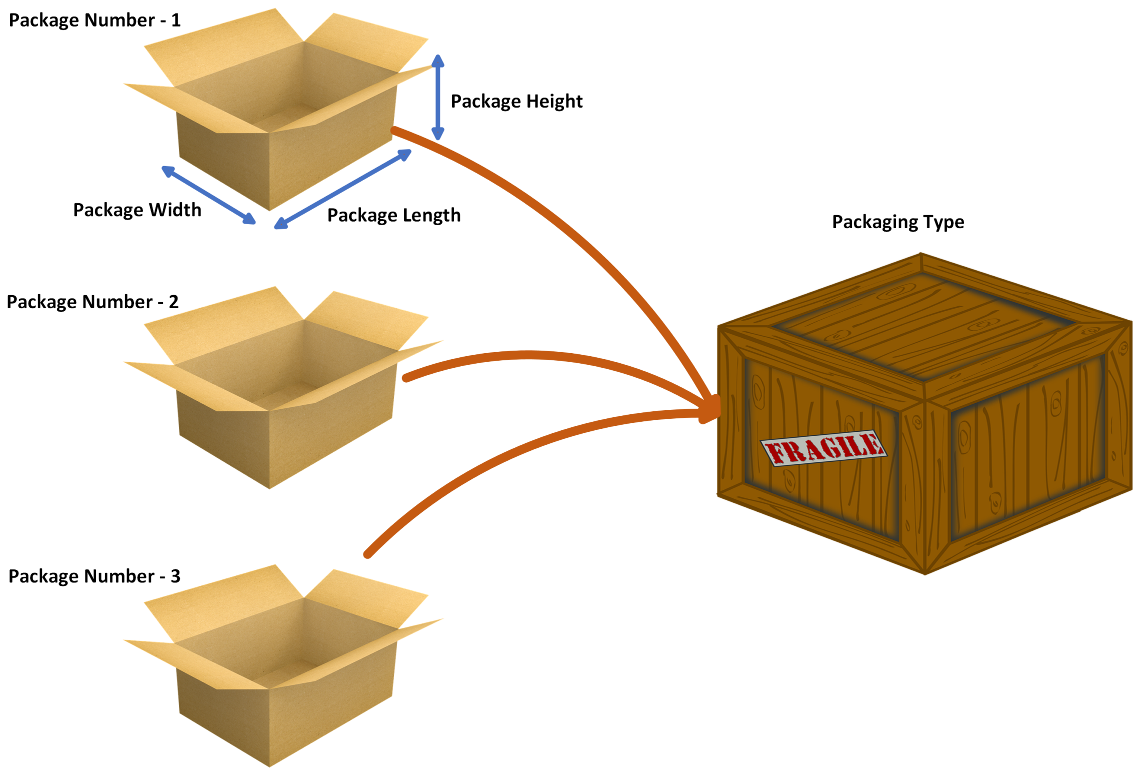

Figure 4.1 Visual Explanation of Packaging Planning Dataset

Once we have this information, our objective is to predict the outputs, which include various properties of the packages. These properties include dimensions like length, width, height, and type. Each package is assigned a package number; for example, in a shipment with three packages, they might be labeled as 1, 2, and 3. In subsequent shipments, if only one package is sent, it will still be labeled as 1. The final output is the packaging type, which defines the outer covering of the packages. For example, even if we use three different packages within one shipment, each enclosed in its own protective material and with information labels, we aim to predict these outer coverings' types and dimensions. Each package is assigned a package number (e.g., 1 and 2). These packages are then placed together inside a larger wooden belted chest-like box, information is affixed to it, and, if the client has specific packaging requirements, they are determined according to the client's standards. Notably, we do not need to predict the dimensions of this outermost layer, as predefined types each come with specific dimensions. Our focus is solely on classifying them based on the available types. Explanation of these outputs are illustrated in Figure 4.1. Our proposed model for the dataset is illustrated in Figure 4.2.

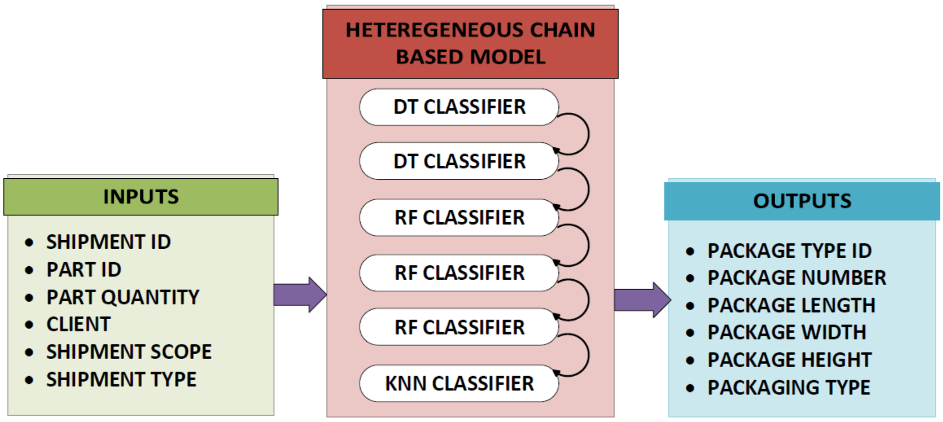

Figure 4.2 The Proposed Model for Packaging Planning

4.2. Proposed Method Development and Dataset-Model Integration

In predicting packaging planning problems, there are multiple outputs that need to be classified. In this problem, correlations between variables like length, width, and height become apparent. If the classifier knows one of them, predicting the next one becomes easier. Based on this observation, our model has adopted a chain structure. Next, we evaluated the need for algorithms based on a single classification algorithm with a chain structure. However, in some cases, such as our problem, each output does not provide the best prediction with the same classification algorithm. Therefore, we still need to maintain the chain perspective but feed the next input group with a different classification algorithm.

Also, we have observed that not every output needs to serve as the input for the subsequent outputs. For instance, based on our understanding of the dataset, we can deduce that the first output influences the predictions of the fourth and sixth outputs positively, but it might adversely impact the accuracy of the second and third outputs. Therefore, we have developed our proposed model with a relational basis. We can specify these output interactions and structure our chain model accordingly. In the results and the continuation of this thesis, we specify that the proposed model's relation is not a fixed parameter, and all outputs influence the subsequent ones. Furthermore, we denote our relation-based proposed model as one in which we can determine the relationships between outputs.

In light of all this information, to assess why we proposed this model and understand how the current process operates, we can thoroughly examine the existing packaging planning process. The step-by-step process in the current workflow is as follows:

- Materials to be shipped arrive at the shipping area.
- Measurements of the materials are taken.
- Planning experts and project managers reach a consensus on how some of the packaging should be done.
- The planning expert enters this information, including packaging details, into the system on a shipment basis.
- Materials are placed in suitable packages, and the shipping process is carried out.

Analyzing these processes, we observe that the primary focus is often on optimizing the workflow with the help of expert opinions. However, we do not always seek the optimal outcome. In some shipments, the packages are determined and even sent by the receiving company, and the packaging should be done the way they want, not necessarily seeking the most optimal result. At times, optimization could be beneficial, but it requires having material information in the system. Since our dataset lacks this information, we do not integrate this study with optimization. However, in future studies, this direction could be considered.

What we are attempting to do in the current situation is to explore whether the planning expert, if aware of the correlation between materials and packages, could make inferences without repeating the above steps each time. The relation based proposed model, which achieved 0.98 accuracy, indicates that this is possible.

With our proposed model, the packaging will be planned for the respective shipment when the packaging planning expert opens the input screen and enters the relevant information. After reviewing these details, the packaging planning expert can either approve the plan and proceed to the next stage for shipment or make adjustments before moving to the next stage. This introduces a significant gain in terms of time for the expert and the department. This gain is not limited to time alone; it also translates into cost savings. The approach here is based on the idea that, similar to previous shipments, the packaging for the new shipment will be planned in the same way it was done before. When examining the dataset, we observe data that supports this concept.

In essence, our approach hinges on the notion that the packaging for a new shipment will be planned similarly to how it was done for relevant parts in previous shipments. This not only saves time for the expert and the department but also yields cost savings. This paradigm shift in planning leverages historical data, promoting consistency and efficiency in the packaging planning process.

Our dataset consists of the following information: shipment id, part id, quantity, client, scope, shipment type, package type, package number, package length, package height, package width, and packaging type. We utilize shipment id, part id, quantity, client, scope, and shipment type as the main inputs for our analysis. The areas we aim to predict, instead of relying on a packaging planning expert, include package type, package number, package length, package height, package width, and packaging type. Since we are attempting to predict multiple outputs, the scope of the problem we are addressing is defined as multi-output classification.

To tackle this, we leveraged the multi-output classification algorithm at the beginning of our study. As base estimators, we utilized RF, DT, and KNN, comparing the results obtained from each. 5.Experimental Results section provides a detailed explanation of the outcomes and their nuances.

For all outputs, we opted for classification algorithms since we cleaned and narrowed down our dataset before commencing the analysis. Consequently, for the fields of package type, package number, package length, package height, package width, and packaging type, the number of values that can be assigned to each label variable was more than one but still limited, making the dataset suitable for multi-class classification. Given that predicting only one output is not sufficient for solving our problem, and we need to predict all six outputs, our problem has transformed into a multi-output classification problem at this stage.

Multi-output classification algorithms, shown in Figure 4.3, typically predict each output independently using a base estimator. However, this approach was inadequate for our needs. Consider the simple example of predicting package dimensions: if, for instance, the width of a package is predicted before predicting its length, incorporating this information into the prediction of the length could significantly improve our accuracy. The order in which these predictions occur is crucial, and any change in order can positively or negatively impact the accuracy obtained in multi-output classification algorithms.

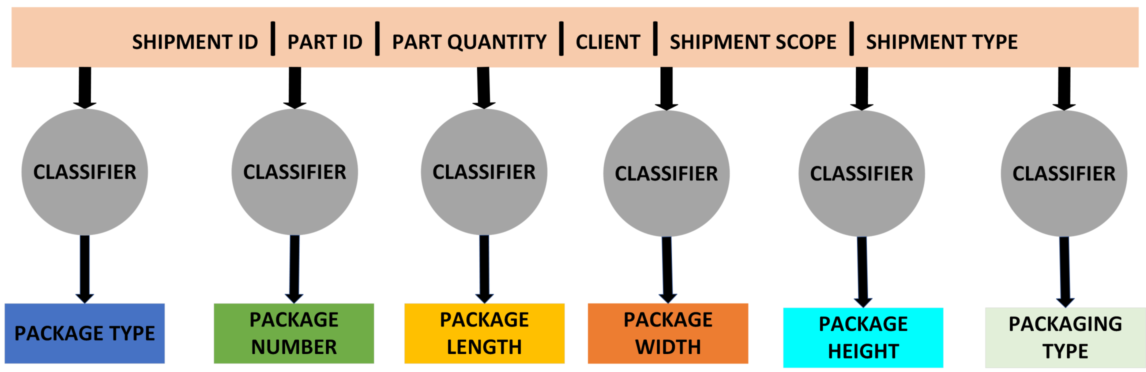

Figure 4.3 Multi-ouput Classification Model for Packaging Planning Problem

What was required was the ability to establish a chain structure with the correct sequence. In this way, each predicted output would become an input for the subsequent classifier in the correct order, potentially improving the overall accuracy. When researching how to achieve this with existing algorithms, we discovered the potential of using the regressor chain structure. While originally designed for regression problems, it accepts classification algorithms as base estimators. Hence, we primarily worked with this algorithm and experienced an increase in accuracy compared to results obtained from traditional multi-output classification algorithms. The details of the results are explained in the 5.Experimental Results section. For this algorithm, we also used RF, DT, and KNN as base estimators.

After conducting these experiments, we developed our own algorithm. Our algorithm was structured in a similar way to the regressor chain. We initially tested our algorithm with a homogeneous structure. In the chain structure we created, each predicted output served as an input for all subsequent outputs, establishing a chain structure. We named this algorithm the homogeneous model, providing a single estimator as the base estimator.

However, we recognized that having a single base estimator for each dataset might be insufficient to address the challenges. To overcome this limitation, we transformed our model into a heterogeneous structure, differentiating it from the regressor chain, which relies on a chain structure built upon a single base estimator. We termed this updated algorithm the heterogeneous model.

When comparing the accuracy rates, our DT-based homogeneous multi-output classification algorithm yielded a 0.98 accuracy, while the heterogeneous multi-output classification algorithm provided a 0.97 accuracy. Although this result implies a slightly lower accuracy for our dataset, we believe that the heterogeneous model may perform better with different datasets. This perspective is supported by our examination of 3.Related Work, where the need for heterogeneous models has been emphasized in previous studies.

With the model developed using these methodologies, the steps of the packaging planning process in the shipment process have been transformed into the following:

- Materials to be shipped arrive at the shipping area.
- When the planning expert opens the screen to enter planning information, the information appears on the screen, and the packaging planning expert reviews this information. If deemed appropriate, they approve it; otherwise, they make changes and proceed to the next stage.
- Materials are placed in suitable packages, and the shipping process is carried out.

Our model has contributed to the packaging planning process in terms of time and cost, providing significant benefits. With a 0.98 accuracy rate, the relation based model reflects choices that packaging planning experts would mostly approve, resulting in savings in time and cost that these individuals would otherwise spend on the process. The developed model is a relationship-based and heterogeneous chain structure multi-output classification model. When reviewing the studies conducted in the literature in this field, such an approach has not been previously realized for the packaging planning process. While there are studies in the literature highlighting similar points and expressing the utility of such enhancements, there is no existing study focusing on a model working on a dataset in this manner, including comparisons. The results of our models and experiments are detailed in the following section.

4.3. Homogeneous Model

When dealing with multi-label datasets, if the number of values assigned to each label variable is binary, we can employ a classifier chain. For multi-class classification problems, chain regression can be utilized with a classification algorithm. However, our packaging planning problem involves multi-output datasets and we explore a chain-based multi-output model for effective packaging planning. Since chain regression models, are able to accept a single base estimator, necessitate performance evaluations with a single classifier. Also, multi-output classification models do not support any chain structure. Chain regression models are primarily designed for solving regression problems. However, in cases where it is required to tackle classification tasks, classifiers can be employed within the chain regression structure as a base estimator. Classifier chains are another model to solve multi-output classification problems. However, our dataset should be suitable for binary classification. Therefore, we need to explore a new model to meet our expectations in the package planning problem. Our proposed homogeneous model, shown in Figure 4.4, works like a chain regression model. Our model allows the chain structure for a multi-output classification dataset. It combines a multi-output classification algorithm and a chain regression model; however, it still accepts a single base estimator.

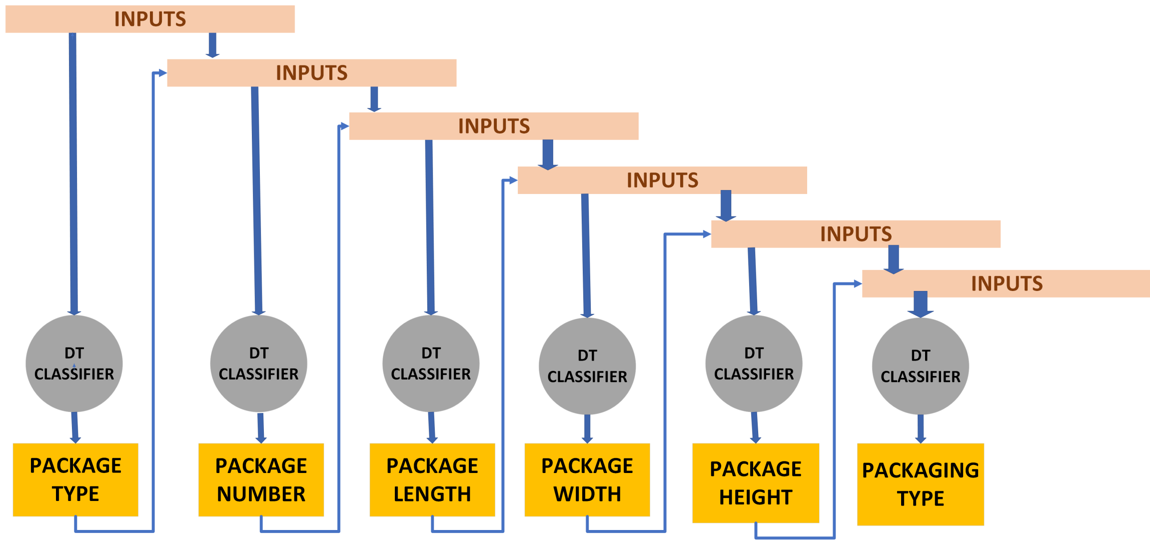

Figure 4.4 Homogeneous Model for Packaging Planning Problem

4.4. Heterogeneous Model

Different from chain regression and multi-output classification algorithms, our heterogeneous model, shown in Figure 4.5 , supports different classifiers flexibly within a chain structure. It sets itself apart from our homogeneous model in its ability to employ different classifiers. Each predicted output affects all subsequent outputs. Each one serves as input to the next classifier. Additionally, in certain scenarios, chain perspective with both regression and classification algorithms can be applied. However, in our model, only classification algorithms are used because of the nature of our problem. The base structure of our improved heterogeneous model is illustrated in Figure 4.6.

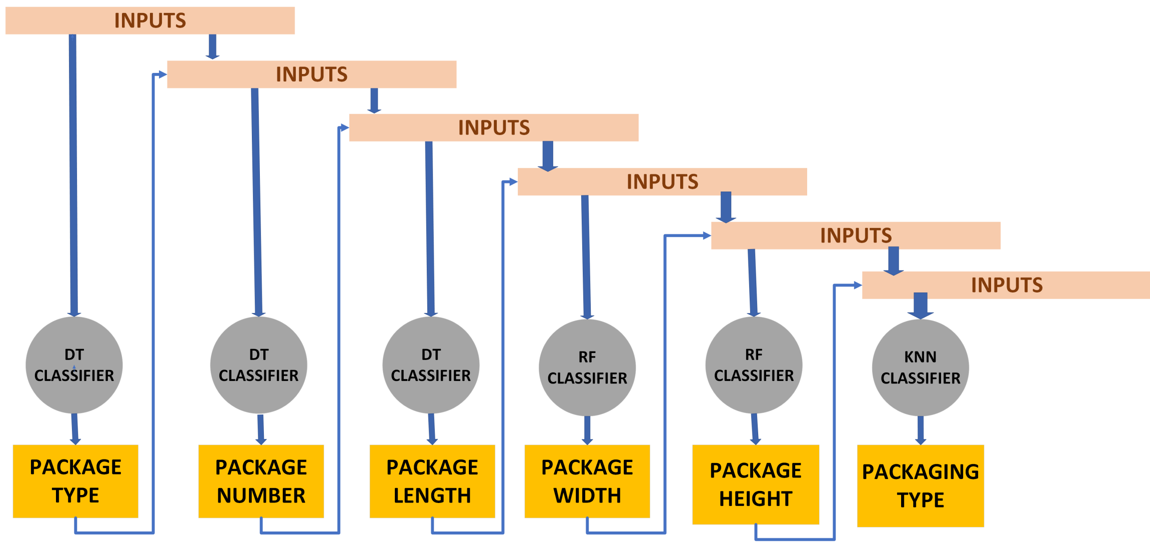

Figure 4.5 Heterogeneous Model for Packaging Planning Problem

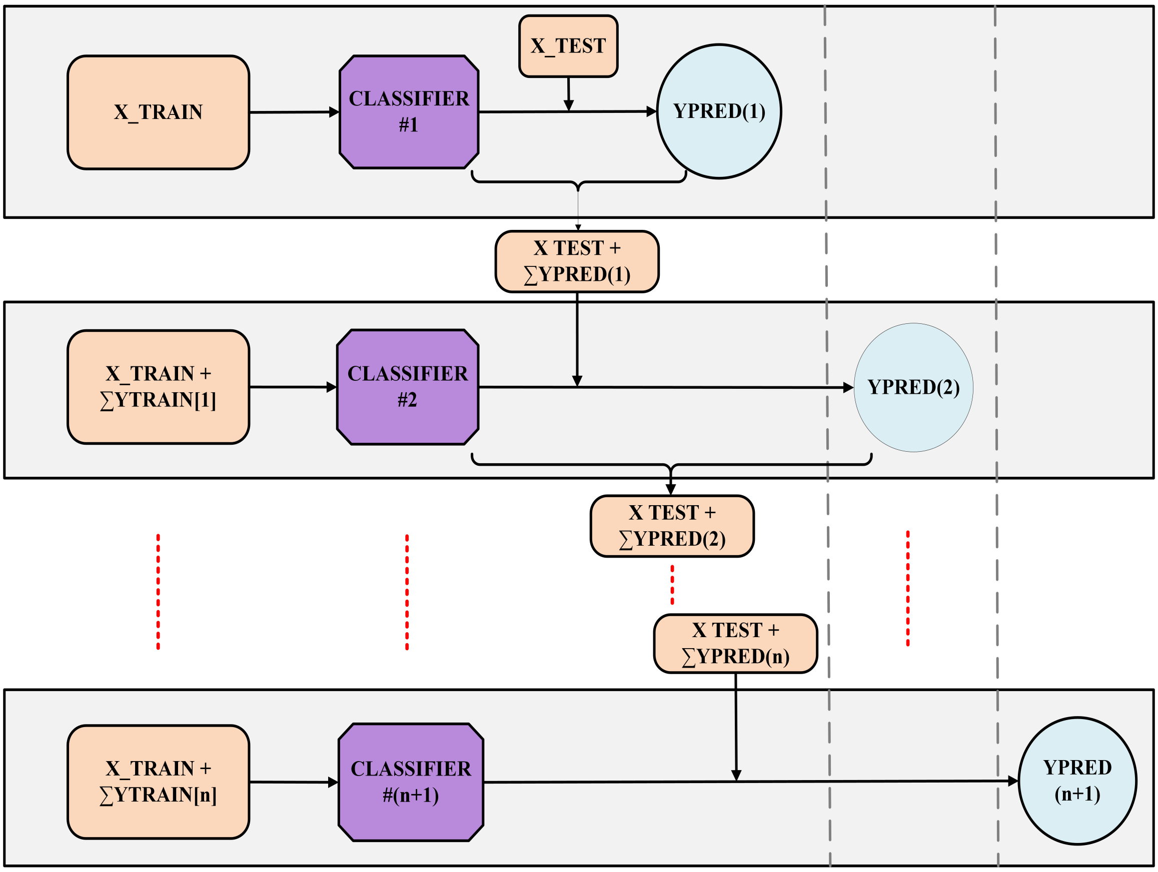

Figure 4.6 The General Structure of Our Heterogeneous Model

4.5. Relation Based Heterogeneous Model

Our model can also evolve into a relation-based framework, and the subsequent phase of our research is referred to as the relation-based heterogeneous chain-based multi-output classification model, shown in Figure 4.7. This innovative approach introduces a new parameter to our heterogeneous chain-based multi-output model, known as the relation parameter. In this setup, each predicted output no longer uniformly influences subsequent ones; instead, it is contingent on the specific relation between outputs.

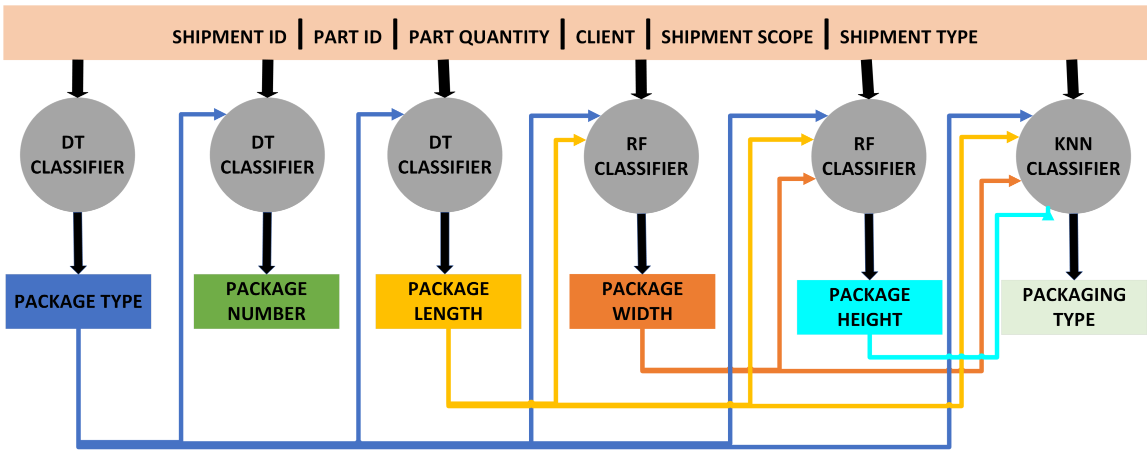

Figure 4.7 Relation Based Heterogeneous Model for Packaging Planning Problem

For instance, if the predicted Output 1 has a discernible relationship with Outputs 2 and 4, it becomes an input for the classifiers of 2 and 4, while the classifiers for 3 and 5 do not incorporate it. This methodology is advantageous as it enables adaptability based on the relationships between different outputs. By considering the relations between outputs, the classifiers are strategically designed to use relevant information for optimal predictions.

This novel approach also addresses the impact of feature correlation. When the correlation is negative or minimal, the classifier is not compelled to utilize that feature. This strategic choice aligns with the encouragement to adopt a chain model. Consequently, the chain-based model can be effectively utilized and tailored according to specific correlations and requirements, offering a flexible and adaptive framework for multi-output classification.

After creating the heterogeneous model, we conducted further investigations on our dataset to contemplate how we could enhance our model. During this analysis, we scrutinized the relationships between predicted outputs. The existing relationship was already built upon order, but we questioned whether it would be beneficial for all outputs to influence all subsequent outputs sequentially.We created a matrix, as illustrated in the Table 4.3 below, as an example.

Table 4.3 Relation Matrix of Outputs

Predicted \ Output	Package Type ID	Package Number	Package Length	Package Width	Package Height	Packaging Type
Package Type ID		X	X	X	X	X
Package Number						
Package Length				X	X	X
Package Width					X	X
Package Height						X
Packaging Type						

After establishing a network as illustrated in the relation matrix, our Relation-Based Heterogeneous Chain-Based Multi-Output Classification model achieved an accuracy rate of 0.98. This enhancement in accuracy indicates that the establishment of a heterogeneous relational chain structure has a positive impact on accuracy. Through this experience, we observed the positive influence of constructing a heterogeneous relational chain structure on the accuracy rate.

5. EXPERIMENTAL RESULTS

5.1. Results and Discussion

To demonstrate the performance of our proposed chain-based models, we integrate traditional multi-output classification models and chain regression models. Chain regression models, being able to accept a single base estimator, necessitate performance evaluations with a single approach. On the other hand, multi-output classification models do not support any chain structure.

We train all of our models with the same training and test dataset, divided into 70% for training and 30% for testing. Our improved chain-based multi-output classification model for our data consists of six training steps. In the first step, it receives our main inputs, shown in Figure 5.1, and makes classifications for package types. In the second step, the second classifier takes the main inputs along with the predicted package type and makes predictions for package numbers. This process continues until the sixth step. In the sixth step, the sixth classifier also receives the main inputs, the predicted package type, package number, package length, package width, and package height, and makes predictions for packaging types. The order is created according to the user's specified process sequence. If the order of the outputs changes, it may affect accuracy.

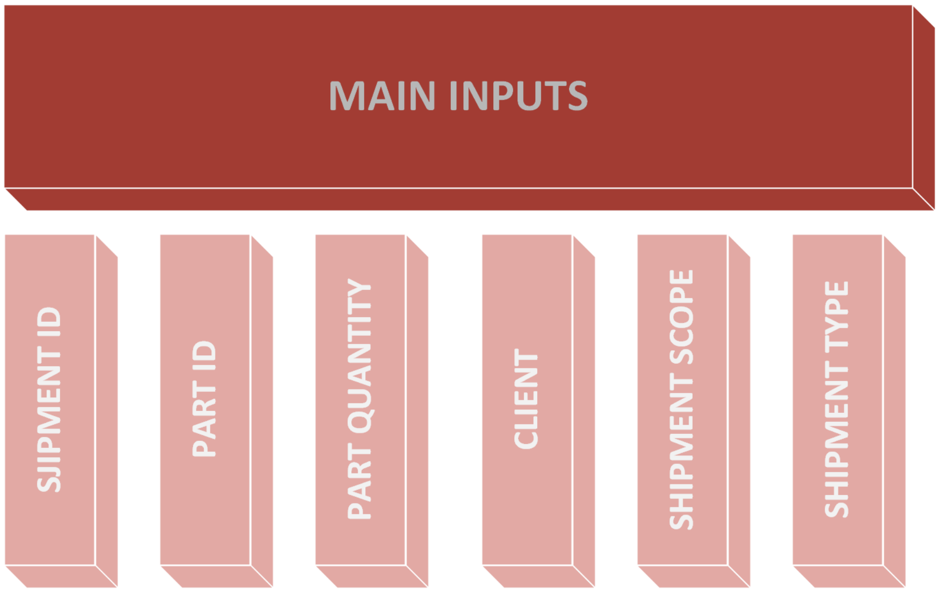

Figure 5.1 Main Inputs

Additionally, our relation-based heterogeneous chain-based multi-output classification model applies a similar technique to our heterogeneous chain-based multi-output classification model, with the difference that the package number output doesn't affect the subsequent outputs.

We employ the accuracy metric to assess the model's performance. Accuracy is a popular metric, especially in classification methods, and it expresses the model's success in classification problems. Given the multi-output classification nature of our problem and the presence of six output variables in our dataset, we calculate accuracy values separately for each of them. The overall accuracy value is then computed by taking the average of these accuracy values for the six output variables. In the evaluation of the results, precision, recall, and F1 score metrics were also examined. A comparison between macro average and weighted average for these metrics was conducted. Macro average calculates the metric values for each class and then takes an equally weighted average by dividing these values by the number of classes. On the other hand, weighted average multiplies the metric values for each class by the actual sample size of that class, adds these values, and then divides them by the total sample size. Therefore, weighted average assigns a weight to each class's performance based on the proportion of actual examples in that class. In our dataset, evaluating the models using weighted average seemed more appropriate because the sample sizes of some classes were small, diminishing their importance. Hence, when assessing the results using weighted average, the outcomes were very similar to accuracy. Consequently, these results were not presented again with the same data and tables. Indicating that the models performed well in a balanced manner across classes, or there was no significant imbalance in the number of examples among classes.

In the experimental analysis, we compare our proposed models with traditional multi-output classification and chain regression models in order to show the success of our proposed model. We first employ multi-output classification models with different single-base estimators. Firstly, we use multi-output classifier with the RF Classifier and get the results in Table 5.1. Subsequently, our exploration extends to employing a multi-output classifier utilizing the DT classifier as its foundation, with the obtained results detailed in Table 5.1. This particular modeling approach, grounded in DT principles, provides a distinct perspective on multi-output prediction. As we scrutinize the outcomes, it becomes apparent that the DT-based multi-output classifier excels in delineating complex relationships among diverse output variables. The nuances unveiled through this analysis contribute to a more profound understanding of the interplay between outputs, underscoring the effectiveness of DT-based methodologies in handling multi-faceted predictive scenarios. In the context of our multi-output classifier, the conclusive implementation involves a model based on the KNN classifier, yielding results expounded in Table 5.1. This strategic choice reflects a tailored approach to multi-output scenarios, leveraging the inherent proximity-based characteristics of the KNN classifier. As we delve into the analysis of the outcomes, it becomes evident that the KNN-based model excels in capturing intricate relationships among multiple outputs. The detailed insights derived from this comprehensive evaluation underscore the efficacy of the KNN classifier in the multi-output context, emphasizing its role as a powerful tool for predictive modeling in scenarios characterized by interdependencies among diverse outputs. According to the results of multi-output classification, the overall accuracy for RF Classifier is 0.87, for DT Classifier is 0.93, and for KNN Classifier is 0.82.

Table 5.1 Accuracy Results of the Multi-output Classification Model based on RF, DT and KNN Classifier

Inputs	**Base Estimator**	**Output**	**Accuracy**
Main Inputs	RF Classifier	Package Type	0.99
Main Inputs	RF Classifier	Package Number	0.96
Main Inputs	RF Classifier	Package Length	0.94
Main Inputs	RF Classifier	Package Width	0.99
Main Inputs	RF Classifier	Package Height	0.94
Main Inputs	RF Classifier	Packaging Type	0.99
Main Inputs	DT Classifier	Package Type	0.99
Main Inputs	DT Classifier	Package Number	0.96
Main Inputs	DT Classifier	Package Length	0.98
Main Inputs	DT Classifier	Package Width	0.99
Main Inputs	DT Classifier	Package Height	0.98
Main Inputs	DT Classifier	Packaging Type	0.99
Main Inputs	KNN Classifier	Package Type	0.98
Main Inputs	KNN Classifier	Package Number	0.93
Main Inputs	KNN Classifier	Package Length	0.93
Main Inputs	KNN Classifier	Package Width	0.98
Main Inputs	KNN Classifier	Package Height	0.93
Main Inputs	KNN Classifier	Packaging Type	0.97

Then, we employ chain regression model with the same single base estimators with multi-output classifications. The overall accuracy for the RF Classifier is 0.93, for DT Classifier is 0.93, and for KNN Classifier is 0.88. Detail of the results explained for RF Classifier in Table 5.2.

Table 5.2 Accuracy Results of the Chain Regression Model based on RF, DT and KNN Classifier

Inputs	**Base Estimator**	**Output**	**Accuracy**
Main Inputs	RF Classifier	Package Type	0.99
Main Inputs Predicted Package Type	RF Classifier	Package Number	0.96
Main Inputs Predicted Package Type Predicted Package Number	RF Classifier	Package Length	0.94
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length	RF Classifier	Package Width	0.99
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width	RF Classifier	Package Height	0.94
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width Predicted Package Height	RF Classifier	Packaging Type	0.99
Main Inputs Predicted Package Type	DT Classifier	Package Number	0.96
Main Inputs Predicted Package Type Predicted Package Number	DT Classifier	Package Length	0.99
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length	DT Classifier	Package Width	0.99
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width	DT Classifier	Package Height	0.98
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width Predicted Package Height	DT Classifier	Packaging Type	0.99
Main Inputs	KNN Classifier	Package Type	0.98
Main Inputs Predicted Package Type	KNN Classifier	Package Number	0.93
Main Inputs Predicted Package Type Predicted Package Number	KNN Classifier	Package Length	0.93
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length	KNN Classifier	Package Width	0.98
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width	KNN Classifier	Package Height	0.92
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width Predicted Package Height	KNN Classifier	Packaging Type	0.97

A detailed examination of the outcomes expounded for the DT Classifier in Table 5.2 reveals insightful observations. It can be inferred that both the multi-output classifier and the chain regression model, when constructed upon the same foundational estimator, exhibit closely aligned accuracy values for each output. However, a nuanced evaluation at the overall accuracy level underscores the prowess of the chain regression model. Moreover, the chain regression model not only showcases accuracy but also imparts a discerning perspective with respect to order. The model's performance is intricately linked to the sequence in which outputs are considered. A noteworthy observation emerges when altering the order of outputs—a misalignment in the chain is induced, leading to a discernible decrement in the accuracy for each output. In summation, these proximate results serve as a testament to the significance of the chosen order, elevating the chain regression model as a robust and sensitive framework for intricate multi-output predictions. A detailed scrutiny of the results presented in Table 5.2 for the KNN Classifier reveals insights.

Our enhanced model operates akin to a chain regression model, adhering to a sequential structure where each output significantly influences the subsequent one. This inherent chain perspective fosters a cohesive building process within the model. As depicted in Table 5.3, our improved model assumes the role of a homogeneous model. In this particular configuration, a singular base estimator, namely the RF Classifier, is exclusively employed. This deliberate choice streamlines the modeling process, harnessing the robust capabilities of the RF Classifier to yield a comprehensive and unified predictive framework. The model's effectiveness in capturing inter-dependencies between successive outputs is a testament to its adaptability and performance in homogeneous settings.

In Table 5.3, our homogeneous model is once again presented, utilizing a single base estimator, with the distinction that this time the chosen estimator is the DT Classifier. As we delve further into the subsequent segments of the comparison, it becomes evident that the homogeneous model built upon the DT Classifier achieves the highest accuracy overall. This noteworthy observation accentuates the efficacy of employing a DT-based approach within a homogeneous framework, showcasing the model's prowess in delivering optimal predictive accuracy across diverse scenarios. For our homogeneous model, we

Table 5.3 Accuracy Results of the Our Homogeneous Model based on RF, DT and KNN Classifier

Inputs	**Base Estimator**	**Output**	**Accuracy**
Main Inputs	RF Classifier	Package Type	0.99
Main Inputs Predicted Package Type	RF Classifier	Package Number	0.96
Main Inputs Predicted Package Type Predicted Package Number	RF Classifier	Package Length	0.94
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length	RF Classifier	Package Width	0.99
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width	RF Classifier	Package Height	0.94
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width Predicted Package Height	RF Classifier	Packaging Type	0.99
Main Inputs	DT Classifier	Package Type	0.99
Main Inputs Predicted Package Type	DT Classifier	Package Number	0.96
Main Inputs Predicted Package Type Predicted Package Number	DT Classifier	Package Length	0.99
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length	DT Classifier	Package Width	0.99
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width	DT Classifier	Package Height	0.98
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width Predicted Package Height	DT Classifier	Packaging Type	0.99
Main Inputs	KNN Classifier	Package Type	0.98
Main Inputs Predicted Package Type	KNN Classifier	Package Number	0.93
Main Inputs Predicted Package Type Predicted Package Number	KNN Classifier	Package Length	0.93
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length	KNN Classifier	Package Width	0.98
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width	KNN Classifier	Package Height	0.92
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width Predicted Package Height	KNN Classifier	Packaging Type	0.97

have ultimately employed the KNN Classifier as the base estimator, yielding results that are elucidated in Table 5.3. To show the superiority of our heterogeneous model, we analyze our model with the same base estimators in comparison with existing models. Also, we apply different estimators within a chain to show the flexibility of our heterogeneous model and its results shown in Table 5.4.

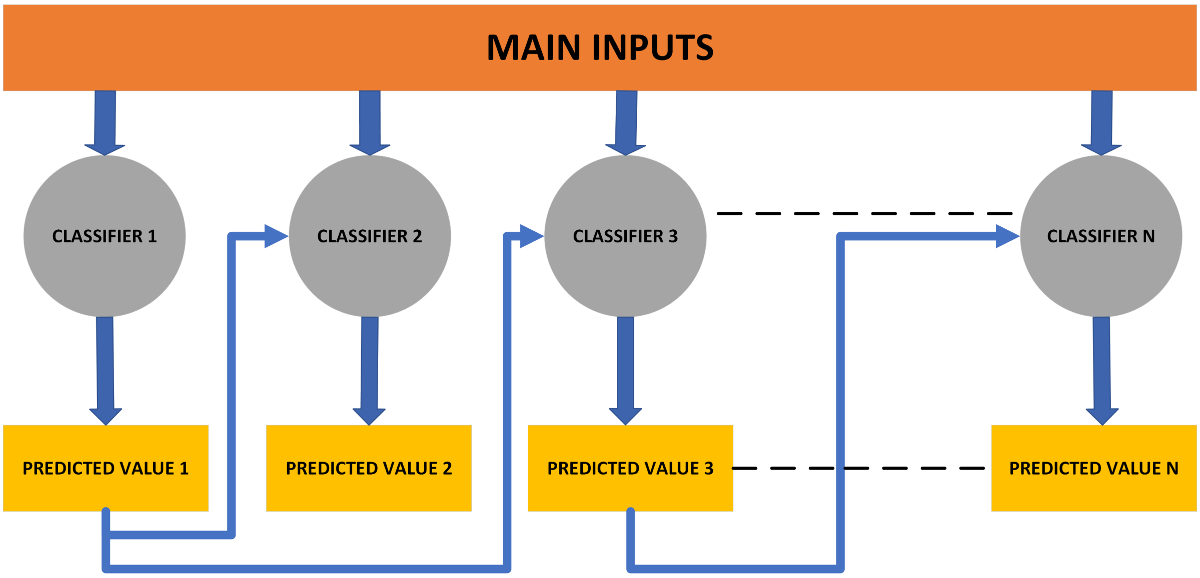

Figure 5.2 The Proposed Relation Based Heterogeneous Model

Our relation-based heterogeneous model is visually represented in Figure 5.2. In contrast to our heterogeneous model, in this approach, each output does not directly feed into the next group. Consequently, after predicting one output, we refrain from incorporating these outputs into our main inputs. Instead, we meticulously assess the correlations between these outputs to guide our decision-making process. For instance, in our dataset, the knowledge of package type influences the package number value, and thus, we utilize this predicted value accordingly. However, recognizing the package number does not exert an impact on other variables; hence, we opt not to include the predicted package number in our main inputs. The detailed information pertaining to the added inputs is elucidated in Table 5.5.

This refined model configuration showcases a thoughtful consideration of inter-variable relationships, enabling a more targeted and efficient utilization of predictive outputs without unnecessarily complicating the input space. The systematic approach to incorporating

Table 5.4 Accuracy Results of the Our Heterogeneous Model

Inputs	**Base Estimator**	**Output**	**Accuracy**
Main Inputs	DT Classifier	Package Type	0.99
Main Inputs Predicted Package Type	DT Classifier	Package Number	0.96
Main Inputs Predicted Package Type Predicted Package Number	DT Classifier	Package Length	0.99
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length	RF Classifier	Package Width	0.99
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width	RF Classifier	Package Height	0.96
Main Inputs Predicted Package Type Predicted Package Number Predicted Package Length Predicted Package Width Predicted Package Height	KNN Classifier	Packaging Type	0.97

relevant predictions enhances the model's ability to capture nuanced dependencies, resulting in a more insightful and accurate predictive framework.

According to the results, the overall accuracy for the RF Classifier is 0.96, for the DT Classifier is 0.98, and for the KNN Classifier is 0.95. When we used the heterogeneous chain-based model for our model, we achieved an overall accuracy of 0.97, and if the relation-based proposed model is used, the overall accuracy is 0.98. The results clearly express that our model with DT and our relation-based proposed model with different classifiers have superior accuracy results than all models. Also, our model with different estimators shows the second-best accuracy results and better results than existing models. It appears to be higher than the accuracy of the heterogeneous model, RF-based chain or KNN-based chain; however, it is lower than the accuracy of the DT-based chain.

Table 5.5 Accuracy Results of the Our Relation Based Heterogeneous Model

Inputs	Base Estimator	Output	Accuracy
Main Inputs	DT Classifier	Package Type	0.99
Main Inputs Predicted Package Type	DT Classifier	Package Number	0.96
Main Inputs Predicted Package Type	DT Classifier	Package Length	0.98
Main Inputs Predicted Package Type Predicted Package Length	RF Classifier	Package Width	0.99
Main Inputs Predicted Package Type Predicted Package Length Predicted Package Width	RF Classifier	Package Height	0.96
Main Inputs Predicted Package Type Predicted Package Length Predicted Package Width Predicted Package Height	KNN Classifier	Packaging Type	0.97

Accordingly, our accuracy values for the recommended models and traditional chain-based models with different base estimators are provided in Table 5.6.

Our inference from the experimental analysis is that if the data is suitable for different algorithms for different outputs, this model will provide an accuracy increase. However, if the dataset is more suitable for based on one algorithm, this model can be used with just one algorithm, and it still results in an accuracy increase. In addition, the order of the predicted outputs is also important. If the order is changed inappropriately, the accuracy will decrease. Order is important because in a chain structure, a relation is created according to the order, and this relation between outputs affects accuracy. Based on this inference, we also added a relation parameter to our proposed model and referred to it as our relation-based proposed model.

In our relation-based proposed model, we eliminated the relation between the package number output and the next outputs, positively impacting our accuracy. Our chain structure transformed, where package type prediction became an input for all subsequent outputs.

Table 5.6 Accuracy Results of the Our Proposed Models and Conventional Models (The size of the chain is determined as six)

Model	Base Estimator	Package Type	Package Number	Package Length	Package Width	Package Height	Packaging Type	Overall
Multi-output Classification	RF Classifier (6)	0.99	0.96	0.94	0.99	0.94	0.99	0.87
Multi-output Classification	DT Classifier (6)	0.99	0.96	0.98	0.99	0.98	0.99	0.93
Multi-output Classification	KNN Classifier (6)	0.98	0.93	0.93	0.98	0.93	0.97	0.82
Chain Regression	RF Classifier (6)	0.99	0.96	0.94	0.99	0.94	0.99	0.93
Chain Regression	DT Classifier (6)	0.99	0.96	0.99	0.99	0.98	0.99	0.93
Chain Regression	KNN Classifier (6)	0.98	0.93	0.93	0.98	0.92	0.97	0.88
Our Homogeneous Model	RF Classifier (6)	0.99	0.96	0.94	0.99	0.94	0.99	0.97
Our Homogeneous Model	DT Classifier (6)	0.99	0.96	0.99	0.99	0.98	0.99	0.98
Our Homogeneous Model	KNN Classifier (6)	0.98	0.93	0.93	0.98	0.92	0.97	0.95
Our Heterogeneous Model	DT Classifier (3) RF Classifier (2) KNN Classifier (1)	0.99	0.96	0.98	0.99	0.96	0.97	0.97
Our Relation Based Heterogeneous Model	DT Classifier (3) RF Classifier (2) KNN Classifier (1)	0.99	0.96	0.99	0.99	0.96	0.97	0.98

We utilized it in predicting the package number, ensuring that this prediction was not used for subsequent predictions. We predicted the package length using the main inputs and the predicted package type. Subsequently, in predicting the package width, we once again employed the main inputs and the predicted package type and package length, and so forth. According to our data, we inferred that the package number is not an important or necessary input for these outputs, so we did not use it. However, if we recognize that the package number doesn't affect four of them but affects one of them, we can use this predicted output as an input for that specific output. The application of these relation-based strategies depends on the dataset and the research necessities. If the selected classifier is wrong in the chain, it will decrease the overall accuracy because it will feed incorrect information to the next classifier. On the other hand, if the selected classifiers are suitable, it will be beneficial for the overall accuracy. As a result of the discussion, the selection of the correct classifier for each output is crucial. If you use the correct classifier with a chain-based structure according to your data, your accuracy will increase. If there is no positive correlation between the outputs, using a chain-based algorithm will be unnecessary and may carry the risk of decreasing the overall accuracy.

In future works, IoT can be adopted in this process, so optimization can also be added to the important processes of supply chain management. Even though we provide an easy-to-manage packaging planning process, it depends on past choices. If the expectations increase, we start to question the past choices. We can investigate whether the packaging planning professionals in the past selected the correct dimensions and types for packaging. This study does not focus on optimizing the process; however, if the dimensions of parts are known, both optimization and AI techniques can be included. The process of obtaining product dimensions through IoT sensors and integrating them with AI for packaging planning plays a significant role in the entire journey of a product, from manufacturing or warehousing to shipping. Initially, IoT sensors are employed to measure the product dimensions in real-time, and this data is recorded in a database. Subsequently, AI models utilize this data to generate the most optimized packaging plan, and they can also make predictions based on past choices. These plans can be presented to professionals, and they can select the most suitable one. Then, they ensure that products are placed in the correct boxes for secure transportation. As a result, this integrated approach enhances logistics processes, reduces transportation costs, and ensures the safe transit of products.

5.2. Expert Opinion

In the preceding section, we conducted a survey targeting packaging planning experts to gather their insights on the rapidly evolving landscape of AI in the industrial sector. In this segment, we will evaluate and analyze the results obtained from the survey to glean valuable perspectives from these experts. The aim is to provide a comprehensive understanding of the current sentiments, challenges, and opportunities perceived by professionals in the field of packaging planning. This examination of expert opinions serves as a crucial step in refining and enhancing our proposed improved heterogeneous chain-based multi-output classification model for effective packaging planning, which is designed to predict dimensions and types of packages for each shipment. By juxtaposing the insights gleaned from the survey with our proposed model, we aim to fortify our approach and contribute to the advancement of AI in the domain of packaging planning.

Participant Information	**Katılımcı Bilgileri**	
Title (Just indicate as engineer, expert or technician.)	**Unvan (Sadece mühendis, uzman veya teknisyen olarak belirtin.)**	

Integration of Artificial Intelligence into Packaging Planning	**Paketleme Planlama Sürecine Yapay Zeka Entegrasyonu**
In the scope of this study, the steps performed by experts for each shipment in the packaging planning process will be automated by the system. The expert can approve this planning or request modifications. As the artificial intelligence adopts a continuously learning approach, it will contribute to making more accurate plans based on the updates made by experts. In the study conducted on current shipment information, accurate outputs were obtained at a rate of 98%. **Current Process:** - Decision on which packages the parts will be placed into is made. - Package type, width, length, and height are determined and entered into the system. - Entered package information is matched with the parts in the system. - Packaging type is determined for these packages and entered into the system. - Approval is given, and the shipment process proceeds to the next step. **After Artificial Intelligence Integration:** - Package and packaging type information for all parts in the shipment is ready on the screen. - The expert approves the information or makes updates, and the shipment process proceeds to the next step.	Bu çalışma kapsamında paketleme planlama sürecinde uzmanların her sevkiyat için yapmış olduğu aşağıda belirtilen adımlar sistem tarafından otomatik olarak yapılacaktır. Uzman bu planlamaya onay verebilir veya değişiklik işlemi yapılabilir. Yapay zeka sürekli öğrenen bir yaklaşım benimseyeceği için uzmanların yaptıkları bu güncellemeler sonrasında gelen planlamaları da daha doğru yapmasına katkı sağlayacaktır. Güncel sevkiyat bilgileri üzerinde yapılan çalışmada %98 oranında doğru çıktılar elde edilmiştir. **Mevcut Süreç:** - Parçaların hangi paketlere yerleştirileceğine karar verilir. - Paketlerin tipi , eni, boyu, yüksekliği belirlenir ve sisteme girilir. - Girilen paket bilgileri ile parçalar sistemde eşleştirilir. - Bu paketler için paketleme tipi belirlenir ve sisteme girilir. - Onay verilir ve sevkiyat süreci sonraki adıma geçer. **Yapay Zeka Entegrasyonu Sonrası Süreç:** - Sevkiyattaki tüm parçalar için paket ve paketleme tipi bilgileri hazır halde ekran açılır. - Uzman bilgileri onaylar veya güncelleme işlemi yapar, sevkiyat süreci sonraki adıma geçer.

Figure 5.3 Survey: Participant Information and Integration of AI into Packaging Planning

In the survey's initial section, we offered a concise overview of our study and requested information about your professional title. Illustrated in the Figure 5.3 is a summary of our study, outlining a system designed to automate expert-performed steps in packaging planning for each shipment. This empowers experts to approve or request modifications to the planning. Artificial intelligence, utilizing a continuous learning approach, refines plan accuracy based on expert updates. Our study demonstrated an impressive 0.98 accuracy rate in analyzing current shipment information. The existing process involves decisions on part-to-package assignment, entry of package details, matching with corresponding parts, determination of packaging type, and approval. Post artificial intelligence integration, package and packaging type information for all shipment parts is conveniently accessible on-screen. The expert can then either approve or update the information, ensuring a smooth progression of the shipment process.

In the second section of the survey, as illustrated in Figure 5.4, we sought information about the expertise of the respondents. Subsequently, we inquired about the impact of artificial intelligence integration, assessing metrics such as time, cost, quality, user-friendliness, and other relevant factors. Respondents were asked to evaluate these metrics on a 5-point Likert scale to gauge the extent to which the integration of artificial intelligence has benefited in terms of these criteria.

In the third section of the survey, as depicted in the Figure 5.5, we examined the users' adaptation to the application. We posed questions to assess the impact of artificial intelligence on users when, upon opening their packaging planning application, data is presented as if they had manually entered it before, despite no visual or functional changes. The effects on users were evaluated in terms of ease of use and whether there was a need for additional training, even when there were no observable alterations in the visual or functional aspects of the packaging planning application.

In the last section, as shown in the Figure 5.6, we inquired about the improvement of the current study through future research endeavors. With this question, our aim was to analyze how crucial optimization is perceived by packaging planning experts, given that optimization stands as a pivotal aspect for these professionals. Understanding that optimization is a critical factor, especially beyond standard packaged shipments tailored to company requirements, we

Expert Experience	Uzman Deneyimi					
1:Very little experienced, 2: Low experienced, 3: Moderately experienced, 4: Experienced, 5: Very experienced	**1: Çok az deneyimliyim, 2: Az deneyimliyim, 3: Orta düzeyde deneyimliyim, 4: Deneyimliyim, 5: Çok deneyimliyim**	**1**	**2**	**3**	**4**	**5**
Evaluate your knowledge level in the packaging planning process.	Paketleme planlama sürecinde bilgi düzeyinizi değerlendirin.					

Impact of Artificial Intelligence Integration on Benefits	Yapay Zeka Entegrasyonu Fayda Etkisi					
1: No benefit at all, 2: Minimal benefit, 3: Some benefit, 4: Beneficial, 5: Very beneficial	**1: Faydası yok, 2: Az Faydalı, 3: Orta düzeyde faydalı, 4: Faydalı, 5: Çok faydalı**	**1**	**2**	**3**	**4**	**5**
Assess the potential integration of artificial intelligence into the packaging planning processes in your company.	Şirketinizdeki paketleme planlama süreçlerine yapay zeka entegrasyonu yapılmasını değerlendirin.					
Evaluate the time contribution of artificial intelligence integration to the packaging planning process.	Yapay zeka entegrasyonunun paketleme planlama sürecine zaman açısından katkısını değerlendirin.					
Assess the cost impact of artificial intelligence integration on the packaging planning process.	Yapay zeka entegrasyonunun paketleme planlama sürecine maliyet açısından katkısını değerlendirin.					
Evaluate the impact of artificial intelligence integration on the packaging planning process from a quality perspective.	Yapay zeka entegrasyonunun paketleme planlama sürecine kalite açısından etkisini değerlendirin.					
Evaluate the impact of artificial intelligence integration on the packaging planning process from a reliability perspective.	Yapay zeka entegrasyonunun paketleme planlama sürecine güvenilirlik açısından etkisini değerlendirin.					
Evaluate the user-friendliness of artificial intelligence integration in the packaging planning process.	Yapay zeka entegrasyonunun paketleme planlama sürecinde kullanım kolaylığını değerlendirin.					

Figure 5.4 Survey: Expert Experience and Impact of AI Integration Benefits

sought to explore the significance of optimization and artificial intelligence working together. While explaining that, at present, our model cannot integrate optimization due to the lack of essential information, it was highlighted that if this information were available, the joint impact of optimization and artificial intelligence was underscored as significant for experts.

After collecting survey responses, an extensive analysis using SPSS (Statistical Package for the Social Sciences) was conducted to delve into the statistical measures. SPSS is a software package widely used in the fields of social sciences and statistical analysis [37]. It provides tools for data analysis, data mining, statistical modeling, reporting, and graphing. Researchers, statisticians, and social scientists commonly use SPSS to analyze datasets,

Usability	Kullanılabilirlik					
1: Very difficult, 2: Difficult, 3: Moderate, 4:Easy, 5: Very easy	**1: Çok zor, 2: Zor, 3: Orta, 4: Kolay, 5: Çok kolay**	**1**	**2**	**3**	**4**	**5**
Evaluate your system's adaptation process after the integration of artificial intelligence into the packaging planning process.	Paketleme planlama sürecine yapay zeka entegrasyonu sonrası sisteme adaptasyon sürecinizi değerlendirin.					
Assess the usability of the system after the integration of artificial intelligence into the packaging planning process without the need for additional training.	Paketleme planlama sürecine yapay zeka entegrasyonu sonrası sistemin ekstra bir eğitim alınmadan kullanılabilirliğini değerlendirin.					
Evaluate the usability of your application without any changes after the integration of artificial intelligence into the packaging planning process.	Paketleme planlama sürecine yapay zeka entegrasyonu sonrası uygulamanızda bir değişiklik olmadan kullanılabilirliğini değerlendirin.					

Method Detail	Metod Detay					
1: No benefit at all, 2: Minimal benefit, 3: Some benefit, 4: Beneficial, 5: Very beneficial	**1: Faydası yok, 2: Az Faydalı, 3: Orta düzeyde faydalı, 4: Faydalı, 5: Çok faydalı**	**1**	**2**	**3**	**4**	**5**
Evaluate the independent prediction of all outputs when predicting package information. Example: Assessing that after predicting the package length, this information is not used as an input for predicting the package width.	Paket bilgileri tahmin edilirken tüm çıktıların bağımsız tahmin edilmesini değerlendirin. Örnek: Paket boyu tahmin edildikten sonra bu bilginin paket eni tahmininde bir girdi olarak kullanılmaması.					
Evaluate the influence of all outputs on the predictions made subsequently when predicting package information. Example: Assessing the use of predicted package length in predicting package width, and then using both pieces of information in predicting package height.	Paket bilgileri tahmin edilirken tüm çıktıların kendinden sonra tahmin edilenleri etkilemesini değerlendirin. Örnek: Paket boyu tahmin edildikten sonra bu bilginin paket eni tahmininde kullanılması ve bu iki bilginin daha sonra paket yüksekliği tahmininde de kullanılması.					
Evaluate only the influence of related outputs on each other when predicting package information. Example: Assessing the use of predicted package length in predicting package width but not using it in predicting package number.	Paket bilgileri tahmin edilirken sadece ilişkili çıktıların birbirini etkilemesini değerlendirin. Örnek: Paket boyu tahmin edildikten sonra bu bilginin paket eni tahmininde de kullanılması ama paket numarasının tahmininde kullanılmaması.					

Figure 5.5 Survey: Usability and Method Detail

identify patterns, conduct hypothesis testing, and report results. Presented as a desktop application with a user-friendly interface, SPSS is favored for its ease of use and is employed by professionals across various disciplines seeking to perform statistical analyses.

Benefit impact of Future Work	Gelecek Çalışmaların Fayda Etkisi					
1: No benefit at all, 2: Minimal benefit, 3: Some benefit, 4: Beneficial, 5: Very beneficial	1: Faydası yok, 2: Az Faydalı, 3: Orta düzeyde faydalı, 4: Faydalı, 5: Çok faydalı	1	2	3	4	5
Due to the absence of dimensional information about the parts in the current process, optimization methods cannot be applied to improve this process. Evaluate the use of artificial intelligence learning from experts' past planning and optimization once dimensional information about the parts is systematically accessible.	Mevcut süreçte parçaların boyut bilgisi sistemsel olarak mevcut olmadığı için optimizasyon yöntemleri kullanılarak bu süreçte iyileştirme yapılamıyor. Parçaların boyut bilgilerine sistemsel olarak erişilebilir olduktan sonra uzmanların eski planlamalarından öğrenen yapay zeka ve optimizasyonun birlikte kullanılmasını değerlendirin.					

Figure 5.6 Survey: Benefit Impact of Future Work

The results were summarized in Table 5.7 detailing mean values and standard deviations. Mean values reflected the average scores, providing insight into central tendencies, while standard deviations quantified data dispersion, indicating variability in responses. This analysis not only summarized survey outcomes but also offered a nuanced understanding of response distribution across variables, enabling a comprehensive interpretation of the collected data.

In order to ascertain the reliability of the collected responses, we performed Reliability Statistics as a crucial step in our analysis. This statistical method aids in evaluating the consistency and dependability of the data collected through the survey. The Reliability Statistics results for different sections of our questionnaire are presented comprehensively in the Table 5.8. These statistics offer valuable insights into the internal consistency of the survey items within each section, shedding light on the extent to which the questions in each part of the questionnaire measure the same underlying construct. A high reliability coefficient suggests that the questions in a particular section are consistently measuring the intended construct, enhancing our confidence in the robustness of the survey instrument. These reliability metrics play a pivotal role in ensuring the validity and trustworthiness of our survey results, contributing to the overall quality of the data analysis and interpretation.

There existed a discernible relationship among the stated methods, each designed with specific focuses. Method 1 aimed to "Evaluate the independent prediction of all outputs

Table 5.7 Descriptive Statistics of Survey

Question	Mean	Std. Deviation
Evaluate your knowledge level in the packaging planning process.	4.2857	.48795
Assess the potential integration of artificial intelligence into the packaging planning processes in your company.	4.1429	.69007
Evaluate the time contribution of artificial intelligence integration to the packaging planning process.	4.2857	.95119
Assess the cost impact of artificial intelligence integration on the packaging planning process.	4.0000	.81650
Evaluate the impact of artificial intelligence integration on the packaging planning process from a quality perspective.	4.1429	.69007
Evaluate the impact of artificial intelligence integration on the packaging planning process from a reliability perspective.	4.1429	.69007
Evaluate the user-friendliness of artificial intelligence integration in the packaging planning process.	4.5714	.53452
Evaluate your system's adaptation process after the integration of artificial intelligence into the packaging planning process.	3.8571	.69007
Assess the usability of the system after the integration of artificial intelligence into the packaging planning process without the need for additional training.	4.0000	.57735
Evaluate the usability of your application without any changes after the integration of artificial intelligence into the packaging planning process.	3.8571	.69007
Evaluate the independent prediction of all outputs when predicting package information.	3.8571	.69007
Evaluate the influence of all outputs on the predictions made subsequently when predicting package information.	4.1429	.69007
Evaluate only the influence of related outputs on each other when predicting package information.	4.4286	.78680
Due to the absence of dimensional information about the parts in the current process, optimization methods cannot be applied to improve this process. Evaluate the use of artificial intelligence learning from experts' past planning and optimization once dimensional information about the parts is systematically accessible.	4.8571	.37796

when predicting package information," emphasizing the autonomy of individual output predictions. In contrast, Method 2 sought to "Evaluate the influence of all outputs on the predictions made subsequently when predicting package information," highlighting the

Table 5.8 Reliability Statistics of Survey

Section	**Cronbach's Alpha**	**Cronbach's Alpha Based on Standardized Items**	**N of Items**
Impact of Artificial Intelligence Integration on Benefits	.859	.862	6
Usability	.750	.764	3
Method Detail and Benefit Impact of Future Work	.794	.839	4

interconnectedness of output variables in influencing subsequent predictions. Method 3 took a distinct approach, concentrating on ”Evaluate only the influence of related outputs on each other when predicting package information,” emphasizing the influence of interrelated outputs. Lastly, the future method proposed a unique perspective, stating that, ”Due to the absence of dimensional information about the parts in the current process, optimization methods cannot be applied to improve this process. Evaluate the use of artificial intelligence learning from experts' past planning and optimization once dimensional information about the parts is systematically accessible,” emphasizing the potential integration of artificial intelligence in the absence of dimensional information.

To gauge the perceptible relationship based on user responses, an Inter-Item Correlation Matrix was constructed and is shown in Table 5.9. This matrix provides a statistical overview of the degree of association between the different methods. Each cell in the matrix represents the correlation coefficient between two methods. A correlation coefficient close to 1 signifies a strong positive relationship, while a value near -1 indicates a strong negative relationship. A value close to 0 implies a weak or no correlation. Examining the results in the matrix, the correlation between the methods diminishes gradually towards the future method, indicating a decreasing relationship strength. Noteworthy is the closer correlation between Method 3 and the future method, suggesting a more aligned influence. Similarly, Method 2 shows proximity to Methods 1 and 3 but exhibits a more distant correlation with the future method, providing valuable insights into the comparative impact of these analytical approaches.

Table 5.9 Inter-Item Correlation Matrix of Methods

	Method 1	**Method 2**	**Method 3**	**Future Method**
Method 1	1.0000	.400	.132	.548
Method 2	.400	1.0000	.789	.730
Method 3	.132	.789	1.000	.801
Future Method	.548	.730	.801	1.000

In summary, based on the insights gathered from expert opinions, professionals in the field of packaging planning have positively evaluated the integration of artificial intelligence and its adaptation. They have expressed the belief that, in the future, combining this integration with optimization will result in a more beneficial model. Additionally, concerns were raised in the examined opinions and additional notes, indicating that the model may only work accurately for specific scope of shipments and might not perform well for new or extreme conditions in shipments. It is acknowledged that such concerns may arise due to the nature of the data, and if the model encounters a situation it has not seen before, it might produce inaccurate results. However, with repeated exposure to similar scenarios, the model is expected to yield useful results. While this study was conducted on a specific dataset, further evaluations can be performed on larger datasets to assess the outcomes. Nevertheless, even in its current state, the study achieved a high accuracy rate, encompassing a significant portion of the shipments.

6. CONCLUSION

This thesis proposes a relation-based heterogeneous chain-based multi-output classification model for automated and effective packaging planning. Our model offers flexibility in determining different classifiers within the traditional chain structure and it provides a valuable contribution to the field of AI-supported packaging planning. Also, the relation between outputs in a chain can be determined. Thus, the chain will not be a straight chain; it will be a relation-based complex chain according to the dataset. The experimental results clearly show that our proposed model enhances the accuracy when compared to traditional chain-based models including multi-output classification and chain regression models. Specifically, our homogeneous model based solely on DT and the relation-based heterogeneous model have superior performance with 0.98 overall accuracy compared to its benchmarks. Furthermore, the heterogeneous model with different classifiers including the DT, RF, and KNN together, shows better performance than the traditional multi-output classification and chain regression models.

This thesis introduces a new framework for applications in supply chain management and the packaging industry. However, the thesis has its limitations, particularly regarding the size and diversity of the dataset, which posed some challenges. Inputs in each shipment process can vary based on their specific shipment processes.

Our upcoming plan includes thoroughly studying bigger and more varied datasets. We'll also compare different algorithms in a detailed way. Additionally, by improving the optimization in our process and adding more data, we hope to find the best solution to our current problem. Combining optimization and artificial intelligence techniques could really improve how well our approach works.

Regrettably, our thesis faced challenges in including optimization because of restrictions from the dataset. But, we plan to expand our research to fix this issue and include optimization strategies. This improvement should make our model work better, adapting well to real-world situations.

The significance of this thesis extends beyond its immediate findings, making a noteworthy contribution to the realm of AI-supported packaging planning by leveraging chain-based model approaches. The thesis also adds value to the field of multi-output classification and the chain of classifiers through systematic experimentation. As we explore new areas, this work gives a strong starting point for future improvements and could help guide future work in this field. Our plan shows we're committed to getting better and finding new ways to solve problems by using both AI and optimization techniques.

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