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Selecting Appropriate Type of Package with Machine Learning Models in Logistic Companies

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ABSTRACT: There are many factors for Logistics Companies to be successful and financially profitable. These factors can be grouped under two main headings, namely, the efficiency values of the processes and the costs. One of the most important costs is the cost of packaging and shifting. When the packaged orders are delivered to the cargo companies, the packaging and shifting costs are incurred in a way that is directly proportional to the volume value of the order. In logistics companies, these costs increase as a result of placing the order in a package with a larger volume value instead of the appropriate package type. Solving the pallet loading or container loading problems with mathematical models, the packaging personnel's output of the mathematical model for each order, and the employee's placing these products in the package according to the results of the model significantly reduce the efficiency value of the processes. For this reason, in this article, it is aimed to examine and learn the historical packaging data with different machine learning models and to inform the packaging personnel about which package type should be used for the current order.

1. INTRODUCTION

According to the Kotlars and Skribans (2016), most of the international business contact with different level of logistic companies according to their needs to optimize all logistic processes from producer to the end user and transportation cost thanks to logistic companies' knowledge and experiences. Diverse needs from the business are increasing and these situations create big problems. They need different type of integration such as management of cargo and storage (Sheikh, Rana 2014).

Diverse needs from companies bring different integration levels. These levels are.

- 1st Party Logistic Companies: these are the individual firms, and these firms have their own cargos.
- 2nd Party Logistic Companies: these are the firms which offers transportation services.
- 3rd Party Logistic Companies: transportation and delivery of the goods. According to the Mcfarland, it is called Light Asset Logistic.
- 4th Party Logistic Companies: in this model in addition to the outsourcing of management of logistic services, implementation throughout the supply chain is outsourced. These companies provide more strategic and innovative insights for the supply chain
- 5th Party Logistic Companies: in this model most of the functions are controlled by the logistic company. Different type of automations, artificial intelligence, and machine learning are used mostly.

For the logistic companies there are several factors to be successful and profitable. These factors can be grouped under two main headings, namely, the efficiency values of the processes and the costs. Top 4 cost which affect the logistic companies' total costs are land and facility cost, manpower cost, capital cost, operational cost. Also, there are different cost types which are related with the operational cost. These are inbound cost, storage cost, picking cost, packaging cost, and shifting cost.

Like other type of costs, packaging and shifting cost is one of the most important types for the warehouse total cost. Logistic processes need determination about appropriate type of package for the orders. If they use large package instead of small package which is appropriate for the orders, company will pay more for the transportation cost. Some products need specific type of packages, and these specifications need to be considered. So, according to the ElMaraghy (2013), increasing changes and different type of products increase the effort for packaging of these products. All products have their specific attributes such as height, length, weight, volume ext. Thinking all these attributes and deciding on appropriate type of package is extremely hard and time confused. Also, when package include more than one product, deciding on appropriate type of package will be more difficult because created model should consider all of the attributes for all of the products.

In literature most of the mathematical models about determinations of appropriate type package deal with pallet loading problem or container loading problem. According to the Gajda, Trivella, Mansini and Pisinger (2020), container loading problem is packaging problem with three dimensions. There are items and these items must be loaded into a container or into a box by satisfying some constraints which are pre-defined. In some problems all items can be loaded, and this is preferred result. However, in some problems all items cannot be loaded, and model tries to maximize some values of loaded items such as their volume, price, profit. These problems are mostly solved by using mathematical models and heuristic approaches. According to the Bortfeldt (2012), Container loading problem is mostly deals with rectangular items. This approach creates a difficulty when there is a nonrectangular item in the models. So, it is concluded that except from geometric characteristic, different attributes and variables such as weight, and fragility are needed for the appropriate model (Bischoff, Wäscher 2013).

In addition to the mathematical models, machine learning has particularly significant role for the logistic process. Within the last years, different industries use machine learning (ML) process for their operations. ML uses algorithms which receive and analyze input data to predict output data within the acceptable range. There are two different type of machine learning process. First one is supervised machine learning which requires some set of data for classification or regression. Second one is unsupervised machine learning which is mostly used for clustering (Kotsiantis, Zaharakis, Pintelas 2007).

In this paper, packaging data in a supply chain company was taken and machine learning models were applied. Applied ML models are Random Forest Classifier, Radial Support Vector Machine Classifier, Linear Support Vector Machine Classifier, Logistic Regression, Decision Tree, K-Nearest Neighbors and Gaussian Naive Bayes.

2. LITERATURE REVIEW

For the determining appropriate type of package, different techniques are improved and used by the companies. Some companies use mathematical models, some of them use machine learning and artificial intelligence. According to the Voskogluo (2006), Mathematical models is transforming of the real word cases to the models or to the mathematical problems. In colloquial speech, real situations are hard and difficult to solve. Thanks to the mathematical models, real situations are simplified by using some variables, parameters, and mathematical functions to reach optimum results.

General idea about pallet loading problem and container loading problem is it is NP hard problem. So, most of the researchers use stochastic methods and nonlinear integer programming (Lau, Chan, Tsui, Ho, Choy 2009). These two methods have a different effect about cost and time. Stochastic method give suboptimal solution and it is not expensive. However, nonlinear integer programming gives optimal solutions with expensive cost.

Gajda, Trivella, Mansini and Pisinger studied container loading problem which has numerical practical constraints. These constraints are weight, weight distribution, balancing, priority of loading, orientations of items, stacking, hazardous items, stability. They developed heuristic algorithms. This algorithm is known as an RCH which is randomized constructive heuristic algorithm. This algorithm produces a solution in few seconds.

Another study about pallet loading problem is done by the Gzara, Elhedhli and Yildiz in 2020. Their mathematical model gives a solution in a minute per pallet. Their approach based on the layer-based column generation approach, and they improve this approach by satisfying some constraints. Some of these constraints are vertical support, reducing support surfaces, items with different shapes, weight limitation. One of the most important constraints is about planogram sequencing. This is referring to an arrangement of products that makes it simple and easy to unload pallets and facilitates effective storage at retail location. Their model proposes second order cone program for item spacing to guarantee the minimum industry support of %70. Additionally, they incorporated diverse item forms and reduced support surfaces into a placement algorithm. This was the first study which consider these features.

Branch and bound method is one of ways to solve container loading problems. Martello et al. (2000) improved a method to fill single container. This is suitable when the amount of item is less than 90.

One of the more complex MIP is studied by Paquay, Limbourg and Schyns (2018). They consider the three-dimensional bin size packing problem of items which have different shapes and sizes, and their aim is minimizing the unused space. They worked with the air cargo company and tried to utilize aircraft which is loaded by pallets. Their study has 2 phases, and these two phases include tailored constructive heuristic. The first phase packing algorithm is improved for the identical bins by satisfying the constraints such as stability and durability of bins, different orientation, weight capacity. In the second phases, they try to do same thing for the different bins. They want to create weight balance between bins. Running time of their algorithm is short like few minutes and it gives a solution in terms of filling rate.

Another study is done by Li, Chen and Huo (2022). They tried to solve large-scale heterogenous container loading problem (HCLP). This is more complex form of the multiple container loading problem. The aim of this study is choosing a set of containers with different dimensions to locate all items by minimizing unused scape rate. For this problem hybrid adaptive large neighborhood search (HALNS) is used to solve. In each iteration, some containers are destroyed and repaired. Weight limit and suspension constraints are more important for this approach.

Except from mathematical models, some studies tried to solve this problem with machine learning models.

According to the Knoll, Munier, Prüglmeier, Reinhart (2019), fill rate is one of the good approaches for this problem. Their machine learning model standardized process for selecting package type and calculate fill rate. They determine 6 different category and 13 features. They use package type and fill rate as a label

1. Dimensions (length, width, height, volume)
2. Shape (length/width, height/length, height/width)
3. Weight (weight, weight/volume)
4. Quality/sensitivity (quality index, electrostatic)
5. Price (part price)
6. Dangerous good (dangerous good)

They firstly create packaging classification model to determine appropriate type of package. After that, they do fill rate regression model. İnput of this model is output of packaging classification model.

Another study is done by Aylak, İnce, Oral, Süer, Almasarwah, Singh and Salah (2021). They try to optimize pallet loading problem by using machine learning methods. According to the Aylak, İnce, Oral, Süer, Almasarwah, Singh and Salah (2021), most of the logistic processes have a significant role in cost reduction. They focus on determining classification method for pallet loading problem. Some key features for the data are humidity and storage duration. Their model has 2 phases. In the first phase aim is maximizing the number of boxes per horizontal layer. In the second phase number of horizontal layers loaded per pallet is determined by considering maximum height, weight, and strength. They categorize the pallets and Support vector classifier, decision tree classifier, K nearest neighbour classifier, random forest classifier and artificial neural network classifiers were used to determine appropriate type of pallet category. Accuracy value of their model is higher than %89 and they get nearly %85 pallet utilization volume. They used 10-fold cross validation. The features of the data set are box width, length, height, and demand.

3. METHODOLOGY

In this article 6 different machine learning models are used to determine appropriate type of package for the orders in third party logistic company. These models are Decision Tree, Support Vector Machines, K-nearest Neighbor, Gaussian Naïve Bayes, Logistic Regression and Random Forest.

Decision Tree Classifier: According to the Bansal, Goyal and Choudhary (2022), Decision Tree (DT) algorithm is one of the supervised algorithms and it is used mostly for the classification. Tree based methods are known with high accuracy and stability. DT models can map nonlinear datasets well. A decision node has two or more branches. The leaf node represents a classification or decision. The top decision node in a tree corresponds to the best determinant, called the root node. Decision trees can handle both categorical and numerical data.

Support Vector Machines: According to the Bansal, Goyal and Choudhary (2022), Support Vector Machines (SVM) algorithm is one of the supervised algorithms. It is used for the regression and classification. Except regression and classification this method is used in different areas such as images, hypertext, text segregation classification vs. In this algorithm, each data item is plotted as a point in n-dimensional space with the value of each feature being the value of a particular coordinate. Next, the classification is performed by finding the hyperplane that distinguishes the two classes quite well. Support Vectors are just the coordinates of the observation. The Support Vector Machine is a boundary that best separates the two classes (hyperplane/line).

K-Nearest Neighbor Algorithm: According to the Bansal, Goyal and Choudhary (2022), K-Nearest Neighbor (K-NN) algorithm is one of the supervised algorithms. This method can be used for the classification and regression projects. K means count of neighbors of the new data point. For the given data set, model examine k neighbors and predict the classification of the new data point. To get better result, most important thing is determination of K value. Low value of K such as 1 or 2 predict noisy results. Extremely high K values takes too much time and model consider more points for prediction and model becomes more resilient to outliers.

Mostly, K values is chosen as a 5. Another method for determining K value is using this formula:

$$K = \sqrt{n}$$

Gaussian Naïve Bayes: According to the Lewis (1998) and Hand and Yu (2001), Naïve Bayes is simple algorithm for prediction. This algorithm depends on the statistic. According to the Lee, Gutierez and Dou (2011), each feature is considered independent of each other in this algorithm. So, its performance is higher than some models such as logistic regression. It can perform well on high dimension data.

There are some negative sides for Naïve Bayes. In real life, every feature has connection with another feature at some point. Relationships between variables cannot be modeled because operations are performed by assuming that the properties are independent of each other.

Logistic Regression: Logistic Regression is a regression method for classification. It is used to classify categorical or numerical data. By using the fewest number of variables, logistic regression analysis aims to explain the relationship between the independent and dependent variables. The assumption that the dependent variable must be continuous is not necessary in logistic regression analysis. When the dependent variable has two or more qualitative values, Logistic Regression can be used (Albert and Lesaffre, 1986; Aldrich and Nelson, 1984; Lemeshow and Hosmer, 2000).

Random Forest Classification: Random Forest is a one of the machine learning algorithms which is developed by Leo Breiman. It allows us to build various models and create classifications by training each decision tree on a different observation sample on multiple decision trees (Akar and Güngör, 2012). In Random Forest training is used on different data sets and thanks to that, variance or overfitting is reduced. This is one of the biggest problems of decision tree models.

4. DATASET, APPLICATION AND RESULTS

4.1. Dataset

Before using machine learning algorithms for determining appropriate type of packages for the orders, attributes should be determined. For the data sets, there will be more columns and some the columns must be eliminated. This process is called dimension reduction approach. According to the Dubey and Bhujade (2021), instead of feature extraction, most used method for this approach is feature selection. According to the Cai, Luo, Wang and Yang (2018), feature selection is important optimization problem. There is different classification for the feature selection methods. These classifications are supervised, unsupervised, wrappers or filters, feature ranking or subset selection, correlation, information gain or Euclidean distance-based approaches. The aim of feature selection is elimination of redundancy and improve relevancy. Using different metrics such as correlation, information gain; redundancy and relevancy of data set can be easily described. After appropriate feature selection, datasets will have low redundancy and high relevancy. Thanks to this elimination, valuable and powerful training model can be developed (Shen, 2021).

For the determining appropriate type of package, some attributes are especially important. According to the Rosenthal (2016), there are different type of packaging characteristics. These are:

- Size such as small load carriers
- Type such as standard or special
- Material such as plastic or metal

According to the Boeckle (2013) and Schulz (2014) size and weight is the main attributes for the packaging decisions.

For this study, packaging data of 196,059 order (853,534 product) is prepared. Some orders include just one product, and these types of orders are called mono SKU order. Some orders include more than one product, and these types of orders are called multi-SKU orders. Details of orders and their type are shown on Table 1.

Table 1: Order Types Amount and Ratios

	Order Amount	Order Ratio	Product Amount	Product Ratio
Mono SKU	43,443	22.2%	43,443	5.1%
Multi SKU	152,616	77.8%	810,091	94.9%

Some order can be packaged with just one package type. However. Sometimes more than one package is needed to package any order. In order to package 196,059 orders, 196,400 package is used.

These orders are put into different type of packages. These package types and their using amount are shown on Table 2.

Table 2: Package Types Usimg Amount and Ratios

Package Type	Order Amount	Order Ratio	Package Amount	Package Ratio
Nylon Bag	8,123	4.1%	8,156	4.2%
Package 1	89,247	45.5%	89,249	45.4%
Package 2	56,094	28.6%	56,094	28.6%
Package 3	32,483	16.6%	32,483	16.5%
Package 4	1,940	1.0%	1,952	1.0%
Package 5	616	0.3%	689	0.4%
Package 6	7,261	3.7%	7,277	3.7%
Special Package	459	0.2%	500	0.3%
Total	196,059	100.0%	196,400	100.0%

After considering all of them, 12 attributes were chosen for the dataset. These attributes are.

- Number of products
- Number of different products
- Total volume of products
- Total height of products
- Max height of products
- Total length of products
- Max length of products
- Total width of products
- Max width of products
- Average height / width
- Average length / height
- Average length / width

These attributes are important for choosing of appropriate type of package. Average height / width, average length / height and average length / width give information about the product shape. For example, all of these three equals 1, then it can be said that this product is cube. Thanks to the Max height, max length and max width; some package types eliminated easily. Every package type volume capacity and total volume of products is crucial factor. Total height, total length and total width also give information about package type and settlement plan. After controlling dimensions, some products do not have any dimension values on database. Because of that, these products and their packages are removed from data set. As shown on the Table 3, 561 package is removed from data set.

Table 3: Amount of Outlier Data

	Amount	Ratio
Outlier	561	0.3%
Not Outlier	195839	99.7%
Total	196400	100.0%

Some package types (Nylon Bag and Special Package) are used for different purposes such as sending to the suppliers or shops. So, these package types removed from data set. Removed package types of amount and ratios are shown on the Table 4.

Table 4: Removed Package Types and Their Usage Amounts

Package Type	Order Amount	Order Ratio	Package Amount	Package Ratio
Package 1	89247	45.5%	89249	45.4%

Package 2	56094	28.6%	56094	28.6%
Package 3	32483	16.6%	32483	16.5%
Package 4	1940	1.0%	1952	1.0%
Package 5	616	0.3%	689	0.4%
Package 6	7261	3.7%	7277	3.7%
Special Package	459	0.2%	500	0.3%
Nylon Bag	8123	4.1%	8156	4.2%

Nylon Bag and Special Package types include 8,656 package and these are also considered as an outlier and removed from data set. After eliminating outliers, final data set includes 187,197 packages.

4.2. Application of Machine Learning Models and Their Results

Before applying any machine learning model, normalization is applied. All dataset is arranged between 0 and 1 after normalization. Before normalization first "Sum of Height" value is 1.5 but, after normalization this value becomes 5.00017858e-04 (0.000500017858).

After normalization, correlation between the attributes is analyzed. According to the correlation values, heat map is created. Larger values means that there is high correlation between these two attributes. However, when value is smaller it means that there is negative high correlation between these two attributes. According to the Figure 1, there is high correlation (0.94) between "Products Amount" and "Sum of Length". This means that if "Products Amount" increase then "Sum of Length" will increase. Another inference is there is negative high correlation (-0.21) between "Max of Width" and "Average of Length/Width".

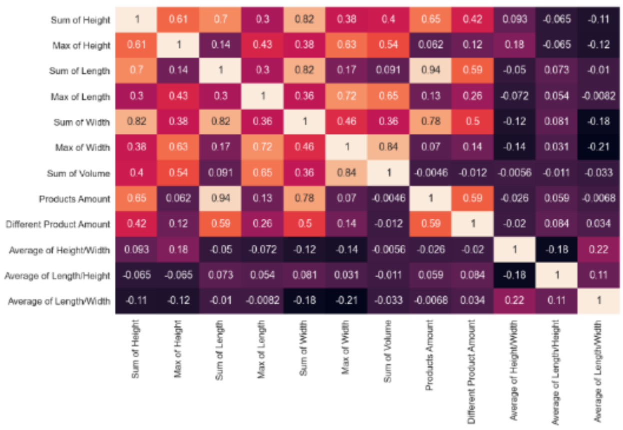

Figure 1: Correlation Values Between Attributes

After doing normalization and observing correlation values between attributes, different machine learning models are Applied to dataset. Dataset is divided into two parts: test (%25) and training data (%75).

Logistic Regression: Logistic Regression has a hyperparameter which is called 'C'. When high C value is chosen, the model gives more weight to the training data. Also, high C value shows that training data is more important, while low C value is just the opposite.

After considering different C values the results are shown on Table 5.

Table 5: Logistic Regression Accuracy Results with Different 'C' Values

Models	Accuracy
Logistic Regression (C = 1.3)	0.790385
Logistic Regression (C = 1.5)	0.790385
Logistic Regression (C = 1.8)	0.790363
Logistic Regression (C = 0.8)	0.790192
Logistic Regression (C = 1.0)	0.790192
Logistic Regression (C = 0.5)	0.790150
Logistic Regression (C = 2.0)	0.790128
Logistic Regression (C = 0.3)	0.789722
Logistic Regression (C = 0.1)	0.788675

K-Nearest Neighbor: Different K values (count of neighbor) are assigned. When high K value is chosen, accuracy will be higher, and model will be less flexible. Ideal K value is calculated by using $K = \sqrt{n}$ formula. So, K =4 will be more accurate for the K-Nearest Neighbor model and its accuracy value is 0.798098. After considering different K values the result is shown on Table 6.

Table 6: K-Nearest Neighbor Accuracy Results with Different 'K' Values

Models	Accuracy
K-Nearest Neighbor (K=10)	0.809145
K-Nearest Neighbor (K=9)	0.807863
K-Nearest Neighbor (K=8)	0.807372
K-Nearest Neighbor (K=7)	0.805150
K-Nearest Neighbor (K=6)	0.803291
K-Nearest Neighbor (K=5)	0.800427
K-Nearest Neighbor (K=4)	0.798098
K-Nearest Neighbor (K=3)	0.790128
K-Nearest Neighbor (K=2)	0.768526
K-Nearest Neighbor (K=1)	0.753910

Support Vector Machine: There are three different Kernel method which are linear, radial, and polynomial. According to these three-kernel method, model results are shown on Table 7. Most accurate model is obtained with Radial Kernel method.

Table 7: SVM Accuracy Results with Different Kernel Methods

Models	Accuracy
Support Vector Machine (Radial)	0.812372
Support Vector Machine (Linear)	0.794124
Support Vector Machine (Poly)	0.738889

Finally, three different model is applied to the dataset. These models are Decision Tree, Random Forest and Gaussian Naïve Bayes. Their results are shown on Table 8.

Table 8: Random Forest, Decision Tree and Gaussian Naïve Bayes Accuracy Results

Models	Accuracy
Random Forest	0.833846
Decision Tree	0,775833
Gaussian Naive Bayes	0.672799

Same models are applied again with cross validation. K-fold cross validation divides the data into equal parts according to a determined k number, ensuring that each part is used for both training and testing, thus minimizing deviations and errors caused by dispersion and fragmentation. N is chosen 10. Results of the same models with cross validation is shown on Table 9.

Table 9: Accuracy Results of Models with Cross Validation

Models	Accuracy
Logistic Regression (C=0.3)	0.788736
Logistic Regression (C=0.5)	0.78896
Logistic Regression (C=0.8)	0.788971
Logistic Regression (C=1.0)	0.788934
Logistic Regression (C=1.3)	0.789147
Logistic Regression (C=1.5)	0.789238
Logistic Regression (C=1.8)	0.789201
Logistic Regression (C=2.0)	0.789185
Logistic Regression (C=0.1)	0.787887
K-Nearest Neighbors (n=10)	0.808549
K-Nearest Neighbors (n=9)	0.807882
K-Nearest Neighbors (n=8)	0.807134
K-Nearest Neighbors (n=7)	0.805771
K-Nearest Neighbors (n=6)	0.803907
K-Nearest Neighbors (n=5)	0.802059
K-Nearest Neighbors (n=4)	0.796845
K-Nearest Neighbors (n=3)	0.788266
K-Nearest Neighbors (n=2)	0.770076
K-Nearest Neighbors (n=1)	0.756022
SVM (Radial)	0.811931
SVM (Linear)	0.792977
SVM (Polynomial)	0.741748
Random Forest	0.831824
Decision Tree	0.773837
Gaussian Naive Bayes	0.672612

4.3. Managerial Impact

The real-world usability of a research is just as important as the research itself. The subject discussed in this study is important for logistics companies. While an order can be sent in a small volume box, sending it in a large volume box increases the company's packaging and shifting costs. By looking at certain features of an order, learning which box was used for that type of order in the past and suggesting it for new orders saves time and effort for the packaging personnel. In this way, the costs of logistics companies will be reduced.

Assuming that the personnel working in the handling processes of logistics companies change frequently, it will prevent loss of time for the selection of the appropriate box for the new arrivals and the personnel who do not have sufficient knowledge of the handling processes and will prevent the delivery of large parcels to the end users.

When a box that is larger than necessary is selected for an order, the products in the order will constantly move inside the box while being transported and it will be possible for the products to be damaged. Too many consumables will be used to prevent the products from moving in the box, and in this case, it will increase the cost of consumables and increase the total cost.

5. CONCLUSION

In third party logistic companies, there are different cost types and packaging & shifting cost is one of them. In order to decrease packaging & shifting cost, pallet loading problems and container loading problems are analyzed and different mathematical models, machine learning models and artificial intelligence models are improved.

In this study, packaging data was obtained, and different machine learning models applied. These models are Decision Tree, Support Vector Machines, K-nearest Neighbor, Gaussian Naïve Bayes, Logistic Regression and Random Forest. These models are applied without cross validation and with cross validation. After cross validation accuracy values decreased little bit but models will be more reliable.

According to the model results with cross validation, random forest classifier has highest accuracy value (0.831824). Second best model is Support Vector Machine with radial kernel (0.811931).

In the future study, it is planned that XGBoost Classifiers will be used. It is a decision tree-based application that uses a gradient boosting framework designed for speed and performance.

Parallel processing is a gradient boosting algorithm optimized by tree pruning, processing missing values, and editing to prevent overfitting.

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