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# Multicriterial Inventory Analysis with MATLAB Application: A Case Study from Health Care

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**Abstract**
Establishing an effective inventory control strategy requires appropriate information about the composition and characteristics of inventories. It is extremely important in the case of organizations with tight budget such as hospitals.In general, obtaining information for inventory-related decisions mainly has two obstacles. Firstly, the number of Stock Keeping Units (SKUs) being on hand at companies often exceeds the amount that can be manageable in singles. Observing the similarity among the SKUs based on one or more criteria can release the complex decision-making processes. One of the most frequently used approach of sorting SKUs into homogenous groups in inventory management is the ABC analysis. Secondly, the non-appropriate interpretation of the classification results of ABC analysis can lead to confusion. Comprehension of the results, especially in inventory management, can be facilitated by data visualization. The purpose of this study is to present an IT-based decision aid framework built on the traditional ABC analysis which supports the application of inventory-related case-based distance model and its visualization. A linear programing method is applied on MATLAB basis to determine the model parameters which is followed by a plotting method of linear and nonlinear separating surfaces. The results of the study are demonstrated through a case study from health care where the database comes from the inventory records of a general hospital.

Keywords: Multicriterial ABC analysis, MATLAB, visualization, case-based distance model;

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## 1. Introduction

In general, obtaining information for inventory related decisions mainly has two obstacles. Firstly, the number of Stock Keeping Units (SKUs) being on hand at companies often exceeds the amount that can be manageable in singles. Observing the similarities among the SKUs based on one or more criteria can release the complex decision making processes (Mohammaditabar, Ghodsypoura, & O'Brien, 2011). Hence, the inventory management and the inventory analysis embedded in it is a popular topic in operational research. Two different approaches of inventory management emerged in the last decades (Zomerdijk & de Vries, 2003). The first approach collects and analyses the factors that make up the organizational context in which the inventory management models work. These factors are the decision-making process, task allocation, communication processes, and behaviour (Zomerdijk & de Vries, 2003). The other approach is the so called traditional one that attempts to construct models on judgmental or statistical basis in order to enhance the decision making process (van Kampen, Akkerman, & van Donk, 2012). Some of these models remain only theoretical ones because the model development process has been overemphasized with less attention toward their implementation related requirements and empirical implementations reducing the option of acceptance and application of the model in practice (Bacchetti, Plebania, Saccania, & Syntetos, 2012). This phenomenon is referred to as theory-and-practice-gap in operations management. Numerous authors deal with this problem, some of them on the field of inventory management (Bacchetti, Plebania, Saccania, & Syntetos, 2012; de Vries, 2005; Daniel, Guide, & Srivastava, 1997; Lenard & Roy, 1995; Bacchetti & Saccani, 2011). Bacchetti, Plebani, Saccani and Syntetos (2012) raise the awareness for the need of case studies because they can serve as a bridge between theory and practice. They pointed out that there are models whose operationalization and application to a real case are missing. It receives more emphasise because the basis of these models is a simple model the so called traditional ABC analysis which is the most frequently used method to classify SKUs (Braglia, Grassi, & Montanari, 2004). Its base is the famous Pareto-observation, the 80-20 rule (Dickie, 1951). This approach has a shortcoming, namely it cannot provide an optimal solution for complex decision problems where more than one criterion has to be taken into consideration (Tsai & Yeh, 2008). Recognizing this problem numerous methods have been developed to relieve the complex multicriterial decision making situation in the last decades. These models like the weighted linear optimization (Ramanathan, 2006), the genetic algorithm (Guvemir & Erel, 1998), the analytic hierarchy process (AHP) (Partovi & Burton, 1993), the fuzzy set theory (Chu, Liang, & Liao, 2008) are capable of taking more than one criterion into account at the same time enabling a more sophisticated analysis framework. The common feature of these models is that they secede from the traditional basis, the 80-20 rule and take another direction based on the tools of operational research and artificial intelligence. Hence during the continuous development of inventory analysis models their complexity has increased dramatically as well. The larger complexity affected negatively the spread of these models in practice. Its other effect is that due to the increased needs for computation the information technology has become the prerequisites of these models. The present research is based on MATLAB application exploiting the option that the multicriteria analysis and its visualization tools can be linked together in one framework. In this sense, visualization tool means the representation of the classification result to facilitate the comprehension of classification process. In general, Kim, Suh and Park (2008) – like Russel (2008) - claimed that visualizing data provides important aids for decision makers to improve the decision making process. Keim (2002) stated that the field of visualizing data is an important part of the research concerning computer science to improve the lucidity of the data visually. Raising the number of factors (criteria) in inventory analysis leads to large, complex, unmanageable databases. This fact makes great demands for another ways of supporting tools in decision aid. One of them is the visualization tool. In particular, “data visualization has the potential to assist humans in analysing and comprehending large volumes of data, and to detect patterns, clusters and outliers that are not obvious using non-graphical forms of presentation” (Lee, Butavicius, & Reilly, 2003, p. 569). Concerning the case-based distance model (Chen, Li, Kilgour, & Hipel, 2008), Volf, Kovács and Szalkai (2011) proposed a visualization tool in order to enable the representation of the classification result in three dimensions.

In general, the inventory analysis models have been constructed to establish an effective inventory control policy that requires appropriate information about the composition and characteristics of inventories. It is extremely important in the case of organizations with tight budget such as hospitals. Even though hospitals carry a large number of inventories and they do not pay enough attention for inventory management, the inventory analysis methods are not unknown for these institutions (Nicholson, Vakharia, & Erenguc, 2004). The analysis of hospital inventories appear in three case studies. First Gupta, Gupta, Jain and Carg (2007) combined an ABC analysis with a VED analysis in the case of hospital inventories. They compared the distributions of SKUs according to two criteria, cost and criticality, and defined nine groups on matrix basis. The second case study demonstrated an AHP based method to sort 47 disposable SKUs coming from a hospital-based respiratory therapy unit (Flores, Olson, & Dorai, 1992). Chen, Li, Kilgour and Hipel (2008) introduced the case-based distance model and applied the model to the same set of the 47 disposable SKUs.

The following statement was the motivation for this research: “It is assumed that the DM would like to provide … information” (Chen, Li, Kilgour, & Hipel, 2008, p. 786) which is the basis of judgment models. Viewing van Kampen’s classification system (van Kampen, Akkerman, & van Donk, 2012) the case-based distance model is a Judgment type. The aim of this research is to give a more statistical meaning to this model via putting the analysis back onto a comprehensible basis which is the traditional 80-20 rule that can be easily understood for decision makers. Since this model has prerequisites like selecting the reference points that can be hardly identified in advance, a general framework will be constructed that removes the pressure of giving information beforehand from the decision maker. This framework will be introduced in the next section which is followed by a case study taken from the health care.

## 2. Structure of the Proposed Framework

The proposed framework consists of three parts (phases):

1. Predefinition of groups based on the traditional ABC analysis;
2. Optimisation of the lower and upper bounds of groups;
3. Visualization of the results.

### *2.1. Predefinition of groups*

Let $O$ be the set of the items $(P_i \mid i = 1,2,...,n)$ being analyzed, where $P_i(x_i, y_i, z_i) \in O_g \subset O \mid g = A,B,C$ based on $q_j \in Q \mid j = 1,2,3$. (For better understanding the three criteria are denoted respect to the axes *(x,y,z)* in a three dimensional coordinate system for visualization purpose.)

The minimum $\left(c_j^{min}\right)$ and the maximum $\left(c_j^{max}\right)$values as lower and upper bounds form an interval on each criteria (Chen, Li, Kilgour, & Hipel, 2008). The Euclidean distances taken from these points determine the position of the given item on criterion $q_j$.

Volf, Kovács and Szalkai (2011) investigated the effect of linear and nonlinear transformation executed in case-based distance model during the analysis. They stated that according to the reference points two distorted spaces are generated (Volf, Kovács, & Szalkai, 2011):

- the minimum distorted space, where the reference point *(lower bound)* is $c_{min}(m_x, m_y, m_z)$

$$P_i^{min} = \xi_i\left(\left(\frac{x_i - m_x}{M_x - m_x}\right)^2, \left(\frac{y_i - m_y}{M_y - m_y}\right)^2, \left(\frac{z_i - m_z}{M_z - m_z}\right)^2\right)$$

- the maximum distorted space, where the reference point *(upper bound)* is $c_{max}(M_x, M_y, M_z)$

$$P_i^{max} = \eta_i\left(\left(\frac{M_x - x_i}{M_x - m_x}\right)^2, \left(\frac{M_y - y_i}{M_y - m_y}\right)^2, \left(\frac{M_z - z_i}{M_z - m_z}\right)^2\right)$$

Since the distance between the lower and upper bound of interval is equal to the absolute value of radius vector on criterion *j*, therefore the Euclidean distances taken from the reference points can be identified as the length of the radius vectors belonging to each item:

- the minimum distorted space

$$D_\xi\left(P_i^{min}\right) = \sqrt{\left(\xi_{i,x}^2 + \xi_{i,y}^2 + \xi_{i,z}^2\right)}$$

- the maximum distorted space

$$D_\eta\left(P_i^{min}\right) = \sqrt{\left(\eta_{i,x}^2 + \eta_{i,y}^2 + \eta_{i,z}^2\right)}$$

Following the mechanism of the traditional ABC analysis, the distance from the “o” origin can serve as the basis of the sorting procedure of the items into descending order. After the decision maker set the desired magnitudes of groups in percentage he/she can predefine the groups. Beginning from the largest distance toward the smallest one he/she sorts the items into A,B and C until he/she reaches the desired extent of the given group (respectively). In this way, the values as groups thresholds can be evaluated which is the basis of the rule of pre-classification (based on Chen, Li, Kilgour and Hipel, (2008)):

In the minimum space:

- $P_i \in C$ if $D_\xi\left(P_i^{min}\right) \le D_c^*$, where $i = 1,2,\ldots,n$
  and $max\left(D_C^\xi\left(P_k^{min}\right)\right) \le D_C^* \le min\left(D_B^\xi\left(P_l^{min}\right)\right) / k = 1,2,\ldots,n_C$ , $l = 1,2,\ldots,n_B$;
- $P_i \in B$ if $D_C^* < D_\xi\left(P_i^{min}\right) \le D_B^*$, where $i = 1,2,\ldots,n$
  and $max\left(D_C^\xi\left(P_l^{min}\right)\right) \le D_B^* \le min\left(D_B^\xi\left(P_r^{min}\right)\right) / l = 1,2,\ldots,n_B$ , $r = 1,2,\ldots,n_A$;
- $P_i \in A$ if $D_\xi\left(P_i^{min}\right) > D_B^*$.

In the maximum space:

- $P_i \in A$ if $D_\eta\left(P_i^{max}\right) \le D_A^*$, where $i = 1,2,\ldots,n$
  and $max\left(D_B^\eta\left(P_l^{max}\right)\right) \le D_A^* \le min\left(D_A^\eta\left(P_r^{max}\right)\right) / l = 1,2,\ldots,n_B$ , $r = 1,2,\ldots,n_A$;

- $P_i \in B$ if $D_B^* \le D_\eta\left(P_i^{max}\right) < D_A^*$, where $i = 1,2,...,n$
  and $max\left(D_C^\eta\left(P_k^{max}\right)\right) \le D_B^* \le min\left(D_B^\eta\left(P_l^{max}\right)\right) / k = 1,2,...,n_C$ , $l = 1,2,...,n_B$;
- $P_i \in A$ if $D_\eta\left(P_i^{max}\right) < D_B^*$

The basic assumption of the case-based distance model is that there are "balls" in the original space involving the items of each group where $D_g^*$ are the radii of these balls (Chen, Li, Kilgour, & Hipel, 2008). Volf, Kovács and Szalkai (2011) discovered that due to nonlinear transformation the assumed "balls" become planes in the distorted spaces. Hence, the distance thresholds in this first phase are determined by $D_g^*$ the separating surfaces due to the nonlinear transformation can be well approached by planes in the minimum and maximum spaces. Consequently, the further task changes to find the best fitting planes onto the predefined groups. For this purpose, the second phase of the framework integrates the Case-based distance model.

*2.2. Optimization of the lower and upper bounds of groups*

In the case of sorting problems to find the best fitting planes means the minimization of grouping errors. In this sense, the second part of framework can be summarized as a least-square method in three dimensions. This part involves the case-based distance model because it incorporates the object function which minimizes the sum of squared errors and the inequality constraints that best suit this purpose. In order to determine the parameters of the best fitting planes the optimization model developed by Chen, Li, Kilgour and Hipel (2008) has been applied. Indicating the introduced transformations in (Volf, Kovács, & Szalkai, 2011) the optimization model for the minimum space is the following:

$$minERR = \sum_{r=1}^{n_A}\left(\alpha_C^r\right)^2 + \sum_{r=1}^{n_B}\left[\left(\alpha_B^r\right)^2 + \left(\beta_B^r\right)^2\right] + \sum_{r=1}^{n_C}\left(\beta_A^r\right)^2 ,$$

where the conditions are:

$$\sum_{j=1}^{3} w_j^- \cdot \xi_j^r + \alpha_C^r \le D_C^* \ / \ r = 1;2;...;n_C$$

$$\sum_{j=1}^{3} w_j^- \cdot \xi_j^r + \alpha_B^r \le D_B^* \ / \ r = 1;2;...;n_B$$

$$\sum_{j=1}^{3} w_j^- \cdot \xi_j^r + \beta_B^r \le D_C^* \ / \ r = 1;2;...;n_B$$

$$\sum_{j=1}^{3} w_j^- \cdot \xi_j^r + \beta_A^r \le D_B^* \ / \ r = 1;2;...;n_A$$

where

$$0 < D_C^* < 1;\ 0 < D_B^* < 1;\ D_C^* < D_B^*;$$
$$-1 \le \alpha_B^r \le 0,\ 0 \le \beta_A^r \le 1,$$
$$-1 \le \alpha_C^r \le 0,\ 0 \le \beta_B^r \le 1,$$
$$w_j^- > 0;\ \sum_{j \in Q} w_j^- = 1.$$

The optimisation model for the maximum space can be constructed in the same way. The model proposed by Chen, Li, Kilgour and Hipel (2008) used to be limited to only a small set of representative items. The classification result based on these selected items was applied to the entire set. Since the decision maker's judgement is in charge of the selection of the representative items, it enables the option of misclassification. In order to avoid the opportunity that leads to this failure all of the items considered in the analysis are involved in this part without any limitation for a small set.

*2.3. Visualization of the results*

As it was mentioned in the first phase the nonlinear transformation transformed the ellipsoids separating the set $g$ into planes. In this way the planes in the distorted spaces after substituting the $D_g^*$ distance thresholds can be given by the following formula (Volf, Kovács, & Szalkai, 2011):

Minimum space:

$$\xi_z = \frac{1}{w_z}\left(D_g^* - \xi_x - \xi_y\right)$$

where $g = B^-, C^-$.

Maximum space:

$$\eta_z = \frac{1}{w_z}\left(D_g^* - \eta_x - \eta_y\right)$$

where $g = A^+, B^+$.

Note that due the transformations above the assumed relation between the minimum and maximum spaces cannot be assessed in distorted spaces. The decision maker has to return back to the original space in order to determine the interaction of the two classifications in the same space.

To get the final groups of items and the ellipsoids separating them in the original space, executing the inverse transformation is needed (Volf, Kovács, & Szalkai, 2011). The formula of the ellipsoid in the minimum space with the original data is (Volf, Kovács, & Szalkai, 2011):

$$z_i = m_z + \sqrt{\frac{(M_z - m_z)^2}{w_z^-}\left(D_g^* - w_x^- \frac{(x_i - m_x)^2}{(M_x - m_x)^2} - w_y^- \frac{(y_i - m_y)^2}{(M_y - m_y)^2}\right)},$$

where $g = B^-, C^-$.

In similar way, in maximum space the equation of the ellipsoids is:

$$z_i = M_z - \sqrt{\frac{(M_z - m_z)^2}{w_z^+}\left(D_g^* - w_x^+ \frac{(M_x - x_i)^2}{(M_x - m_x)^2} - w_y^+ \frac{(M_y - y_i)^2}{(M_y - m_y)^2}\right)},$$

where $g = A^+, B^+$.

## 2. Case Study

The presented data registered on 23rd of February, 2012 come from a general hospital. That time 267 items were in the inventory (Figure 1.). Recorded data were:

- time expired from the last outbound (time);
- volume (vol);
- value (val).

The software MATLAB V7.7.0 was used to calculate the necessary model parameters and to plot the surfaces. Based on the Pareto-rule, the magnitudes of groups have been predefined to 20%, 30% and 50% respectively to the groups A, B and C at the beginning of the analysis. To construct the least square method we used the **lsqlin** function. According to the case-based distance model, we can obtain the weights for each criterion and the cutoff values for radii ( $D_g^*$ ) in both spaces (Table 1.).

Table 1. Results of the least square method

| Parameters | Minimum space | Maximum space |
|---|---|---|
| $w_x$ (time) | 0.3333333333333 | 0.3426933478744 |
| $w_y$ (vol) | 0.3333333333333 | 0.3286533260628 |
| $w_z$ (val) | 0.3333333333333 | 0.3286533260628 |
| $D_A^*$ | - | 0.8179830807301 |
| $D_B^*$ | 0.0191053974022 | 0.9105976369928 |
| $D_C^*$ | 0.0031617769071 | - |
| *f(x)* | 0.0000107257676 | 0.0011321610518 |

Applying the results of the least square method we can define nine groups of SKUs. Table 2 shows the distribution of SKUs after the two classification results have been combined.

Table 2. Results of the classification process (amount of items in each group)

| Groups | Maximum space | | | Sum |
|---|---|---|---|---|
| Minimum space | $A^{max}$ | $B^{max}$ | $C^{max}$ | |
| $A^{min}$ | 34 | 14 | 0 | 48 *(0.1798)* |
| $B^{min}$ | 16 | 56 | 11 | 83 *(0.3109)* |
| $C^{min}$ | 0 | 14 | 122 | 135 *(0.5093)* |
| Sum | 50 *(0.1872)* | 84 *(0.3146)* | 133 *(0.4982)* | 267 *(1)* |

The result shows that the model embedded in the proposed framework kept the extents of the groups in both spaces and only a few items have been reclassified. The percentages in brackets (Table 2) show the optimized magnitudes of groups A, B and C according to the spaces. After getting the necessary parameters, we can apply them to the visualization tool. Using the equations introduced by Volf, Kovács and Szalkai (2011), we can plot the ellipsoids that are the lower and upper bounds of the groups. Since the linear and nonlinear transformations affect not only the coordinates but the separating surfaces too, the assumed nonlinear surfaces (ellipsoids) are planes in the distorted spaces (Figure 2).

The final groups on matrix basis can be represented in the three dimensional co-ordinate system because the inverse transformation ensures the feasibility of representation of the real categories of items and their separating nonlinear surfaces in the same space. Figure 3 demonstrates the positions of the groups in minimum and maximum spaces using the original data, and Figure 4 shows the combination of the two classification results representing the groups AA, BB and CC based on Table 2.

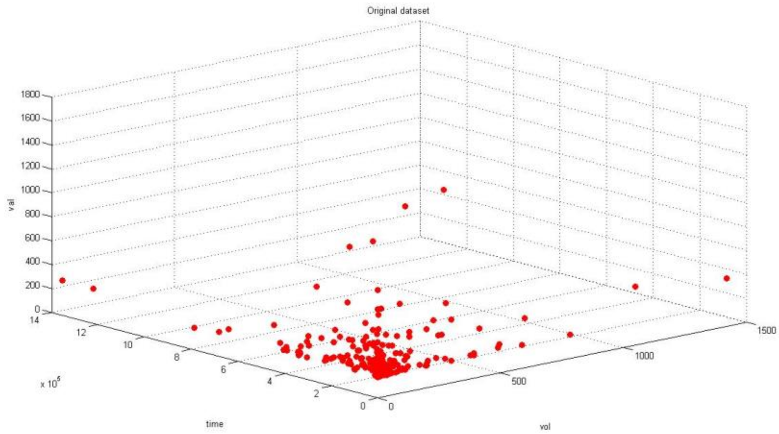


Figure 1. Representation of the original dataset

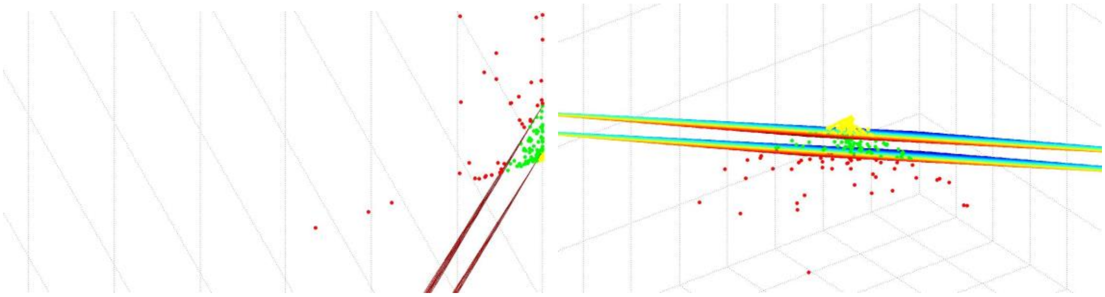

Figure 2. Representation of groups A (red), B (green) and C (yellow) with planes in (a) minimum space and (b) maximum space

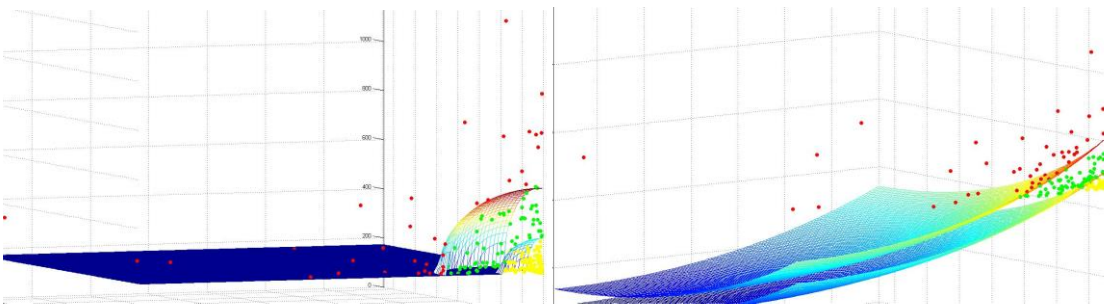

Figure 3. Representation of groups A (red), B (green) and C (yellow) with ellipsoids in (a) minimum space and (b) maximum space

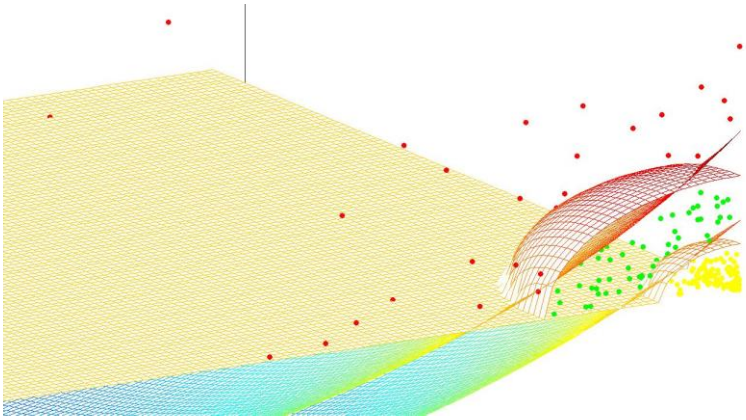

Figure 4. Representation of the ellipsoids and the groups AA (red), BB (green), CC (yellow) in one space

## 4. Summary

Acquiring a comprehensive and reliable report from the inventories becomes more and more important due to the increasing number of SKUs. Discovering similarities among SKUs helps to assign them into different groups and support decision makers to manage inventories. This is extremely important in the case of organizations with tight budget such as hospitals where the stock-out is not allowed. In these cases, inventory analysis based on one criterion is no more sufficient. However, not only the selection of the adequate criteria causes trouble for decision makers, but some models require information beforehand. Such kind of information can be the reference profiles like the representative items, group thresholds, etc. This kind of information can relieve the analysis, but applying the result to the entire set is sensitive to the selected items that can lead to misclassification. Hence, the aim of the present research was to establish a framework that removes the pressure of giving information in advance and makes the analysis more robust. Through the pre-definition of the magnitudes of groups the decision maker can set the desired extents of the groups in an iterative way while during the iteration the proposed framework will provide optimized solution for the entire set of SKUs in every case. Choosing the well-known Pareto-rule for starting point and exploiting the opportunity of representation supported the comprehension and interpretation of the classification process and its result which possesses high priority relating a sophisticated model.

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