# A New Integration of AdaBoost and Profile Matching Algorithm to Improve ABC Analysis for Drug Inventory

*by* Eko Darmanto

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Eko Darmanto[1], Subanar[2], Retantyo Wardoyo[3], Sri Hartati[4]

[1] Information Systems, Faculty of Engineering, Universitas Muria Kudus, Jawa Tengah, Indonesia
[2] Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada, Yogyakarta, Indonesia
[1,3,4] Department of Computer Science and Electronics, Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada, Yogyakarta, Indonesia

[1] eko.darmanto@umk.ac.id [2] subanar@ugm.ac.id [3] rw@ugm.ac.id [4] shartati@ugm.ac.id

**Abstract**— At the planning stage in the pharmaceutical supply cycle there are planning evaluation activities using consumption methods and morbidity for recommendations on adjusting drug procurement. Planning evaluation activities generally use the ABC Analysis method which refers to the cost aspect (the amount of drug used in a full period) so that it only meets the consumption method. It is necessary to excavate information on drug use for a full period that refers to the formulary list of essential medicines as a support for planning evaluation to fulfill therapeutic aspects. ABC analysis needs to be improved in order to be able to adopt consumption methods (cost aspects) and methods of morbidity (aspects of therapy), by adding new classification criteria, namely the level of drug diversity and the prevalence of drug use. In this study, a drug inventory classification model was developed with the name ABC-PMBoost model which is a combination of ABC analysis, profile matching (PM) and adaptive boosting (AdaBoost) methods which can adopt both aspects. The ABC-PMBoost model has succeeded in increasing the ability of ABC analysis with the presence of multi-criteria, namely the criteria for the number of stocks, drug prices, the level of diversity and the prevalence rate of drug use which includes the cost aspects and aspects of therapy. Based on the results of the experiment, using 57 data from the Antibiotic therapy class with a setting of prevalence values above 70% and a diversity level below 10%, indicating the class of drug inventory data based on cost and therapy aspects. The cost aspect uses the criteria for the number of stocks and the number of costs, while the therapeutic aspects use aspects of drug diversity and prevalence rates. The priority setting of each aspect is 60:40, resulting in an average accuracy of 87.72% for the cost aspect, and an accuracy rate of 81.82% for the therapeutic aspect. The accuracy of the model with the same priority is 85.71%. This model also provides an output in the form of recommendations for revisions to the plan for pharmaceutical supplies based on cost aspects and/or aspects of therapy.

**Index Terms**— ABC Analysis; Profile Matching; AdaBoost; Model ABC-PMBoost.

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## 1 INTRODUCTION

The inventory system is a series of policies and controls that monitor inventory levels and determine the level of inventory that must be maintained, when inventory must be filled, and how much the order must be done. The purpose of the inventory system is to determine and guarantee the availability of the right type and amount of drugs at the right time. Minimizing the annual total costs by determining the type of drug, the number of drugs and the timing of orders optimally. Control of the supply of pharmaceutical fields is taken through steps in the cycle of pharmaceutical supplies. The first stage in the cycle of pharmaceutical supplies is planning. Planning activities start from choosing the type of medication, compiling usage, calculating needs, and evaluating the design of drug supplies. Planning evaluation activities are carried out using inventory classification methods based on cost aspects. The method used in the classification based on aspects of cost usage is ABC analysis [1].

ABC analysis has been used extensively in various cases of classification of inventory. The principle of classification of ABC analysis is the 80-20 rule. ABC analysis is used to classify material goods into classes A, B, and C, a single criterion based on cost aspects. This criterion is the total annual cost of each item

of goods. Classification uses ABC analysis based on data on annual drug usage in ascending order. The cost of each item is calculated based on the cumulative cost. Cumulative total calculations are used as a comparison of each cumulative cost of drug items to determine the percentage. Based on the percentage, it was included in three groups A, B and C with percentages in order of 70%, 20% and 10%, [2], [3] which stated that ABC is a preparation grouped in the categories Always, Better and Control.

Drug classification is carried out based on cost aspects (consumption method) and therapeutic aspects (morbidity method). The therapeutic aspects are generally grouped into vital, essential and desirable or non-essential (VED/VEN). ABC analysis focuses on the cost aspect while VED/VEN emphasizes the therapeutic level of drug use [2], [3] - [5]. The use of ABC and VEN analysis can be done separately or combine them. The disadvantages of ABC analysis are only single criteria based on cost aspects. This method has been developed by combining with other methods to add new criteria. The use of ABC analysis combined with fuzzy methods and artificial neural networks for

classification purposes has been carried out by many research-ers. ABC analysis combined with fuzzy-classification has been shown to be able to handle nominal or non-nominal independent variable values [6], with quantitative and qualitative data values of each attribute [7] all of which are related to manager's experience or expert opinion in their fields so as to influence the results of the classification. Fuzzy-classification is used to handle all attributes related to the value of linguistic data. Some uses of data values in linguistic terms are used to modify single criteria in ABC analysis to be multi-criteria [6], [8].

Another combination that utilizes Artificial Intelligent (AI) techniques based on fuzzy logic and artificial neural networks with the addition of several criteria proved to be able to correct the weaknesses of ABC analysis. The AI-based multi-criteria ABC analysis showed superior accuracy compared to the conventional method using multiple discriminant analysis (MDA) [9], [10]. The use of MDA is compared with AI techniques by benchmarking. The AI techniques used are Support Vector Machines (SVM) algorithms, Back Propagation Networks (BPN), and k-Nearest Neighbor (k-NN) [10]. Most of the criteria used by researchers are the unit price, annual usage, critical factors and lead time [4], [10] - [12]. In the classification of drug preparations, the criteria that are generally added are the level of importance of the drug, priority of diseases related to the drug, and frequency of drug use in prioritizing the supply of medicinal items. To determine the level of importance of the drug, it is necessary to extract data on drug use and aspects of therapy or treatment.

In this study, the classification of drug supplies in terms of cost aspects and therapeutic aspects for evaluation analysis of pharmaceutical supplies planning proposed new criteria in improving the ability of ABC analysis by adding criteria for the level of drug diversity and prevalence of drug use. The therapeutic aspects and cost aspects are determined based on priority values and standard values of Decision Makers (DM). This is the background of the use of the Profile Matching (PM) method. The PM method provides support for class determination decisions in the form of ranking scores. The score of the best PM method is used as a "weak learner" in machine learning techniques that use adaptive boosting (AdaBoost). AdaBoost is an ensemble classification technique/method which is a predictive model consisting of weighted combinations of several classification models to improve performance in class predictions by voting for learners.

## 2 METHODOLOGY

The framework for improving the ABC analysis model for the classification of drug supplies describes the development flow and methods used. The development flow section is the main points to be carried out, while the method section explains what methods or algorithms are involved, presented in Fig.1.

Contributions from each method need to be explained with a mapping chart of the contribution of ABC Analysis, PM method, and AdaBoost. Data in the form of results from ABC Analysis, determined variables and criteria that were analyzed using PM, then combined with AdaBoost. The form of the combination method is in the form of an integration model or joint model by utilizing the formulation/rules of the ABC analysis and the PM method in determining the learner (weak classifier) on AdaBoost. While the basic boosting algorithm used is AdaBoost.M1 [13]. The basic algorithm is modified by combining ABC Analysis for training data and test data, PM Method for determining criteria and AdaBoost for training. A simple description of the combination mapping of the three methods is presented in Fig. 2.
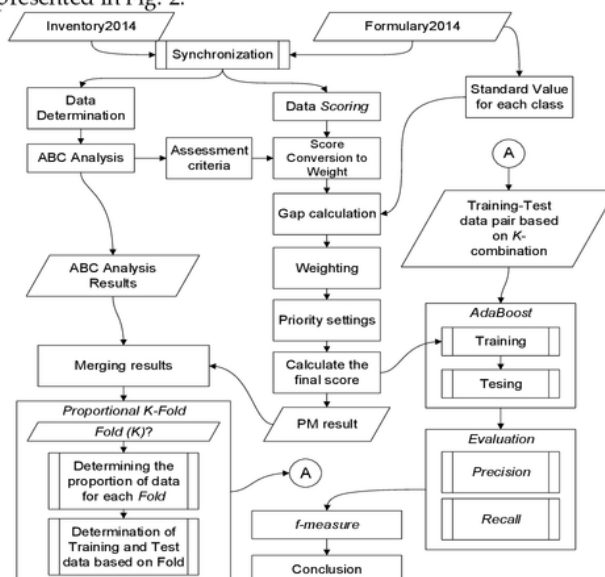


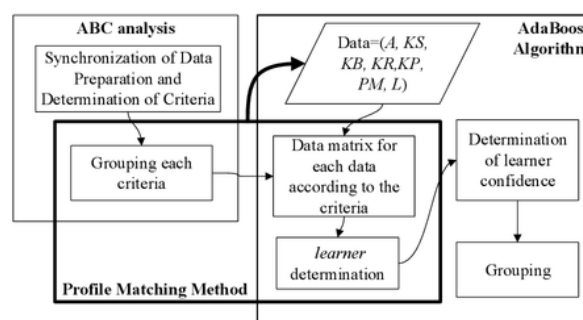Figure 1. The flow of improvement in the drug inventory classification model



Figure 2. Mapping the contribution of each method involved in developing the ABC-PMBoost Model

## 3 METHODS ADAPTED

The adapted method is ABC Analysis, the profile matching method, and AdaBoost algorithm. Classifier at AdaBoost is formulated using ABC analysis formulation which is combined

with PM method. Whereas to determine training data and test data used the K-Fold method and know the level of accuracy of the class using the confusion matrix technique for multi-classes.

### 3.1 ABC Analysis

Grouping of drug supply items with ABC analysis techniques is done by knowing how much the annual cost is to meet its availability needs. The cumulative total calculation is used as a comparison of each cumulative cost of a drug item to determine its percentage. Based on the percentage, it was included in three groups, namely A, B, and C, with percentages of 70%, 20% and 10% [2], [3] respectively. ABC analysis has procedures to classify drugs into classes A, B, and C.

In this study the rules of the ABC analysis steps for the supply of drugs based on the analysis used in the ABC inventory classification of goods in general. While in general the rules for ABC analysis are presented in Table 1.

TABLE 1
THE RANGE OF TOTAL COST AND ITEMS IN THE ABC ANALYSIS RULES

| Class | Total Cost | Items |
|-------|-----------|-------|
| A | 70%-80% | 15%-20% |
| B | 15%-25% | 30%-40% |
| C | 10%-15% | >40% |

### 3.2 AdaBoost

The AdaBoost algorithm stands for adaptive boosting. Freund and Schapire introduced a new algorithm that was used to improve the classifier's adaptive abilities using a set of test data [13]. The main purpose of this algorithm is to train classifiers. AdaBoost adaptively changes the distribution of training data sets based on the performance of classifiers formed sequentially. Each classifier is used adaptively to refine and weight the training data set, so the next classifiers in the sequence are those who have a higher probability of choosing a pattern that was not classified (miss-classified). The term 'boosting' arises because of a group of weak classifiers (the committee of weak classifiers). The main idea of AdaBoost is a better predictive combination of each classifier than just using an individual classifier. The Ada-Boost algorithm in its development was expanded again to multi-class classification and for regression problems by researchers both theoretically and empirically which are used in various aspects of use [13] - [16]. The basic idea of using the extension of the AdaBoost algorithm is the first form called Ada-Boost.M1 [13].

### 3.3 Profile Matching

The Matching Profile (PM) method is a mechanism that is often used as an auxiliary procedure for decision making assuming that there is an ideal level of predictor variable that must be fulfilled [17], from the minimum level that must be met or passed. Broadly speaking, the PM method is the process of comparing the value of the actual data from the profile that will be assessed by the value of the expected profile, so that it can be a difference in competence (referred to as a gap). If a small gap value is obtained, it will have a large weight value. In general,

the PM method has a step that is determining the assessment criteria, converting the initial value into assessment (usually linguistics) and the score, determining the benchmark / standard value, calculating the gap value, gap value weighting conversion based on a standard value, determining the priority of each aspect used and calculate the final score [18] - [24].

## 4 PROPOSED METHODS

### 4.1 The Data and criteria used

Drug data used were obtained from drug use during 2014 at a district-level local government hospital, Central Java province, Indonesia. The sample data for the experiment is data on generic drugs in the Antibiotic therapy class category which has 57 data. The criteria in the classification are the results of the synchronization process from the database of drug use with formulary and ABC analysis, including the number of drug items used during the year ($Js$) and drug prices ($p$). Calculation of the cost aspect is concerned with the total costs ($Jc$) attached to each drug, which are presented in (1).

$$Jc = Js.p, \qquad (1)$$

Drug diversity ($f$) shows the number of drugs ($A_n$) substitutes included in the same generic name ($d$), which are formulated in (2).

$$f(d) = \frac{1}{A_n}, \qquad (2)$$

The prevalence variable shows how much each type of drug appears in the use of prescriptions obtained from the drug use database. If the number of recipes is $R_d$ which contains the name of the generic drug that corresponds to the formulary and the total number of recipes for a year is $\Sigma R$, then the prevalence rate is $Prev_{(d)}$ of a generic drug name ($d$) that is formulated in (3).

$$Prev_{(d)} = \frac{R_d}{\Sigma R}, \qquad (3)$$

Based on equation (3), evaluation of drug planning from the aspect of therapy is carried out if the type of drug is large, so to make a choice based on a "drug of choice" from a disease of high prevalence [1]. Drug selection in hospitals refers to the List of National Essential Medicines (*Daftar Obat Esensial Nasional*-DOEN), hospital formulary and Drug Price Ceiling List (*Daftar Plafon Harga Obat*-DPHO). Prevalence is obtained by analyzing compilation usage calculations. Compilation of usage consists of calculating the amount, percentage and average annual drug stock usage. In this study, the prevalence of the use of drugs to treat a disease is represented by a doctor's prescription. A prescription is a written request from a doctor to a pharmacist to make or deliver drugs to patients [25]. Prevalence is calculated by comparing the number of prescriptions contained in drug compositions which are intended by the number of all recipes over a period of time [26], [27].

### 4.2 ABC-PMBoost Model

The ABC-PMBoost model is a combination of ABC analysis, PM algorithm and AdaBoost algorithm which has the following steps;

## Data Input Preparation

Prepare data in the order of a number ($m$) of sample data; $\langle(x_1, y_1), \ldots, (x_m, y_m)\rangle$ with labels $y_i \in Y = \{1, \ldots, k\}$

Use the PM algorithm as "WeakLearn", with the following settings;

1. Determining the assessment criteria, these values are grouped into several groups, for example, namely *important*, *ordinary*, and *unimportant*. Determination of the range of scores for each of these groups. Criteria for diversity variables and prevalence criteria are presented in Table 2.

TABLE 2
ASSESSMENT CRITERIA FOR DIVERSITY AND PREVALENCE

| Assessment criteria | Diversity | Prevalence |
|---|---|---|
| *important* | <10% | >70% |
| *ordinary* | 10%-20% | 20%-70% |
| *unimportant* | >20% | <20% |

2. The initial value conversion becomes an assessment. In this study, the score of each criterion was determined based on Table 3.

TABLE 3
SCORING FOR EACH CRITERIA

| Assessment criteria | Score |
|---|---|
| *important* | 3 |
| *ordinary* | 2 |
| *unimportant* | 1 |

3. Determine the standard value with a combination (for example a combination of initial values in Table 4) for each column in the score conversion, which will be used to calculate the gap value.

TABLE 4
COMBINATION OF INITIAL STANDARD VALUES FOR EACH CLASS

| Class Target | Items | Cost | Diversity | Prevalence |
|---|---|---|---|---|
| A | 3 | 3 | 3 | 3 |
| B | 2 | 2 | 2 | 2 |
| C | 1 | 1 | 1 | 1 |

4. Determine the gap value, which is the difference from the conversion score (step 2) with the predetermined standard value (step 3). If the target or standard profile is ($Ps$) and the object profile is ($Po$), then the gap is formulated in (4).
$$Gap = Ps - Po \qquad (4)$$

5. Conversion weighting gap values into weighting criteria, which are used in calculating the final score. In this study, we used a weighting standard from the gap value presented in Table 5.

TABLE 5
WEIGHTING GAP VALUES

| gap | weight | description |
|---|---|---|
| 0 | 3 | In accordance with the target class and important to maintain |
| 1 | 2.5 | Less suitable with the target class of excess 1 level |
| -1 | 2 | Less suitable for the target class lacking 1 level |
| 2 | 1.5 | Not according to the target class of excess 2 levels |
| -2 | 1 | Not according to the target class lacking 2 levels |

6. Determine the Core Factor (CF) and Secondary Factor (SF) from each column. The CF is a more decisive factor than other factors, so the calculation of the value will be higher than other columns. If the weight value of CF is ($W_{CF}$) and the data item in CF is ($IC$), then the average CF value ($NCF$) is formulated in (5).

$$NCF = \frac{\sum W_{CF}}{\sum IC} \qquad (5)$$

If the weight value of the SF is ($W_{SF}$) and data items is ($IS$), then the averages of the CF is ($NSF$).

$$NSF = \frac{\sum W_{SF}}{\sum IS} \qquad (6)$$

In this study comparing several combinations of aspects of classification determinants. If the important aspect is the cost aspect, then the CF is the variable $Jc$ and $Js$ and the other is SF. If what is important is the aspect of therapy, then the CF is the prevalence and diversity of drugs, while the other is SF. Table 6 presents a scenario of a combination of CF and SF in terms of several important aspects.

TABLE 6
SCENARIOS OF CF AND SF COMBINATIONS BASED ON ASPECT INTEREST LEVELS

| Aspects | CF | SF |
|---|---|---|
| Cost | Jc | Prevalence |
| | Js | Diversity |
| Therapy | Prevalence | Jc |
| | Diversity | Js |

7. Calculate the final score on each row, calculate the sum of the values in the CF column, and the SF column, then calculate the average for each of these totals. If the percentage preference weighting criteria of CF are ($Pc$) and the percentage preference weighting criteria from SF are ($Ps$), the total value ($Nt$) of the assessment aspect (criteria) is formulated in (7).

$$Nt = (Pc \times NCF) + (Ps \times NSF) \qquad (7)$$

## Initialize all the best results data from the PM method

All data ($m$) on the best results from the PM process are given weight by distribution ($D$) of all sample data ($i$) with;

$$D_1(i) = 1/m \text{ for all } i$$

## Determine the number of repetitions

Determine the number of loops ($T$) to train the sample data, so that it can do repetitions of as many as $t = 1, 2, \ldots, T$. In the loop do the following steps;

1. Call the results from the PM algorithm as weakLearn with the weight distributed in $D_t$.
2. Call weakLearn, Providing it with the distribution $D_t$.
3. Get back a hypothesis $h_t: X \rightarrow Y$.
4. Calculate the error of $h_t$: $\epsilon_t = \sum_{i=h_t(x_i) \neq y_i} D_t(i)$ (8)

   If $\epsilon_t > \frac{1}{2}$, then set $T = t - 1$ and abort loop.
5. Set $\beta_t = \epsilon_t / (1 - \epsilon_t)$. (9)
6. Update distribution $D_t$:

   $$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} \beta_t & if \ h_t(x_i) = y_i \\ 1 & otherwise \end{cases} \qquad (10)$$

Where $Z_t$ is a normalization constant (chosen so that $D_{t+1}$ will be a distribution).

**Output** the final hypothesis:

$$h_{fin}(x) = \underset{y \in Y}{\arg\max} \sum_{t:h_t(x)=y} \log \frac{1}{\beta_t} \qquad (11)$$

## 5 RESULT AND DISCUSSION

### 5.1 Classification Using ABC Analysis

Classification of drug inventory using ABC analysis of each class generally leads to the conclusion presented in Table 7.

TABLE 7
CLASSIFICATIONS RESULT USING ABC ANALYSIS

| Class | Items | Total Stock | Total Cost (IDR) |
|---|---|---|---|
| A | 10 | 124,358 | 356,153,199.90 |
| B | 5 | 66,178 | 71,303,263.30 |
| C | 42 | 53,419 | 81,985,332.70 |

Based on the results of the ABC Analysis a range of values from the Stock and Cost variables are presented in Table 8.

TABLE 8
THE VALUE RANGE OF EACH CLASS BASED ON ITEMS AND COSTS

| Description | Class | | |
|---|---|---|---|
| | A | B | C |
| Items | 10 | 5 | 42 |
| MinStock | 1,282 | 6,354 | 1 |
| MaxStock | 36,975 | 15,697 | 21,192 |
| MinCost | 22,210,629.20 | 9,815,797.60 | 14,400.00 |
| MaxCost | 54,505,323.25 | 20,438,383.70 | 9,574,495.80 |

In the PM method, each generic drug item is called alternative (A). Variables or attributes are called aspects and ranges of limiting values of each attribute called criteria. The value of each alternative is called the score. The variables or attributes used are the results of ABC analysis in the form of criteria for the number of stocks ($KS$), Cost Criteria ($KB$), label class ($L$), drug diversity ($KR$) and prevalence of drug use ($KP$).

### 5.2 Assessment Criteria for Each Variable

In some cases, the assessment criteria are determined by the decision maker, in this case, taken from the data that has been analyzed using the ABC Analysis method whose results refer to Table 9.

TABLE 9
ASSESSMENT CRITERIA IN ALL VARIABLES

| Vari-abels | Assessment criteria | | |
|---|---|---|---|
| | Important | Ordinary | Unimportant |
| KS | $MinSt_A \le ds_A$ $\le MaxSt_A$ | $MinSt_B \le ds_B$ $\le MaxSt_B$ | $MinSt_C \le ds_C$ $\le MaxSt_C$ |
| KB | $MinC_A \le db_A$ $\le MaxC_A$ | $MinC_B \le db_B$ $\le MaxC_B$ | $MinC_C \le db_C$ $\le MaxC_C$ |
| KR | $f(d) \le 10\%$ | $10\% < f(d)$ $\le 70\%$ | $f(d) > 70\%$ |
| KP | $Prev(d) \ge 70\%$ | $10\% \le Prev(d)$ $< 70\%$ | $Prev(d) < 10\%$ |

The $KS$ and $KB$ variables are based on the results of ABC analysis, while the $KR$ and $KP$ are based on rules ABC analysis which states the percentage of use of the number of drug items. The assessment criteria for each variable are presented in Table 10.

TABLE 10
ASSESSMENT CRITERIA FOR KS, KB, KR, AND KP

| Criteria | | Assessment criteria | | |
|---|---|---|---|---|
| | | Important | Ordinary | Unimportant |
| KS | Min | 1282 | 6354 | 1 |
| | Max | 36975 | 15697 | 21192 |
| KB | Min | 22210629 | 9815797.6 | 14400 |
| | Max | 54505323 | 20438384 | 9574495.8 |
| KR | Min | 0% | 10% | 70% |
| | Max | 10% | 70% | 100% |
| KP | Min | 70% | 10% | 0% |
| | Max | 100% | 70% | 10% |

In the range of assessment criteria, there are problems in the data that are not in the order, it is possible that there are values in several ranges. For example in the $KS$-$Min$ and $KS$-$Max$ rows, if the data is KS = 9000, then there is a range of values in $Important$, $Ordinary$ and $Unimportant$. Solution to problem criteria values that are not in order, using algorithms presented in Table 11.

TABLE 11
STEPS TO IMPROVE THE RANGE OF THE ASSESSMENT CRITERIA THAT ARE NOT IN ORDER

| Steps | Description |
|---|---|
| A | Min-*Important* < Max-*Ordinary*? If Min-*Important* < Max-*Ordinary*, then Min-*Important* and Max-*Ordinary* ← (Min-*Important* and Max-*Ordinary*)/2, |
| B | Min-*Ordinary* < Max-*Ordinary*? |
| B.1 | If Min-*Ordinary* < Max-*Ordinary*, then go to C, |
| B.2 | If Min-*Ordinary* > Max-*Ordinary*, then Min-*Ordinary* ← Max-*Ordinary*, test by repeating from step A |
| C | Max-*Unimportant* > Min-*Ordinary*? If Max-*Unimportant* > Min-*Ordinary*, then Max-*Unimportant* and Min-*Ordinary* ← (Max-*Unimportant* + Min-*Ordinary*)/2 |
| D | Repeat until (Max-*Unimportant* = Min-*Ordinary*) and (Max-*Ordinary* = Min-*Important*) |

Other problems arise in the KB variable, there is a possibility that the data is not included in the range of values because there are jumping ranges (out of scope). The solution to the problem is solved in Table 12.

TABLE 12
STEPS TO IMPROVE THE RANGE OF THE ASSESSMENT CRITERIA THAT ARE OUT OF SCOPE

| Step | Uraian |
|---|---|
| A | Are there data gaps that are not covered? if Min-*Important* ≠ Max-*Ordinary*, then Min-*Important* and Max-*Ordinary* ← (Min-*Important* + Max-*Ordinary*)/2 |
| B | Max-*Unimportant* > Min-*Ordinary*? If Max-*Unimportant* > Min-*Ordinary*, then Max-*Unimportant* and Min-*Ordinary* ← (Max-*Unimportant* + Min-*Ordinary*)/2 |
| C | Repeat until Max-*Unimportant* = Min-*Ordinary* AND Max-*Ordinary* = Min-*Important* |

As a result of improving the range of assessment criteria using the steps in Table 11 and Table 12, the results of the latest ranges are presented in Table 13.

### TABLE 13
#### THE RESULTS OF THE ASSESSMENT CRITERIA RANGE IMPROVEMENT

| Criteria | | Assessment criteria | | |
|---|---|---|---|---|
| | | Important | Ordinary | Unimportant |
| KS | Min | 13,773.00 | 11,131.25 | 1.00 |
| | Max | 36,975.00 | 13,773.00 | 11,131.25 |
| KB | Min | 21,324,506.45 | 9,695,146.70 | 14,400.00 |
| | Max | 54,505,323.25 | 21,324,506.45 | 9,695,146.70 |
| KR | Min | 0 | 0,1 | 0,7 |
| | Max | 0,1 | 0,7 | 1 |
| KP | Min | 0,7 | 0,1 | 0 |
| | Max | 1 | 0,7 | 0,1 |

At this stage to facilitate reading the data, each generic name will be represented by a short name, in the order from the first data to the last data (A1, A2,..., A57) which still refers to the sequence of results of ABC Analysis. The value of each of the criteria data are converted to a weight value, the conversion results are presented in Table 14.

### TABLE 14
#### PIECES OF DATA CONVERSION RESULTS ARE ASSESSED

| A | Data | | | | Assessment (Score) | | | |
|---|---|---|---|---|---|---|---|---|
| | KS | KB | KR | KP | KS | KB | KR | KP |
| A1 | 22376 | 22210629 | 0.67 | 10.63 | 3 | 3 | 2 | 2 |
| A2 | 3357 | 35921369 | 1 | 1.62 | 1 | 3 | 1 | 1 |
| A3 | 2612 | 33520446 | 1 | 1.09 | 1 | 3 | 1 | 1 |
| A4 | 25899 | 46083623 | 1 | 14.4 | 3 | 3 | 1 | 2 |
| A5 | 1342 | 35961369.6 | 1 | 0.87 | 1 | 3 | 1 | 1 |
| A6 | 36975 | 54505323.25 | 1 | 20.74 | 3 | 3 | 1 | 2 |
| A7 | 1282 | 29606500 | 1 | 0.88 | 1 | 3 | 1 | 1 |
| A8 | 2094 | 34086770.6 | 1 | 1.3 | 1 | 3 | 1 | 1 |
| A9 | 24208 | 38177216.8 | 1 | 8.73 | 3 | 3 | 1 | 1 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| A57 | 5 | 896286.6 | 1 | 0.02 | 1 | 1 | 1 | 1 |

## 5.3 Determination of Standard Values

Determination of standard values is given as a reference for calculating gap values. In this study, the initial standard values are arranged like Table 15. It is possible to make the right combination of the standard values. Combinations are used to determine suitability for certain drug therapy classes. For example, setting a standard value for a therapeutic class Antibiotics can be different from setting a standard value for the Anti-Inflammatory therapy class. Some researchers even made consensus on pharmaceutical experts or parts involved in the pharmacy committee team to get the right standard values.

### TABLE 15
#### DETERMINATION OF STANDARD VALUES FOR WEIGHTING

| Class | Assessment (score) | | | |
|---|---|---|---|---|
| | KS | KB | KR | KP |
| A | 3 | 3 | 2 | 2 |
| B | 2 | 2 | 2 | 1 |
| C | 1 | 1 | 1 | 1 |

Based on Table 15, it can be explained that for the criteria in class A, it is important to note in terms of the cost criteria and

criteria for the number of drugs, while the level of diversity and prevalence rates are considered ordinary (not too much attention). The priority of the number of items/stocks and costs/investments in class B does not emphasize the prevalence of drug use. If we want to reduce the number of drugs, it is enough to see in class C, which all the criteria are considered not important to note.

Determination of standard values has an effect on determining the importance of a drug. For example, if pegged to an important standard of all (with a value of 3), in theory all drugs that succeed in exceeding the standard calculation are applied, but for the types of drugs that are important for life support, such as heart drugs, the standard setting method must be given a low value to be included in the standard criteria expected.

## 5.4 Gap calculation

The gap is obtained from calculating the difference between the standard value and the weight value of each class. If the criteria are KS, KB, KR, and KP, then the array scheme of each criterion is Scheme(this) = (KS, KB, KR, KP). If the standard values are Class (A) = (3,3,2,2), Class (B) = (2,2,2,1), Class (C) = (1,1,1,1) and drug data has a score in the Alternative (A1) = (3,3,2,2), then the difference in the score from the alternative to the standard value is Gap (A1-A) = (0,0,0,0), Gap (A1-B) = (1,1,0,1), and Gap (A1-C)=(2,2,1,1). The gap calculation is carried out by all alternatives per class so that it will look like in Table 16.

### TABLE 16
#### PIECES OF GAP CALCULATION

| A | Assessment (score) | | | | Gap A | | | | Gap B | | | | Gap C | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | KS | KB | KR | KP | KS | KB | KR | KP | KS | KB | KR | KP | KS | KB | KR | KP |
| A1 | 3 | 3 | 2 | 2 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 2 | 2 | 1 | 1 |
| A2 | 1 | 3 | 1 | 1 | -2 | 0 | -1 | -1 | -1 | 1 | -1 | 0 | 0 | 2 | 0 | 0 |
| A3 | 1 | 3 | 1 | 1 | -2 | 0 | -1 | -1 | -1 | 1 | -1 | 0 | 0 | 2 | 0 | 0 |
| A4 | 3 | 3 | 1 | 2 | 0 | 0 | -1 | 0 | 1 | 1 | -1 | 1 | 2 | 2 | 0 | 1 |
| A5 | 1 | 3 | 1 | 1 | -2 | 0 | -1 | -1 | -1 | 1 | -1 | 0 | 0 | 2 | 0 | 0 |
| A6 | 3 | 3 | 1 | 2 | 0 | 0 | -1 | 0 | 1 | 1 | -1 | 1 | 2 | 2 | 0 | 1 |
| A7 | 1 | 3 | 1 | 1 | -2 | 0 | -1 | -1 | -1 | 1 | -1 | 0 | 0 | 2 | 0 | 0 |
| A8 | 1 | 3 | 1 | 1 | -2 | 0 | -1 | -1 | -1 | 1 | -1 | 0 | 0 | 2 | 0 | 0 |
| A9 | 3 | 3 | 1 | 1 | 0 | 0 | -1 | -1 | 1 | 1 | -1 | 0 | 2 | 2 | 0 | 0 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| A57 | -2 | -2 | -1 | -1 | -1 | -1 | -1 | 0 | 0 | 0 | 0 | 0 | -2 | -2 | -1 | -1 |

## 5.5 Final score calculation based on the priority of CF and SF values

In this study, the calculation of CF and SF values was based on a combination of CF and SF scenarios (Table 6) based on the level of importance of the aspects. In the study using a ratio of CF: SF is 60%: 40%.

### Analysis based on cost aspects

The CF value has a priority of 60%, while 40% for SF. The weighted score of CF is prioritized for the criteria for the number of items (KS) and cost/investment (KB), while SF for the criteria for diversity level (KR) and prevalence rate (KP). If the weight value of the name alternative medicine A in class k is (A1-k), and if the Weight Score (A1-A) = (3, 3, 3, 3), WeightScore (A1-B) =

(2.5, 2.5, 3 , 2.5), and WeightScore (A1-C) = (1.5, 1.5, 2, 1.5), then the total alternative score to each class (Nt (Ak)) is;

$$Nt_{(A1-A)} = \left(\frac{3+3}{2} \times 60\%\right) + \left(\frac{3+3}{2} \times 40\%\right) = 3,$$

$$Nt_{(A1-B)} = \left(\frac{2.5+2.5}{2} \times 60\%\right) + \left(\frac{3+2.5}{2} \times 40\%\right) = 2.6,$$

$$Nt_{(A1-B)} = \left(\frac{1.5+1.5}{2} \times 60\%\right) + \left(\frac{2+1.5}{2} \times 40\%\right) = 1.9,$$

Class (K) will lean on the choice based on the results of calculations with the largest value.

$$K = max\left(Nt_{(A1-A)}, Nt_{(A1-B)}, Nt_{(A1-C)}\right),$$
$$K = max(3, 2.6, 1.9),$$

Thus, the A1 into the A class with the largest score value is 3. This calculation process is performed on all alternatives, in order to obtain results as shown in Table 17.

TABLE 17.
PIECES OF THE FINAL SCORE AND CLASS BASED ON THE COST ASPECT SCENARIO

| A | Weight (A) | | | | Weight (B) | | | | Weight (C) | | | | Final Score | | | Fin. Clas |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | KS | KB | KR | KP | KS | KB | KR | KP | KS | KB | KR | KP | A | B | C | |
| A1 | 3 | 3 | 3 | 3 | 2.5 | 2.5 | 3 | 2.5 | 1.5 | 1.5 | 2.5 | 2.5 | 3 | 2.6 | 1.9 | A |
| A2 | 1 | 3 | 2 | 2 | 2 | 2.5 | 2 | 3 | 3 | 1.5 | 3 | 3 | 2 | 2.35 | 2.55 | C |
| A3 | 1 | 3 | 2 | 2 | 2 | 2.5 | 2 | 3 | 3 | 1.5 | 3 | 3 | 2 | 2.35 | 2.55 | C |
| A4 | 3 | 3 | 2 | 3 | 2.5 | 2.5 | 2 | 2.5 | 1.5 | 1.5 | 3 | 2.5 | 2.8 | 2.4 | 2 | A |
| A5 | 1 | 3 | 2 | 2 | 2 | 2.5 | 2 | 3 | 3 | 1.5 | 3 | 3 | 2 | 2.35 | 2.55 | C |
| A6 | 3 | 3 | 2 | 3 | 2.5 | 2.5 | 2 | 2.5 | 1.5 | 1.5 | 3 | 2.5 | 2.8 | 2.4 | 2 | A |
| A7 | 1 | 3 | 2 | 2 | 2 | 2.5 | 2 | 3 | 3 | 1.5 | 3 | 3 | 2 | 2.35 | 2.55 | C |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| A57 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 1.4 | 2.2 | 3 | C |

The final class is obtained from Table 17, compared to the final results of ABC Analysis so that it will be seen in Table 18.

TABLE 18
CONFUSION MATRIX CLASSIFICATION RESULTS USING ABC-PM WITH PRIORITIES OF COST ASPECT

| Confusion Matrix | | PM Method | | |
|---|---|---|---|---|
| | | A | B | C |
| ABC Analysis | A | 4 | 0 | 6 |
| | B | 0 | 4 | 1 |
| | C | 0 | 1 | 41 |

Based on Table 18 there are 10 data in class A shifting 6 data into class C, in class B shifts 5 data into class C, from 42 data in class C which shifts to class B as much as 1 data. This shows that in class A there are 6 non-essential data to be prioritized based on the aspect of the investment amount. However, if we want to prioritize cost reduction and reduce the number of drug items that are considered, 41 data in class C.

### Analysis based on therapy aspects

The analysis was based on aspects of therapy with a comparison arrangement in CF: SF of 60%: 40%. There are differences in the criteria in CF and SF. The weighted score of CF is prioritized for the criteria for diversity (KR) and prevalence (KP), while SF for the criteria for the number of items/stock (KS) and the value

of investment/cost (KB). If the weight value of the name alternative medicine A in class k is (A1-k), and if the WeightScore (A1-A) = (3, 3, 3, 3), WeightScore (A1-B) = (2.5, 2.5, 3 , 2.5), and WeightScore (A1-C) = (1.5, 1.5, 2, 1.5), then the total alternative score to each class (Nt (Ak)) is;

$$Nt_{(A1-A)} = \left(\frac{3+3}{2} \times 60\%\right) + \left(\frac{3+3}{2} \times 40\%\right) = 3$$

$$Nt_{(A1-B)} = \left(\frac{3+2.5}{2} \times 60\%\right) + \left(\frac{2.5+2.5}{2} \times 40\%\right) = 2.65$$

$$Nt_{(A1-B)} = \left(\frac{2+1.5}{2} \times 60\%\right) + \left(\frac{1.5+1.5}{2} \times 40\%\right) = 2.1$$

Class (K) will lean on the choice based on the results of calculations with the largest value;

$$K = max\left(Nt_{(A1-A)}, Nt_{(A1-B)}, Nt_{(A1-C)}\right),$$

$$K = max(3, 2.65, 2.1),$$

Thus, the A1 into the A class with the largest score value is 3. This calculation process is performed on all alternatives, in order to obtain results as shown in Table 19.

TABLE 19
PIECES OF THE FINAL SCORE AND CLASS BASED ON THE THERAPY ASPECT SCENARIO

| A | Weight (A) | | | | Weight (B) | | | | Weight (C) | | | | Final Score | | | Final Clas |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | KS | KB | KR | KP | KS | KB | KR | KP | KS | KB | KR | KP | A | B | C | |
| A1 | 3 | 3 | 3 | 3 | 2.5 | 2.5 | 3 | 2.5 | 1.5 | 1.5 | 2.5 | 2.5 | 3 | 2.65 | 2.1 | A |
| A2 | 1 | 3 | 2 | 2 | 2 | 2.5 | 2 | 3 | 3 | 1.5 | 3 | 3 | 2 | 2.4 | 2.7 | C |
| A3 | 1 | 3 | 2 | 2 | 2 | 2.5 | 2 | 3 | 3 | 1.5 | 3 | 3 | 2 | 2.4 | 2.7 | C |
| A4 | 3 | 3 | 2 | 3 | 2.5 | 2.5 | 2 | 2.5 | 1.5 | 1.5 | 3 | 2.5 | 2.7 | 2.35 | 2.25 | A |
| A5 | 1 | 3 | 2 | 2 | 2 | 2.5 | 2 | 3 | 3 | 1.5 | 3 | 3 | 2 | 2.4 | 2.7 | C |
| A6 | 3 | 3 | 2 | 3 | 2.5 | 2.5 | 2 | 2.5 | 1.5 | 1.5 | 3 | 2.5 | 2.7 | 2.35 | 2.25 | A |
| A7 | 1 | 3 | 2 | 2 | 2 | 2.5 | 2 | 3 | 3 | 1.5 | 3 | 3 | 2 | 2.4 | 2.7 | C |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| A57 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 1.6 | 2.3 | 3 | C |

The classification results from Table 19 are summarized in Table 20 of the following confusion matrix.

TABLE 20
CONFUSION MATRIX CLASSIFICATION RESULTS USING ABC-PM WITH PRIORITIES OF THE THERAPY ASPECT SCENARIO

| Confusion Matrix | | PM Method | | |
|---|---|---|---|---|
| | | A | B | C |
| ABC Analysis | A | 3 | 1 | 6 |
| | B | 0 | 4 | 1 |
| | C | 0 | 1 | 41 |

Based on Table 20, it can be explained that the original ABC analysis contained 10 data in class A, currently, only 3 data are right in the same class. One data shifts to class B, and as much as 6 data to class C. In class B which was originally 5 data, shifted to C as much as 1 data. In class C there are 42 data, shifting to class B as much as 1 data. This shows that based on the therapeutic aspect, the criticality of the preparation items is that there are 3 data in class A that are important to note, meaning that these three items must not be empty. While there are 6 data that

are not important to prioritize based on the critical aspects of the goods. However, if you want to prioritize cost reduction and reduce the number of drug items, based on this aspect of therapy, 41 data in class C are considered, with the recommendation of the lowest score.

### 5.6 Combination of sample data for training on AdaBoost

The data used in the training process and testing are taken by sampling, which can represent data from each class. In Table 21, 11 data were taken consisting of 2 data from class A, 3 data from class B and 6 data from class C. Parameters used were the number of stocks/items, the number of costs, the level of diversity and the prevalence rate.

TABLE 21
SAMPLE DATA FOR TRAINING PROCESS ADABOOST

| A | KS | KB | KR | KP | Kelas |
|---|---|---|---|---|---|
| A1 | 36975 | 54505323.3 | 0.67 | 10.63 | A |
| A2 | 25899 | 46083623.5 | 1 | 1.62 | A |
| A12 | 15697 | 15020657.6 | 1 | 5.34 | B |
| A13 | 15682 | 14604857.6 | 0.67 | 2.39 | B |
| A14 | 14090 | 11423566.8 | 0.5 | 4.51 | B |
| A16 | 10360 | 9574495.8 | 1 | 0.04 | C |
| A17 | 103 | 7410387.6 | 1 | 0.12 | C |
| A18 | 153 | 7303546.8 | 1 | 0.32 | C |
| A19 | 203 | 6212408.1 | 1 | 0.18 | C |
| A20 | 35 | 4965504.5 | 1 | 0.82 | C |
| A21 | 443 | 4251635.8 | 0.5 | 0.18 | C |

### 5.7 Determination of Learner Rules

Based on Table 21, training was conducted to find the rules of each "learner". The results of this process are lessons that state that the student has the accuracy in calculating the hypothesis with the target value with the lowest (best) error rate. Based on a combination of criteria groups with sample training data, 10 lessons were obtained as follows;

```
[0] IF KS = MinKS_A-MaxKS_A THEN Class = B (error rate = 1.00)
[1] IF KS = MinKS_C-MaxKS_C THEN Class = B (error rate = 0.60)
[2] IF KB = MinKB_A-MaxKB_A THEN Class = B (error rate = 1.00)
[3] IF KB = MinKB_B-MaxKB_B THEN Class = B (error rate = 1.00)
[4] IF KB = MinKB_C-MaxKB_C THEN Class = B (error rate = 0.00)
[5] IF KR = 10%-70% THEN Class = B (error rate = 0.75)
[6] IF KR = 70%-100% THEN Class = B (error rate = 0.86)
[7] IF KP = 70%-100% THEN Class = B (error rate = 0.67)
[8] IF KP = 10%-70% THEN Class = B (error rate = 1.00)
[9] IF KP = 0%-10% THEN Class = B (error rate = 1.00)
```

### 5.8 Calculation of the confidence

Each learner is compared based on the level of confidence ($\alpha$) of the hypothesis. The best level of trust from each learner is used as a reference for voting. While the results of the best ($\alpha$) values of each student on their adaptability in learning are presented in Table 22.

TABLE 22
BEST $\alpha$ FROM THE LEARNER

| learner Index | [0] | [1] | [2] | [3] | [4] |
|---|---|---|---|---|---|
| $\alpha$ | -3.88 | 0.26 | -9.71 | 0.52 | 6.91 |
| learner Index | [5] | [6] | [7] | [8] | [9] |
| $\alpha$ | 0.55 | -1.37 | 0.44 | -0.97 | 1.04 |

### 5.9 Class determination based on voting

Class determination for new data uses voting based on ($\alpha$). Each variable is compared with the criteria included in the rules of the student. If it matches the criteria, then take ($\alpha$) at the learner. For example, there are 4 input variables and a target variable, so each case of test data or new data is compared with the 4 best learners who have ($\alpha$). In Table 23 an example of 3 new data is presented which are not yet known in class.

TABLE 23
NEW DATA FOR TESTING

| A | KS | KB | KR | KP |
|---|---|---|---|---|
| T-1 | 203 | 6212408.1 | 1 | 0.18 |
| T-2 | 35 | 4965504.5 | 1 | 0.82 |
| T-3 | 443 | 4251635.8 | 0.5 | 0.18 |

The voting process from the test data in Table 23 is carried out by the following steps;

```
A= T-1: KS = 203, KB = 6212408.1, KR = 1, KP = 0.18
Learner index 0, alpha = -3.88, result = +1 then vote = -3.88
Learner index 2, alpha = -9.71, result = +1 then vote = -9.71
Learner index 5, alpha = 0.55, result = +1 then vote = 0.55
Learner index 8, alpha = -0.97, result = +1 then vote = -0.97
Sum of vote = -14.01 (negative) => Class: C

A= T-2: KS = 35, KB = 4965504.5, KR = 1, KP = 0.82.
Learner index 0, alpha = -3.88, result = +1 then vote = -3.88
Learner index 4, alpha = 6.91, result = +1 then vote = 6.91
Learner index 6, alpha = -1.37, result = +1 then vote = -1.37
Learner index 7, alpha = 0.44, result = +1 then vote = 0.44
Sum of vote = 2.09 (positive) => Class: B

A= T-3: KS = 443, KB = 4251635.8, KR = 0.5, KP = 0.18.
Learner index 0, alpha = -3.88, result = +1 then vote = -3.88
Learner index 2, alpha = -9.71, result = +1 then vote = -9.71
Learner index 6, alpha = -1.37, result = +1 then vote = -1.37
Learner index 8, alpha = -0.97, result = +1 then vote = -0.97
Sum of vote = -15.93 (negative) => Class: C
```

The voting process for new data T-2 has the same criteria as the A20 data in Table 21 which are categories in C, the results are not in accordance with the class, but when compared with the results of the ABC-PM method the final results of grouping use the appropriate therapeutic aspect scenario class B because the priority is set at the level of diversity and prevalence of the drug.

### 5.10 Accuracy and Precision Analysis

In this study, the analysis was conducted by setting the standard values, while the priority values for CF and SF were set at a ratio of 60:40. Based on experiments with various combinations of setting standard values obtained the highest level of accuracy and precision in setting the standard values presented in Table 24.

TABLE 24
THE BEST STANDARD VALUE COMBINATION RESULTS

| Class | Assessment (score) | | | |
|---|---|---|---|---|
| | KS | KB | KR | KP |
| A | 3 | 3 | 2 | 2 |
| B | 2 | 2 | 1 | 2 |
| C | 1 | 1 | 1 | 1 |

The ABC-PMBoost model provides an output with a level of accuracy and precision depending on the scenario aspects that are prioritized. Accuracy results with different CF and SF score settings are presented in Table 25 and Table 26, while the same priority settings are presented in Table 27.

TABLE 25
PRECISION AND ACCURACY RATE BASED ON THE COST ASPECT

| Confusion Matrix | | ABC-PM Model | | | Class | Precision |
|---|---|---|---|---|---|---|
| | | A | B | C | A | 40.00% |
| ABC Analysis | A | 4 | 0 | 6 | B | 80.00% |
| | B | 0 | 4 | 1 | C | 100.00% |
| | C | 0 | 0 | 42 | Average | 73.33% |
| | | | | | Accuracy | 87.72% |

TABLE 26
PRECISION AND ACCURACY RATE BASED ON THE THERAPY ASPECT

| Confusion Matrix | | ABC-PM Model | | | Class | Precision |
|---|---|---|---|---|---|---|
| | | A | B | C | A | 10.00% |
| ABC Analysis | A | 1 | 3 | 6 | B | 66.67% |
| | B | 0 | 2 | 1 | C | 100.00% |
| | C | 0 | 0 | 42 | Average | 58.89% |
| | | | | | Accuracy | 81.82% |

TABLE 27
PRECISION AND ACCURACY RATE WITHOUT PRIORITY DIFFERENCES

| Confusion Matrix | | ABC-PMBoost Model | | | Class | Precision |
|---|---|---|---|---|---|---|
| | | A | B | C | A | 40.00% |
| ABC Analysis | A | 4 | 6 | 0 | B | 66.67% |
| | B | 0 | 2 | 1 | C | 97.67% |
| | C | 0 | 1 | 42 | Average | 68.11% |
| | | | | | Accuracy | 85.71% |

Based on Table 26 and Table 27, the drug group in C did not change the class so much, because the focus of the therapeutic aspect and the cost aspect that was considered important to consider as a critical drug supply was class A (a drug that was considered important).

## 6 CONCLUSION

Conclusions from improvements ABC analysis with a combination of several methods into a new model, namely the ABC-PMBoost Model can be summarized as follows;

1. The ABC-PMBoost model succeeded in improving the ability of ABC Analysis to use the Cost Aspect (consumption method) and Therapy Aspect (morbidity method). The classification criteria used are the number of items, drug prices, level of diversity and prevalence of drug use. All criteria are obtained from synchronizing the database of drug use with an essential formulary list of drugs.

2. The analysis shows that the Profile Matching method has an effect on the criticality of the drug in the therapeutic aspect which has a prevalence value of more than 70% and a diversity level of less than 10% by setting priorities of the aspects that are the top priority. Combined experimentally, the Ada-Boost Algorithm simply uses sampling training data of 57 data from the Antibiotic therapy class with priority settings of each aspect, namely 60:40, resulting in an accuracy rate of 87.72% for the cost aspect, and an accuracy rate of 81.82% for

therapeutic aspects. The accuracy of the model with the same priority is 85.71%. This model also provides an output in the form of recommendations for revisions to the plan for pharmaceutical supplies based on cost aspects and aspects of therapy.

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