# DATA MODELING FOR TREND COLOR PREDICTION 

Yuli Maharetta Arianti, Achmad Benny Mutiara, Setia Wirawan and Lily Wulandari

Faculty of Computer Science and Information Technology Gunadarma University
Jl. Margonda Raya No. 100, Depok 16424, Indonesia
\{ yuli_maharetta; amutiara; setiawan; lily \}@staff.gunadarma.ac.id
Received February 2021; accepted May 2021


#### Abstract

Data modeling techniques in predicting color trends are not described in detail in a study, so it is sometimes a little confusing if you want to create a color trend prediction model. While we know that data modeling techniques into a dataset are very important in building a model, which can be used as a reference later. Based on references from several previous studies on prediction of color trends, it can be seen the type of data used, namely using historical data on sales of fashion products by paying attention to the variables Hue (H), Saturation (S), and Value (V). The proposed data model is a combination of historical data on sales of fashion products, product image data, color classification based on color space theory, which takes account of the prevailing seasonal factors in Korea. After matching the dataset to the prevailing seasons in Korea, a suitability rate of $85.8 \%$ was obtained, which is based on the truth value of the total data.


Keywords: Color, Data modeling, Image data

1. Introduction. Color is very important for the clothing industry besides the quality of the material, the price, and the quality of the stitches. Research on predicting color trends is still limited, considering that many factors influence consumer moods, political and economic climate, global trends, environmental and technological issues [1], which are sometimes difficult to do because they are considered the domain of color authority companies. Predicting a color that will become popular in the future is not an easy matter; it is necessary to think carefully and consider various aspects so that it can be used as a reference for fashion product color trends. In general, predictive theory applies to all activities, which have goals and can systematically anticipate and understand the potential direction, level of characteristics, speed, and effects of technological change, especially discovery, innovation, and adoption [2]. Color has three dimensions, namely Hue (Color), a term used to indicate the name of a color, such as red, yellow, and green; Intensity (Saturation), often referred to as chroma, is the level of purity or saturation of a color (bright or gloomy color); Value (Brightness), a dimension related to the lightness of the color (in relation to light intensity).

Prediction is one of the basic functions of data mining, where before carrying out the prediction process, the important thing that must be done is to prepare data, especially for color prediction. Data preparation or data modeling is essential because: 1) real-world data may be incomplete, noisy and inconsistent, which can mask useful patterns; 2) data preparation results in a smaller dataset than the original, which can significantly increase the efficiency of data mining; and 3) data preparation produces quality data, which leads to a quality pattern as well. Data preparation takes about $50 \%-70 \%$, sometimes $80 \%$ or
even up to $90 \%$ of the research time, because real data may be incomplete, noisy and inconsistent [3].

At the data preparation stage, a series of tasks that have a closer relationship with the data mining objectives to be achieved in a study can be described, consisting of

1) Format data. Change the data type and syntactic data structure of attributes and values (if needed).
2) Construction data. Identify, acquire, and create new attributes (if necessary) or fill in missing values via arithmetic operations.
3) Data integration. Identify, fix integration conflicts, build data relationships and select data integration schemes [3].
Data preparation is a method of collecting, cleaning, processing, and consolidating data for use in analysis. This enriches the data, transforms it and improves the accuracy of the results later. Data preparation carried out in this study is called data modeling. Types and data modeling techniques used in the process of predicting color trends are not detailed in previous studies. Generally, the data model used in previous research is to use the HSV (Hue, Saturation, Value) value from the conversion results to the RGB (Red, Green, Blue) value [4,6-8], which comes from historical data on product sales fashion or the like $[9,10,12]$.

The proposed data model is a combination of historical sales data and Ralph Lauren brand image data. Image data is used to find RGB (Red, Green, Blue) values which will then be converted into HSV (Hue, Saturation, Value). Based on the available color types, they will be classified according to the color range in the HSV color space (Hue, Saturation, Value) which refers to Munsell's theory.
2. Research Framework. The steps that must be taken when carrying out the data modeling process for predicting color trends can be seen in Figure 1.


Figure 1. Data modeling flowchart

There are five stages in the data modeling process, namely collecting and cleaning sales data, forming sales data series per week, collecting clothing sample image data, looking for RGB values, looking for HSV values as shown in Figure 1. The explanation of each stage is as follows.

## A. Collection and Cleaning of Sales Data

The historical data used is the sales data for garment products belonging to a garment company in the Bogor area, West Java, Indonesia, the Ralph Lauren brand for the period July 2017 to February 2021. The data is obtained in the form of Excel files (.xls) as many as 20 files, 1,747 records where generally one file represents quarterly sales reports. The data obtained is not in the form of a neat table but must first be cleaned of noise, inconsistent data, missing data as follows.

1) After merging all the data, there is still a lot of noise, such as duplicate data. Types of goods with the same Purchase Order (PO) number, transaction date, and total transaction are sometimes recorded 2 to 3 times, so they need to be tidied up.
2) Based on the data received, there are some inconsistent data such as the location of the attributes in each file that are not the same. This will make it difficult to do the merging process of the contents of all files. For this reason, it is necessary to unify the location of the attributes. In addition, the number of attributes of a file is not all the same, for example, there are season and product category attributes in the first file, but these attributes are not found in other files, so that when all files are merged, the data looks messy and messy. The form of inconsistency is also shown in the naming of an attribute, for example, the item name attribute, some of which write Model Long Descriptions, but some are writing Model Descriptions. For this reason, it is necessary to unify the naming of attributes.
3) After checking, there is a lot of missing data. Because not all attributes are used in the color prediction process, there are only a few attributes such as date, color, total PO, the missing data filling process only focuses on the attributes used, while other attributes are ignored. In September 2017, the company did not conduct sales transactions, resulting in missing value. Considering that in the prediction process, a data series is used which must be filled in all the data, while the type of data series used is per week, so there are 4 missing data pieces that we must enter, assuming there are 4 weeks in one month. The technique used to complete the missing data is to use the data mining concept, which is to find the average value of the total sales of the month before and the month after.

## B. Establishment of Sales Data Series per Week

Data series per week were chosen in forming a dataset because the amount of data obtained was relatively small. As it is known that data modeling requires a long time, even when a dataset has been formed and a training process is carried out on the predictive color trend model, it is still possible to change the existing dataset to find the shape or composition of the data model that is most optimal. As is the case with the garment product sales data used in this study, several changes were made to the point that a data series per week was selected. For that it is necessary to carry out the following stages.

1) Of all recorded transactions, an accumulation of total sales for the same product color and the same transaction month is carried out.
2) Choose the 4 colors with the highest sales value for the month, where the 4 colors selected represent transactions each week, assuming there are 4 weeks or 4 transactions in one month.
3) Delete transaction data other than the 4 selected colors.

After passing through the steps above, the data has shrunk to 176 records and 16 types of colors. As additional information, based on the trials conducted, the type of color available is directly proportional to the amount of data used. The more types of colors
you have, the greater the number of data series that must be prepared. This is expected to produce a relatively small error value in the process of predicting the color trend later. The formed dataset can be seen in Table 1.

Table 1. Garment product sales data

| No | Week | Date | Color | Total PO OrderQty |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | $09 / 07 / 2017$ | Cream | 3798 |
| 2 | 2 | $12 / 07 / 2017$ | Navy | 9996 |
| 3 | 3 | $23 / 07 / 2017$ | Olive | 3798 |
| 4 | 4 | $31 / 07 / 2017$ | Black | 514 |
| 5 | 1 | $01 / 08 / 2017$ | Black | 10222 |
| 6 | 2 | $10 / 08 / 2017$ | Navy | 5044 |
| 7 | 3 | $17 / 08 / 2017$ | Red | 2000 |
| 8 | 4 | $27 / 08 / 2017$ | Sapphire Star | 1900 |
| 9 | 1 | $01 / 09 / 2017$ | Black | 5384 |
| 10 | 2 | $10 / 09 / 2017$ | Navy | 4577 |
| 11 | 3 | $19 / 09 / 2017$ | Grey | 2450 |
| 12 | 4 | $29 / 09 / 2017$ | Black | 19167 |
| 13 | 1 | $02 / 10 / 2017$ | Navy | 545 |
| 14 | 2 | $12 / 10 / 2017$ | Black | 4109 |
| 15 | 3 | $19 / 10 / 2017$ | Grey | 2900 |
| 16 | 4 | $27 / 10 / 2017$ | Navy | 1060 |
| 17 | 1 | $01 / 11 / 2017$ | Black | 2145 |
| 18 | 2 | $12 / 11 / 2017$ | Blue | 4246 |
| 19 | 3 | $22 / 11 / 2017$ | Grey | 2003 |
| 20 | 4 | $28 / 11 / 2017$ | Navy | 6355 |
| $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ |
| 169 | 1 | $03 / 01 / 2021$ | Navy | 10028 |
| 170 | 2 | $13 / 01 / 2021$ | White | 6565 |
| 171 | 3 | $22 / 01 / 2021$ | Blackwatch Plaid | 3665 |
| 172 | 4 | $27 / 01 / 2021$ | Red | 3430 |
| 173 | 1 | $04 / 02 / 2021$ | Blue | 18 |
| 174 | 2 | $14 / 02 / 2021$ | Navy | 4050 |
| 175 | 3 | $21 / 02 / 2021$ | Navy | 3696 |
| 176 | 4 | $28 / 02 / 2021$ | White | 300 |

## C. Clothing Sample Image Data Collection

The color data obtained from the garment product sales report is in the form of qualitative data, namely in the form of text such as sapphire star, navy, and gray, while we need quantitative data in the form of the RGB value of the image to then look for the HSV value. Given that hue, saturation, and value are used as input and output variables in the process of predicting future color trends. For that we need to find image data in the form of color samples from these clothes.

Based on the 16 types of colors available, the color image is searched through the https://www.ralphlauren.com/ page. This page was chosen considering that garment products are produced to meet the demands of the Korean market, so that there are relatively more color variants on this page when compared to the Ralph Lauren Indonesia page. All samples from the product color image are taken which can be seen in Table 2.

Table 2. (color online) Garment product image data

| No | Color | Product image |
| :---: | :---: | :---: |
| 1 | Baker Red |  |
| 2 | Blackwatch Plaid |  |
| 3 | Black |  |
| 4 | Blue Mist |  |
| 5 | Blue | $\square$ |
| 6 | Cream |  |
| 7 | Green |  |
| 8 | Grey |  |
| 9 | Mango |  |
| 10 | Multi |  |
| 11 | Navy |  |
| 12 | New Olive |  |
| 13 | Pink | $\square$ |
| 14 | Red | $\square$ |
| 15 | Sapphire Star | $\square$ |
| 16 | White |  |

## D. Looking for RGB Value

In this process, the first array is taken as a sample to find out the RGB (Red, Green, Blue) value of each clothing color image, in a set of arrays that make up the image. Suppose the color taken as an example is Navy. To find out what the R, G, and B values of this color are, the steps that must be done are

- Upload a folder containing 16 color image data to Google Drive.
- Using Google Colaboratory or commonly known as Colab as a tool for data processing purposes.
- Import the required libraries and modules, most of which are already available on Google Colab.
- Data is read based on the path, which generally has a size of $24 \times 24$ pixels, with a combination of 3 numbers indicating that the image is colored. By default OpenCV will render a Blue Green Red (BGR) image.
- With a specific function, change the BRG image to RGB.

Table 3. Garment product RGB value

| No | Color | RGB |
| :---: | :---: | :---: |
| 1 | Baker Red | $(163,2,20)$ |
| 2 | Blackwatch Plaid | $(36,83,91)$ |
| 3 | Black | $(60,55,61)$ |
| 4 | Blue Mist | $(129,155,214)$ |
| 5 | Blue | $(24,40,92)$ |
| 6 | Cream | $(237,233,222)$ |
| 7 | Green | $(128,199,131)$ |
| 8 | Grey | $(176,176,176)$ |
| 9 | Mango | $(251,113,84)$ |
| 10 | Multi | $(0,199,255)$ |
| 11 | Navy | $(0,0,128)$ |
| 12 | New Olive | $(88,75,40)$ |
| 13 | Pink | $(228,61,141)$ |
| 14 | Red | $(177,10,38)$ |
| 15 | Sapphire Star | $(3,82,183)$ |
| 16 | White | $(252,252,252)$ |

## E. Finding the HSV Value

To find the HSV (Hue, Saturation, Value) value of all the garment sample image data obtained, a formula can be used. Supposing Navy is taken as an example of a color image, then the steps in the conversion process from RGB to HSV in a calculation can be seen in the following formula [13]:

$$
\begin{align*}
& H=\tan \left(\frac{3(G-B)}{(R-G)+(R+B)}\right)  \tag{1}\\
& S=1-\frac{(R, G, B)}{V}  \tag{2}\\
& V=\frac{(R+G+B)}{3} \tag{3}
\end{align*}
$$

where $R=$ Red, $G=$ Green, $B=$ Blue, $H=$ Hue, $S=$ Saturation, and $V=$ Value.
If the value of $S=0$, then the value of $H$ is undefined, so the RGB value normalization process is required first. The process of normalizing RGB values can be seen in the formula

$$
\begin{align*}
r & =\frac{R}{R+G+B}  \tag{4}\\
g & =\frac{G}{R+G+B}  \tag{5}\\
b & =\frac{B}{R+G+B} \tag{6}
\end{align*}
$$

After the $r, g$, and $b$ values are obtained from the normalization process, then the RGB to HSV transformation process can use a different formula.

$$
\begin{equation*}
V=\max (r, g, b) \tag{7}
\end{equation*}
$$

$$
\begin{align*}
& S= \begin{cases}0 & \text { If } V=0 \\
V-\frac{\min (r, g, b)}{V} & \text { If } V>0\end{cases}  \tag{8}\\
& H= \begin{cases}0 & \text { If } S=0 \\
\frac{60 *(g-b)}{S * V} & \text { If } V=r \\
60 *\left[2+\frac{b-r}{S * V}\right] & \text { If } V=g \\
60 *\left[4+\frac{r-g}{S * V}\right] & \text { If } V=b\end{cases}  \tag{9}\\
& H=H+360 \quad \text { If } H<0 \tag{10}
\end{align*}
$$

For example, the RGB values in Table 3, namely Navy, are 0,0 and 128. Then the normalized values for $r, g$, and $b$ are obtained as follows. Each RGB value $(0,0,128)$ is changed in the range [0,1] by dividing each value with 255 .

$$
\begin{aligned}
r & =\frac{0}{255} \\
r & =0 \\
g & =\frac{0}{255} \\
g & =0 \\
b & =\frac{128}{255} \\
b & =0.5
\end{aligned}
$$

Then the calculation is carried out to find the HSV value according to Formulae (7)-(10) where the value of $V$ is the largest value of $r, g$, and $b$.

$$
\begin{aligned}
& V=0.5 \times 100=50 \\
& S=\frac{0.5-0}{0.5} \times 100 \\
& S=100 \\
& H=60 \times\left[4+\frac{0-0}{100 \times 0.5}\right] \\
& H=60 \times\left[4+\frac{0}{50}\right] \\
& H=60 \times[4+0] \\
& H=60 \times 4 \\
& H=240
\end{aligned}
$$

Based on the calculations that have been done, the value of Hue is 240, Saturation is 100 , and a Value is 50 . The calculation process is repeated until all color types have HSV values.

TABLE 4. HSV value of garment products

| No | Color | Hue | Saturation | Value |
| :---: | :---: | :---: | :---: | :---: |
| 1 | Baker Red | 353 | 99 | 64 |
| 2 | Blackwatch Plaid | 189 | 60 | 36 |
| 3 | Black | 290 | 10 | 24 |
| 4 | Blue Mist | 222 | 40 | 84 |
| 5 | Blue | 226 | 74 | 36 |
| 6 | Cream | 44 | 6 | 93 |
| 7 | Green | 123 | 36 | 78 |
| 8 | Grey | 0 | 0 | 69 |
| 9 | Mango | 10 | 67 | 98 |
| 10 | Multi | 193 | 100 | 100 |
| 11 | Navy | 240 | 100 | 50 |
| 12 | New Olive | 44 | 55 | 35 |
| 13 | Pink | 331 | 73 | 89 |
| $\mathbf{1 4}$ | Red | 350 | 94 | 69 |
| 15 | Sapphire Star | 214 | 98 | 72 |
| 16 | White | 0 | 0 | 99 |

3. Results and Discussion. Based on the raw data obtained in the form of sales reports for garment products of the Ralph Lauren brand from garment companies in the Bogor area, West Java, as many as 20 files in the form of Excel, for the period July 2017 to February 2021, 1,747 data records were obtained. After cleaning the data, such as incomplete, inconsistent, duplicate data, as well as the accumulated total sales transactions for one month with the same product name and color, to form a data series per week, 176 records were generated, 16 types of product colors were produced.

To get a small error value when the dataset is used in the process of calculating color trend predictions, it is possible to create a hue class based on a color map that is on the color spectrum. The color range formed adopts the Munsell color concept, where Munsell divides the hue color circle into 10 radian ranges and calls it the colors Red, YellowRed, Yellow, Green-Yellow, Green, Blue-Green, Blue, Purple-Blue, Purple, Red-Purple. Munsell color map can be seen in Figure 2.


Figure 2. (color online) Munsell color system (Source: Jacob Rus, 2007, CC-BY-SA 3.0)

Hue represents color angles ranging from $0^{\circ}$ for red, $30^{\circ}$ for orange, $60^{\circ}$ for yellow, $120^{\circ}$ for green, $180^{\circ}$ for cyan, $240^{\circ}$ for blue, and $300^{\circ}$ for purple [13]. Color components that have an intensity value of $\mathrm{I} \leq 15$ are very dark or close to black. So in this intensity range the color of each of these components can be expressed as a dark color. Thus with the difference between the maximum and minimum values R, G, B in the range 0 and 15 $(\max (R, G, B)-\min (R, G, B) \leq 15)$, this color looks like a gray-level. Then the two facts above can be used to form a gray-level color map [14]. Referring to the above concept, classes can be formed based on color ranges as in Table 5.

Table 5. Class based on color range

| Class | Color | Value range |
| :---: | :---: | :---: |
| 0 | Dark | 0 |
| 1 | Red | $1-15$ and $346-360$ |
| 2 | Yellow Red | $16-45$ |
| 3 | Yellow | $46-75$ |
| 4 | Green Yellow | $76-115$ |
| 5 | Green | $116-165$ |
| 6 | Blue Green | $166-195$ |
| 7 | Blue | $196-255$ |
| 8 | Purple Blue | $256-285$ |
| 9 | Purple | $286-315$ |
| 10 | Red Purple | $316-345$ |

So of the 16 types of colors that exist in the dataset, they can be grouped by class according to the existing color range, which can be seen in Table 6 .

Table 6. Garment product class

| Color | Hue | Class |
| :---: | :---: | :---: |
| Grey | 0 | 0 |
| White | 0 | 0 |
| Mango | 10 | 1 |
| New Olive | 44 | 2 |
| Cream | 44 | 2 |
| Green | 123 | 4 |
| Blackwatch Plaid | 189 | 6 |
| Multi | 193 | 6 |
| Sapphire Star | 214 | 7 |
| Blue Mist | 222 | 7 |
| Blue | 226 | 7 |
| Navy | 240 | 7 |
| Black | 290 | 9 |
| Pink | 331 | 10 |
| Red | 350 | 1 |
| Baker Red | 353 | 1 |

The last step carried out was analyzing the existing dataset based on the prevailing season in Korea based on the visitkorea.or.kr page, with the Angela Wright's system with the HSV value [4] which can be seen in Table 8.

Table 7. Season of Korea region

| No | Season | Month |
| :---: | :---: | :---: |
| 1 | Spring | March-May |
| 2 | Summer | June-August |
| 3 | Fall/Auturm | September-November |
| 4 | Winter | December-February |

Table 8. Angela Wright's system with HSV value [4]

| Pallets type | HSV | HSV value |
| :---: | :---: | :---: |
| Spring | Hue: Warm | $\mathrm{H}=0-118$ |
|  | Saturation: Any | $\mathrm{S}=0-255$ |
|  | Value: Light | $\mathrm{V}=129-255$ |
| Summer | Hue: Cool | $\mathrm{H}=119-255$ |
|  | Saturation: Low | $\mathrm{S}=0-189$ |
|  | Value: Any | $\mathrm{V}=0-127,129-255$ |
| Autumn | Hue: Warm | $\mathrm{H}=0-118$ |
|  | Saturation: High | $\mathrm{S}=190-255$ |
|  | Value: Dark | $\mathrm{V}=0-127$ |
| Winter | Hue: Cool | $\mathrm{H}=119-255$ |
|  | Saturation: Low | $\mathrm{S}=0-189$ |
|  | Value: Pure | $\mathrm{V}=128$ |

Table 9. Comparison table

| No. | Sales data |  |  |  | H | S | Y | Season (Korea) | Angela Wright |  |  |  | Result |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | W | M | Y | Color |  |  |  |  | Category | Hue | Saturation | Value |  |
| 1 | 1 | 7 | 2017 | Cream | 44 | 6 | 93 | Summer | Warm | Spring/Autumn | Summer/Winter | Summer/Autumn | T |
| 2 | 2 | 7 | 2017 | Navy | 240 | 100 | 50 | Summer | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 3 | 3 | 7 | 2017 | New Olive | 44 | 55 | 35 | Summer | Warm | Spring/Autumn | Summer/Winter | Summer/Autumn | T |
| 4 | 4 | 7 | 2017 | Black | 290 | 10 | 24 | Summer | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 5 | 1 | 8 | 2017 | Black | 290 | 10 | 24 | Summer | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 6 | 2 | 8 | 2017 | Navy | 240 | 100 | 50 | Summer | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 7 | 3 | 8 | 2017 | Red | 350 | 94 | 69 | Summer | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 8 | 4 | 8 | 2017 | Sapphire Star | 214 | 98 | 72 | Summer | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 9 | 1 | 9 | 2017 | Black | 290 | 10 | 24 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 10 | 2 | 9 | 2017 | Navy | 240 | 100 | 50 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 11 | 3 | 9 | 2017 | Grey | 0 | 0 | 69 | Fall/Autumn | Warm | Spring/Autumn | Summer/Winter | Summer/Autumn | T |
| 12 | 4 | 9 | 2017 | Sapphire Star | 214 | 98 | 72 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| : | : | : | : | : | $\vdots$ | : | : | : | : |  |  |  |  |
| 157 | 1 | 10 | 2020 | Navy | 240 | 100 | 50 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 158 | 2 | 10 | 2020 | Baker Red | 353 | 99 | 64 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 159 | 3 | 10 | 2020 | Black | 290 | 10 | 24 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 160 | 4 | 10 | 2020 | Red | 350 | 94 | 69 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 161 | 1 | 11 | 2020 | Multi | 193 | 100 | 100 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 162 | 2 | 11 | 2020 | Blue | 226 | 74 | 36 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 163 | 3 | 11 | 2020 | Blue | 226 | 74 | 36 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 164 | 4 | 11 | 2020 | Navy | 240 | 100 | 50 | Fall/Autumn | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 165 | 1 | 12 | 2020 | Navy | 240 | 100 | 50 | Winter | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 166 | 2 | 12 | 2020 | Blue | 226 | 74 | 36 | Winter | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 167 | 3 | 12 | 2020 | Multi | 193 | 100 | 100 | Winter | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 168 | 4 | 12 | 2020 | White | 0 | 0 | 99 | Winter | Warm | Spring/Autumn | Summer/Winter | Summer/Autumn | T |
| 169 | 1 | 1 | 2021 | Navy | 240 | 100 | 50 | Winter | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 170 | 2 | 1 | 2021 | White | 0 | 0 | 99 | Winter | Warm | Spring/Autumn | Summer/Winter | Summer/Autumn | T |
| 171 | 3 | 1 | 2021 | Blackwatch Plaid | 189 | 60 | 36 | Winter | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 172 | 4 | 1 | 2021 | Red | 350 | 94 | 69 | Winter | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 173 | 1 | 2 | 2021 | Blue | 226 | 74 | 36 | Winter | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 174 | 2 | 2 | 2021 | Navy | 240 | 100 | 50 | Winter | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 175 | 3 | 2 | 2021 | Navy | 240 | 100 | 50 | Winter | Cool | Summer/Winter | Summer/Winter | Summer/Autumn | T |
| 176 | 4 | 2 | 2021 | White | 0 | 0 | 99 | Winter | Warm | Spring/Autumn | Summer/Winter | Summer/Autumn | T |

Based on the dataset obtained from the results of data modeling, it can be analyzed of the level of suitability of the two comparators above. For example, in July 2017 the second week of navy color with a hue of 240 , when viewed from the Angela Wright table, the 119-255 hue value range is in the cool category, with the summer or winter season. Then we match it with the season in Korea where in July 2017 the summer season occurs. So it can be concluded that navy is suitable as an alternative color that can be used in July considering the summer season in Korea. The results of data analysis can be seen in Table 9.
4. Conclution and Future Work. Referring to the matching results shown in Table 9, it can be concluded that the data modeling carried out in this study has a suitability level of $(151 / 176) * 100=85.8 \%$. So this data modeling can be used for a prediction system for color trends in the garment industry which will be marketed in the country of Korea.

This paper produces a data modeling method for predicting color trends that is different from previous studies, which combines historical sales data and garment product image data. In addition, a color map was made based on the color range according to Munsell's theory. Next it will be seen of the level of suitability based on the season in effect in the country of Korea. Season and class variables (according to the color range) will later be used as additional variables in the color prediction process that will be carried out in the hope of obtaining a relatively small error value.

## REFERENCES

[1] M. Bruce, L. M. Benson, D. Oulton and M. K. Hogg, The colour conspiracy: A summary of colour forecasting in the textile \& clothing industry and its in uence on future predictions for a UK mail order company, Design Journal, vol.1, no.4, pp.311-320, 1999.
[2] A. K. Firat, S. Madnick and W. L. Woon, Technological Forecasting - A Review, Working Paper CISL\# 2008-15, pp.1-19, 2008.
[3] J. Perez, E. Iturbide, V. Olivares, M. Hidalgo, A. Martínez and N. Almanza, A data preparation methodology in data mining applied to mortality population databases, J. Med. Syst., vol.39, no.152, DOI: 10.1007/s10916-015-0312-5, 2015.
[4] T. D. Cassidy, Personal colour analysis, consumer colour preferences and colour forecasting for the fashion and textile industries, Colour: Design EG Creativity, vol.1, no.1, pp.1-14, 2007.
[5] T. D. Cassidy and T. Cassidy, Using soft systems methodology to improve the colour forecasting process, Journal of the International Colour Association, vol.7, pp.27-50, 2012.
[6] L. Chang, W. Gao, X. Zhang, Y. Lu and R. Pan, Review of researches on fashion color prediction based on grey systems theory, Proc. of 2009 IEEE International Conference on Grey Systems and Intelligent Services, Nanjing, China, 2009.
[7] L. Chang, J. Xie, W. Gao and X. Yan, Fashion colour predicting research based on grey theory and rough set theory, 2009 IEEE 10th International Conference on Computer-Aided Industrial Design $\mathcal{E}^{3}$ Conceptual Design, pp.1584-1588, DOI: 10.1109/CAIDCD.2009.5375162, 2009.
[8] L.-X. Chang, W.-D. Gao and X. Zhang, Discussion on fashion color forecasting researches for textile and fashion industries, Journal of Fiber Bioengineering and Informatics (JFBI), vol.2, no.1, 2009.
[9] J. J. Lin, P. T. Sun, J. J. R. Chen, L. J. Wang, H. C. Kuo and W. G. Kuo, Applying gray model to predicting trend of textile fashion colors, The Journal of the Textile Institute, vol.101, no.4, pp.360368, 2010.
[10] Y. Yu, C.-L. Hui and T.-M. Choi, An empirical study of intelligent expert system on forecasting of fashion color trend, Expert System with Applications, vol.39, pp.4383-4389, DOI: 10.1016/ j.eswa.2011.09.153, 2012.
[11] T.-M. Choi, C.-L. Hui, S.-F. Ng and Y. Yu, Color trend forecasting of fashionable products with very few historical data, IEEE Trans. Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol.42, no.6, pp.1003-1010, 2012.
[12] X. Kong, L. Chang and J. Xu, Fashion colour forecasting based on BP neural network, Computer Modelling $\xi^{2}$ New Technologies, vol.18, no.11, pp.584-591, 2014.
[13] S. Madenda, Digital Image E Video Processing; Theory, Application and Programming Using Matlab, Erlangga Publisher, Jakarta, 2015.
[14] T. Acharya and A. K. Ray, Image Processing: Principles and Applications, J Wiley, New Jersey, US, 2005.

