Performance of Cans Classification System for Different Conveyor Belt Speed using Naïve Bayes

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Abstract
The classification system in the sorting process in the can recycling industry can be made based on digital images by exploring the basic color pixel values of images such as R, G, and B as variable inputs. In real time, the classification of cans in the sorting process occurs when cans placed on a conveyor belt move at a certain speed. This paper discusses the performance of can classification systems using the Naïve Bayes method. This method can handle all types of variables, including when all variables are continuous. Two types of conveyor belts are designed to get different speeds, and all images of the cans are captured on both conveyor belts. Two models of Bayes naive are built on the basis of the different distribution assumptions; the original model (all Gaussian distributed) and the model based on the best distribution. Performance of the classification system is built by dividing data into the learning data and the testing data with a composition of 50:50 in which each data is designed into 50 groups with different percentages on each type of cans using sampling technique without replacement. The results obtained are first, the speed of the conveyor belt when capturing an image affects the pixel values of red, green, and blue and ultimately affects the results of the classification of cans. Second, not all input variables are Gaussian distributed. The classification system was built using assumption that the best distribution model for each input variable has the better average accuracy level than the model that assumes all input variables are Gaussian distributed, and the accuracy level of classification on the first speed of conveyor belt with a gear ratio of 12:30 and a diameter of 35 mm has an accuracy that is better than the other speed, both on the original model and the model based on the best distribution. However, it is necessary to test more statistical distribution models to obtain significant results.

Keywords
Classification System, Conveyor Belt Speed, Naïve Bayes

1. INTRODUCTION
The automation technology of an industrial system that uses intelligent computing systems has continued to develop rapidly recently (Kamboj et al. (2019); Nikhil et al. (2017); Oladapo et al. (2016); Bargal et al. (2016); Fluke (2015); Rosenblat et al. (2014)) including the automation of sorting systems in the can recycling industry that uses object classification techniques based on digital images (Resti et al. (2018); Resti et al. (2017b)). Classification of cans based on digital images of cans placed on a static conveyor belt can be seen in (Resti et al. (2019); Resti et al. (2017a); Resti (2015); Yani et al.; Yani et al. (2009)). In real time, the classification of cans in a sorting system occurs when cans placed on a conveyor belt move at a certain speed. Obtaining a higher level of accuracy becomes important in the classification system (Sin & Wang, 2019; Aronoff et al. (1982)).

Naïve Bayes is one method that is widely used in classification models (Harzevili and Alizadeh, 2018; Agarwal et al. (2015)) especially digital object classification models can be seen in (Mansour (2018); Pérez-Díaz et al. (2017); Nikhil et al. (2017); Salinas-Gutiérrez et al. (2010); Jayech and Mahjoub (2010)). This method can handle various types of input variables. When the input variables are continuous type, generally this method is built by assuming all input variables are Gaussian distributed, and the accuracy level of classification on the first speed of conveyor belt with a gear ratio of 12:30 and a diameter of 35 mm has an accuracy that is better than the other speed, both on the original model and the model based on the best distribution. However, it is necessary to test more statistical distribution models to obtain significant results.
We also propose two models of Bayes; the original model and with different percentages on each type of cans using sampling technique without replacement. The percentage of cans in each composition of 50:50, where each data is designed into 50 groups with different percentages on each type of cans using sampling technique without replacement. The percentage of cans in each type of the learning data and the testing data, respectively is presented in Table 2.

### Table 2. Design of the learning and the testing data

| Group | Percentage of Cans in Each Type |
|-------|---------------------------------|
|       | Learning | Testing |
|       | Can Type | Can Type |
|       | 1st | 2nd | 3rd | 1st | 2nd | 3rd |
| 1     | 33.6 | 35.2 | 31.2 | 25.6 | 31.2 | 43.2 |
| 2     | 32.8 | 32.0 | 35.2 | 25.6 | 31.2 | 43.2 |
| 3     | 30.4 | 33.6 | 36.0 | 28.8 | 32.8 | 38.4 |
| 4     | 28.0 | 30.4 | 41.6 | 31.2 | 36.0 | 32.8 |
| 5     | 38.4 | 22.4 | 39.2 | 25.6 | 31.2 | 43.2 |
| ...   | ...   | ...   | ...   | ...   | ...   | ...   |
| 50    | 30.4 | 32.0 | 37.6 | 28.8 | 34.4 | 36.8 |

2. EXPERIMENTAL SECTION

#### 2.1 Methods

The stages of this research are as follows:

1. Designing 2 types of conveyor-belts, the first using a gear with a ratio of 12:30 and diameter of 35 mm, and the second, using a gear with a ratio of 14:30 and diameter of 42 mm. These designs produced the speed of 0.181 m/s (the first conveyor-belt) and 0.086 m/s (the second conveyor-belt) respectively.

2. Capturing images of the cans placed on the first conveyor-belt. The cans were captured using a web camera connected to a computer with the illumination of the light-emitting diode (LED) lamp set at an angle of 30° as shown in Figure 1. Then, the cans are placed on the second conveyor belt and the image capturing process is done the same way.

Furthermore, the can image data is processed using the RGB color model with a color depth of 8 bits where the region of interest in each image is obtained using image processing cropping techniques. Data summary of the pixel values of R, G, and B of the two data are presented in Table 1.

3. Divide the data into learning data and testing data with a composition of 50:50, where each data is designed into 50 groups with different percentages on each type of can using sampling technique without replacement. The percentage of cans in each type of the learning data and the testing data, respectively is presented in Table 2.

![Figure 1. The cans image capturing system](image-url)
Kolmogorov-Smirnov [28], Cramer von Mises [29], Anderson-Darling [30], Akaike Information Criteria and Bayesian Information Criteria [31]. The first assumption is called original model (OM), while the second assumption is called the best model (BM).

\[
P(R_k; \mu_{rk}, \sigma_{rk}) = \frac{1}{\sigma_{rk} \sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{r_k - \mu_{rk}}{\sigma_{rk}} \right)^2 \right)
\]

(2)

5. Measuring the performance of can classification for each conveyor-belt type data (first speed and second speed) and both model assumptions; original model (OM) and model based on best distribution (BM). OM assumes all input variables are Gaussian distributed while BM is a model based on the best distribution of input variables. The accuracy performance is calculated as the mean of accuracy level.

3. RESULTS AND DISCUSSION

3.1 The best distribution model of input variables

All variables from the two data are tested with 5 goodness of fit tests to determine the suitability of each variable with the Gaussian and Gamma distribution models. The results of 5 goodness of fit tests for the 1st speed data are given in Table 3, while the parameters of the best distribution models are given in Table 5.

The distribution model that has smaller goodness of fit value is a better model. Each of the input variables has 2 - 5 tests that support it as the best model. The best distribution model of the input variables R, G, and B are all Gamma distributions, on the 2nd can type are all Gaussian distributions, while on the 3rd cans type are Gamma, Gaussian, and Gamma distributions, respectively.

The results of the goodness of fit tests of all input variables for each can type of the second conveyor belts speed and the parameters of the best distribution models are given in Table 5 and Table 6 successively.

Table 5 informs that on the 1st can type, the best distribution model of the input variables R, G, and B are all Gamma distribution, on the 2nd can type are Gamma, Gaussian, Gamma distributions, while on the 3rd cans type are Gamma distributions. In the 2nd speed, at least each input variable has three tests that support it as the best model, and on average it has four tests that support it.

3.2 Performance of Classification

Table 7 shows the accuracy level of each conveyor-belt type both in the original model (OM) and the best distribution model (BM).

Each group has a different accuracy level for each conveyor-belt type both in the original model (OM) and the best distribution model (BM). To that end, classification performance is measured as the mean of the accuracy levels of the 50 groups.

The variances, bias and confidence interval of the mean of the 50 groups are also presented in Table 7.

The mean of the classification accuracy level of 50 groups noted that BM has better accuracy than OM, both on the 1st data speed (the 1st conveyor-belt type) with a difference of 0.4%, and the 2nd data speed (the 2nd conveyor-belt type) with a difference of 0.1%. The variance, bias, and confidence interval of the mean in both data also show that BM has better performance than OM. This small difference in the four statistics can be caused by the variable distribution model adjusted for each input variable only two, namely Gaussian and Gamma.

Fitting the distribution of input variables to more distribution models allows a more appropriate distribution model to be obtained so that the level of accuracy can be higher. Comparison of the measurement of accuracy of the 1st and 2nd speeds for both OM and BM has a difference of around 6-7%, a bias difference of around 5-8%, and a confidence interval of more than 7%. These measurements show that the performance of can classification at the 1st speed is better than the 2nd speed at both OM and BM.

4. CONCLUSIONS

This paper proposed the performance of a can classification system based on the digital image built using 2 types of conveyor belts and 2 types of models in the Naive Bayes method to obtain the highest level of accuracy. The performance of the classification accuracy is built by dividing data into the learning data and testing data with a composition of 50:50 in which each data is designed into 50 groups with different percentages on each type of cans using resampling techniques with replacement. The results show that the classification system was built using assumption the best distribution model for each input variable has a better performance of accuracy than the model that assumes all input variables are Gaussian distributed, and the performance of accuracy on the first speed is better than the second speed, both on the original model (OM) and the model based on the best (BM) distribution. Overall, the best classification performance is owned by the Naive Bayes method which assumes the best distribution model for each input variable where image data is obtained from the capturing system with a conveyor belt speed of 0.181 m/s. Important notes from the results of this study are first, the conveyor belt speed when capturing images affects the pixel value of red, green, and blue and ultimately affects the results of the classification of cans. Second, not all input variables are Gaussian distributed. Implementation of the best statistical distribution model on the Naive Bayes method can influence the results of classification but it is necessary to test more statistical distribution models to obtain significant results.

5. ACKNOWLEDGEMENT

This research was supported by DIPA, University of Sriwijaya, No. SP DIPA-042.01.2.400953/2019, for the Competitive Research, No. 0015 /UN9/LSLP2M.PT/2019.
Table 3. Goodness-of-fit test for the 1st speed

| Input Variable | Goodness of fit | The 1st cans type | The 2nd cans type | The 3rd cans type |
|----------------|---------------|------------------|------------------|------------------|
|                |               | Gaussian         | Gamma            | Gaussian         | Gamma            |
| R1             | KS            | 0.12             | 0.12             | 0.07             | 0.06             | 0.06             | 0.06             |
|                | CVM           | 0.20             | 0.17             | 0.06             | 0.07             | 0.04             | 0.04             |
|                | AD            | 1.47             | 1.28             | 0.55             | 0.58             | 0.27             | 0.26             |
|                | AIC           | 599.42           | 595.44           | 404.34           | 405.02           | 619.17           | 618.61           |
|                | BIC           | 604.03           | 600.05           | 409.18           | 409.86           | 624.24           | 623.67           |
| G1             | KS            | 0.11             | 0.11             | 0.09             | 0.13             | 0.12             | 0.09             |
|                | CVM           | 0.13             | 0.12             | 0.16             | 0.16             | 0.05             | 0.06             |
|                | AD            | 1.02             | 0.95             | 1.33             | 1.40             | 0.34             | 0.39             |
|                | AIC           | 555.60           | 553.72           | 399.01           | 400.00           | 548.47           | 548.81           |
|                | BIC           | 560.21           | 558.33           | 403.84           | 404.84           | 553.54           | 553.87           |
| B1             | KS            | 0.12             | 0.11             | 0.12             | 0.13             | 0.06             | 0.06             |
|                | CVM           | 0.32             | 0.27             | 0.16             | 0.16             | 0.06             | 0.06             |
|                | AD            | 2.20             | 1.87             | 1.06             | 1.13             | 0.40             | 0.40             |
|                | AIC           | 573.56           | 568.51           | 426.78           | 428.04           | 576.68           | 575.79           |
|                | BIC           | 578.17           | 573.12           | 431.62           | 432.88           | 581.74           | 580.85           |

Table 4. Parameter of the best distribution model for the 1st speed

| Input Variable | The 1st cans type | The 2nd cans type | The 3rd cans type |
|----------------|------------------|------------------|------------------|
|                | Parameter        | Parameter        | Parameter        |
| R1             | $\theta_{r_1}$  | 144.89           | $\mu_{r_2}$     | 150.87           | $\beta_{r_3}$   | 565.11           |
|                | $\beta_{r_1}$   | 0.91             | $\sigma_{r_2}$  | 12.49            | $\beta_{r_3}$   | 3.61             |
| G1             | $\theta_{g_1}$  | 249.84           | $\mu_{g_2}$     | 154.02           | $\mu_{g_3}$     | 158.03           |
|                | $\beta_{g_1}$   | 1.59             | $\sigma_{g_2}$  | 2.63             | $\sigma_{g_3}$  | 4.54             |
| B1             | $\theta_{b_1}$  | 193.40           | $\mu_{b_2}$     | 150.84           | $\beta_{b_3}$   | 866.93           |
|                | $\beta_{b_1}$   | 1.27             | $\sigma_{b_2}$  | 3.11             | $\beta_{b_3}$   | 5.62             |

Table 5. Goodness-of-fit test for the 2nd speed

| Input Variable | Goodness of fit | The 1st cans type | The 2nd cans type | The 3rd cans type |
|----------------|---------------|------------------|------------------|------------------|
|                |               | Gaussian         | Gamma            | Gaussian         | Gamma            | Gaussian         | Gamma            |
| R2             | KS            | 0.13             | 0.12             | 0.07             | 0.07             | 0.11             | 0.11             |
|                | CVM           | 0.32             | 0.26             | 0.09             | 0.09             | 0.25             | 0.22             |
|                | AD            | 1.79             | 1.45             | 0.62             | 0.60             | 1.28             | 1.13             |
|                | AIC           | 603.33           | 598.39           | 460.68           | 460.54           | 627.62           | 625.43           |
|                | BIC           | 607.94           | 603.00           | 465.52           | 465.38           | 632.68           | 630.49           |
| G2             | KS            | 0.08             | 0.08             | 0.08             | 0.08             | 0.06             | 0.05             |
|                | CVM           | 0.11             | 0.08             | 0.09             | 0.10             | 0.05             | 0.04             |
|                | AD            | 0.70             | 0.54             | 0.61             | 0.66             | 0.31             | 0.27             |
|                | AIC           | 552.90           | 550.84           | 441.79           | 442.09           | 597.78           | 596.59           |
|                | BIC           | 557.51           | 555.45           | 446.62           | 446.93           | 602.85           | 601.65           |
| B2             | KS            | 0.15             | 0.14             | 0.07             | 0.07             | 0.08             | 0.08             |
|                | CVM           | 0.41             | 0.34             | 0.04             | 0.04             | 0.17             | 0.15             |
|                | AD            | 2.41             | 1.96             | 0.31             | 0.32             | 1.31             | 1.09             |
|                | AIC           | 576.11           | 570.59           | 445.38           | 445.40           | 608.33           | 604.17           |
|                | BIC           | 580.71           | 575.20           | 450.22           | 450.22           | 613.39           | 609.23           |
Table 6. Parameter of the best distribution model for the 2nd speed

| Input Variable | The 1\textsuperscript{st} cans type Parameter | The 2\textsuperscript{nd} cans type Parameter | The 3\textsuperscript{rd} cans type Parameter |
|---------------|---------------------------------|---------------------------------|---------------------------------|
| R           | $\theta_{r21}$ 132.13          | $\theta_{r22}$ 1518.32         | $\theta_{r23}$ 477.43          |
|               | $\beta_{r21}$ 0.85            | $\beta_{r22}$ 10.29           | $\beta_{r23}$ 3.19            |
| G           | $\theta_{g21}$ 246.83         | $\mu_{g22}$ 150.63           | $\theta_{g23}$ 663.66         |
|               | $\beta_{g21}$ 1.61            | $\sigma_{g22}$ 3.38          | $\beta_{g23}$ 4.40            |
| B           | $\theta_{b21}$ 180.19         | $\mu_{b22}$ 147.95           | $\theta_{b23}$ 585.61         |
|               | $\beta_{b21}$ 1.20            | $\sigma_{b22}$ 3.46          | $\beta_{b23}$ 3.97            |

Table 7. Performance of Naive Bayes

| Group | Accuracy level of classification (%) |
|-------|--------------------------------------|
|       | 1\textsuperscript{st} speed | 2\textsuperscript{nd} speed |
| OM | BM | OM | BM |
| 1    | 73.6  | 72.8  | 64.8  | 66.4  |
| 2    | 75.2  | 76.0  | 72.0  | 71.2  |
| 3    | 78.4  | 77.6  | 69.6  | 69.6  |
| 4    | 71.2  | 72.8  | 67.2  | 69.6  |
| 5    | 80.0  | 78.4  | 79.2  | 76.8  |
| ≥50  | ≥81.6 | ≥81.6 | ≥68.8 | ≥69.6 |
| Mean | 76.6  | 77.0  | 69.2  | 69.3  |
| Variance | 11.5  | 9.7   | 17.5  | 16.9  |
| Biased of mean | 12.2  | 9.5   | 17.2  | 17.0  |

| confidence interval of mean | 76.1 - 77.2 | 76.5 - 77.6 | 68.6 - 69.8 | 68.7 - 69.9 |

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