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# Object retrieval analysis on plastic bottle waste recycling-based image control using convex hull algorithm and autoregressive integrated moving average prediction method

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**ABSTRACT**

In Indonesia, plastic garbage bottles are the most common sort of waste. Given that waste is expected to grow annually, managing plastic waste is a major challenge. The results of the study were achieved by comparing the reference, which was a collection of manually created contour images, with 50 sets of vortex images with different forms and vortex areas as experimental objects. The results indicate that the suggested approach reports a mean error of 2.84%, a correlation coefficient of 0.9965, and a root mean square error of 0.2903 when compared to the manual extraction method. These findings imply that the extract area determined by the procedure outlined in this research is more accurate and nearer to the actual values. The proposed method can therefore be used in place of the traditional process for investigating cooling parameters through manual testing. With measurement values mean absolute percentage error (MAPE)=121,842, mean absolute deviation (MAD)=20,140, and mean squared deviation (MSD)=776,712, the trend analysis of plastic bottles for autoregressive integrated moving average (ARIMA) modeling leads to the conclusion that the waste from plastic bottles will continue to rise annually and that efforts must be made to address this trend with knowledge and waste recycling technology. Plastic that is advantageous to industry and society.



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## 1. INTRODUCTION

The Today's globalization and rapid technological development have explained all means of meaning under the theory of convex hull algorithm. According to one definition, a convex hull algorithm is any verbal and visual semiotic tool that may be used to identify the different kinds and degrees of dialogic involvement in a text [1]. Convex hull algorithms are useful for learning. By highlighting the various ways that meaning is created in texts and how particular decisions help to accomplish intended communicative objectives, the convex hull algorithm approach seeks to create a product of knowledgeable readers and producers of convex hull algorithm texts [2]. Additionally, a convex hull algorithm technique ensures inclusivity that fosters intellectual excellence and gives users a wide range of learning opportunities by accommodating difference. Based on dominant understandings, enterprises can use a convex hull algorithm technique to self-select learning objects, or representations, that optimally fit their modal preferences [3].

This enables the industry to accommodate various employees' needs in a learning environment so they can comprehend the goods that will be advertised and sold [4]. Global changes due to rapid technological advances, competition between industries is becoming increasingly aggressive to survive. Technological innovation to business management is to reduce product costs, improve functionality and constantly increase competitive strength [5]. Industries today desire to maintain the functional performance of products within the limits of accepted standards and reduce production costs. Industries need to meet customer demands to be more effective and consistent in improving product performance [6]. Today, information and communication technologies (ICTs) influence the way people live, communicate, work and play. This is because technological elements are found in almost everything [7]. Businesses rely significantly on mobile devices and the internet to obtain information and access a variety of knowledge sources at the touch of a screen. A growing discussion that real life, should be the starting point rather than the end point in teaching early literacy and that skills such as phonetics should be used as a tool to help make sense of the printed media seen around [8]. The dynamic nature of knowledge does not end at knowledge of grammar, phonetics and vocabulary, but also involves practical learning to interpret everything [9].

Technology has penetrated into the industrial in the world, this does not change the attitude of the industry in developing innovation. An understanding of technology must be balanced with industrial mastery/skills in innovation management. The aspect of reading skills, for example, is important in understanding the signs of language recorded in it. As is well known, the reading proficiency of Indonesians remains quite low. Indonesia's literacy culture ranked second out of 65 nations in the world in 2012, according to the program for international student assessment (PISA) research. Indonesia is ranked 64$^{th}$ out of 65 nations. Vietnam is in the top 20 at the same time. The reading proficiency of Indonesia was ranked 57$^{th}$ out of 65 countries in the same survey by PISA. In Indonesia, the reading interest index has only reached 0.001, which means that just one person out of every 1,000 is interested in reading, according to UNESCO 2012 statistics [10].

Recycling recycled plastic bottles is a crucial energy-saving and environmental protection strategy. varied colored bottles have varied recycling values. Classifying plastic bottles based on image recognition during recycling is an efficient method, where position and color identification are the main technologies. The initial step in classifying plastic bottles is to identify the location into three categories: overlapping, adjacent, and discontinuous. Based on its picture, discontinuous can be easily detected by the ratio of concave to convex areas. A combination technique known as distance transformation and threshold segmentation is suggested for bottles that are adjacent and overlap in order to differentiate their positional relationship. Once neighboring bottles have been located, nearby recycled bottles will be further separated using a concave point search technique based on convex hull. The color of the separated and adjacent bottles is then determined since it is too complex and challenging to distinguish the color and separate the bottles that overlap. During the sorting process, recycled bottles' colors are separated into seven categories in the color recognition aspect. In order to avoid shape inaccuracies caused by bottle caps and labels at the top and middle of the bottle, respectively, the bottom color is utilized to represent one of the recycled bottles.

Previous research conducted by Wei *et al.* [11], after the vortex picture has been preprocessed using iterative adaptive binarization and mean filtering, the convex hull algorithm and edge function are applied to the preprocessed image in order to identify the vortex image's precise shape and determine its area. Under various experimental conditions, the vortex shape and area can be extracted using this method without the need for user intervention, according to experimental data. The suggested approach is more suitable for exposing the actual state of the vortex, as evidenced by the average absolute error rate of 2.84%, root mean square error (RMSE) of 0.2903, and correlation coefficient of 0.9965 reported by this method in comparison to the vortex area results acquired using the manual extraction method. The extraction technique has been standardized to set a baseline for further studies on vortex images. A scientific basis for the real-time tracking study of agricultural crop protection unmanned aerial vehicles (UAVs) and vortices is established by the methodology in this publication. In order to solve a number of important issues, including determining the positional relationships between nearby bottles, handling nearby bottles, and classifying all bottles by color, as well as forecasting the pattern of waste accumulation in Indonesia—particularly plastic waste, which is increasing daily—and finding alternate recycling uses for such waste, the study aims to identify a systematic method for sorting plastic bottles in various colors for recycling purposes.

## 2. METHODOLOGY

Based on the theoretical basis and the explanation above on the methodology that describes the framework of how the theories of the conceptual model related to the various factors identified as problems to explain theoretically between the variables to be studied. Before carrying out the process of processing plastic recycling images, a research methodology is first used which starts from defining the problem, the approach used, development, to implementation to the public, measuring accuracy and drawing conclusions. The detailed image processing methodology is shown in Figure 1.

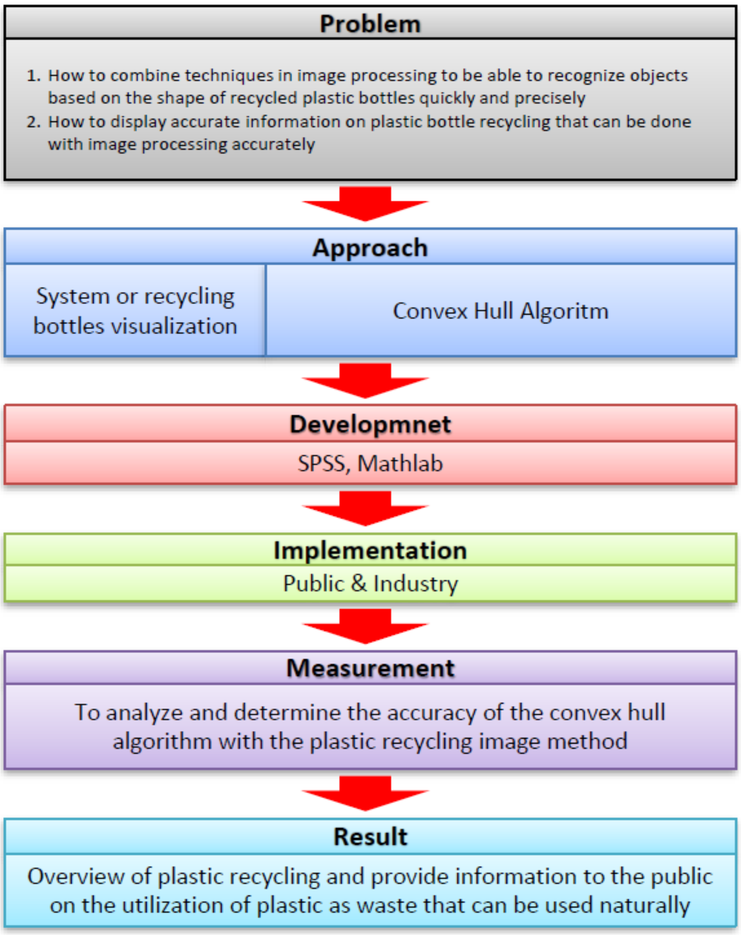


Figure 1. Research framework

## 3. RESULTS AND DISCUSSION

In the research, an applied research approach will be carried out, namely as engineering research on the application of science to an analysis to obtain performance results in accordance with predetermined requirements. The process of research results used in this approach is i) analysis to determine the specifications of object measurement accuracy, and ii) results to choose one of the best models and can be scientifically accounted for in accordance with research rules. The research approach process as material for detailed analysis is as follows:

### 3.1. Data training

Training data is or known as training datasets, learning sets and training sets, is part of a collection of datasets that are provided to be material for model learning so that the model can generalize (find patterns) data so that it can later be used to predict new data and is a set of data used to train or build models. machine learning algorithms will change the parameters on themselves to adjust to the data provided during training [12]. The study's training data comes from the Ministry of Environment and Forestry of the Republic of Indonesia's national waste management information system (*https://sipsn.menlhk.go.id/sipsn*). Specifically, it provides information on the amount of waste categories in Indonesia by province in 2023. Table 1 lists the training data in tons for glass, rubber-leather, fabric, paper-cardboard, metal, plastic, wood-twigs, food waste, and other materials.

Total waste that has been collected based on 38 provinces (Nanggroe Aceh Darussalam, North Sumatera, South Sumatera, West Sumatera, Bengkulu, Riau, Riau Islands, Jambi, Lampung, Bangka Belitung, West Kalimantan, East Kalimantan, South Kalimantan, Central Kalimantan, North Kalimantan, Banten, DKI Jakarta, West Java, Central Java, Special Region of Yogyakarta, East Java, Bali, East Nusa Tenggara, West Sulawesi, Central Sulawesi, North Sulawesi, Southeast Sulawesi, South Sulawesi, North Maluku, Maluku, West Papua, Central Papua, Mountainous Papua, South Papua, Southwest Papua) are waste that has been separated by type so that it is easy to manage nationally, as in the Figure 2.

In this study, the data that will be used as a sample is data on plastic water bottle packaging as much as 675,050 tons or 27.36% of the total national plastic waste of 2,367,280 tons or 72.64%, as in Table 2. A comparison of the quantity of plastic waste in bottles and the quantity of plastic garbage in general is shown in Figure 3, indicating that plastic waste in Indonesia is extremely high in relation to other waste and dispersed throughout 38 provinces.

Table 1. Total volume of waste types in Indonesia by province in 2023

| No. | Province | Type of waste (Ton) | | | | | |
|---|---|---|---|---|---|---|---|
| | | Others | Glass | Rubber-leather | Plastic | Wood-twigs | Food scraps |
| 1 | Nanggroe Aceh Darussalam | 79.85 | 41.25 | 47.50 | 252.70 | 171.40 | 395.70 |
| 2 | North Sumatera | 91.24 | 14.34 | 8.34 | 58.30 | 71.89 | 76.65 |
| 3 | South Sumatera | 8.72 | 3.81 | 0.70 | 67.52 | 19.50 | 166.77 |
| 4 | West Sumatera | 86.87 | 22.37 | 12.67 | 241.08 | 138.05 | 606.55 |
| 5 | Bengkulu | 0.50 | 0.40 | 0.30 | 5.60 | 5.40 | 76.50 |
| … | … | … | … | … | … | … | … |
| … | … | … | … | … | … | … | … |
| 37 | South Papua | 0 | 0 | 0 | 0 | 0 | 0 |
| 38 | Southwest Papua | 9.10 | 7.70 | 18.50 | 89.60 | 34.50 | 75.20 |
| | Total | 849.81 | 293.21 | 241.58 | 2.367.28 | 1.358.22 | 5.355.08 |

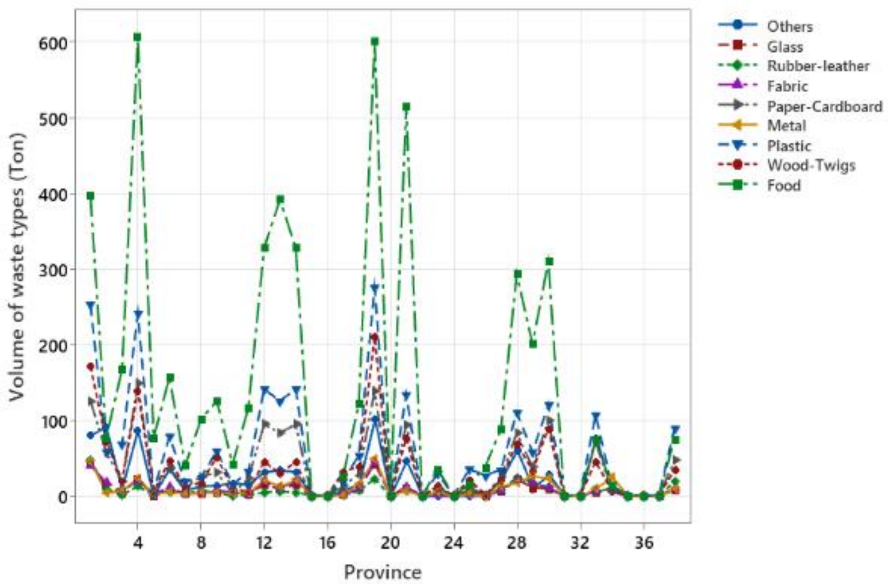


Figure 2. Total volume of waste types in Indonesia by province in 2023

Table 2. Total volume waste in Indonesia by province and plastic bottle waste type, 2023

| No | Province | Ton | |
|---|---|---|---|
| | | All plastic waste | Plastic bottle waste |
| 1 | Nanggroe Aceh Darussalam | 252.70 | 69.14 |
| 2 | North Sumatera | 58.30 | 15.95 |
| 3 | South Sumatera | 67.52 | 18.47 |
| 4 | West Sumatera | 241.08 | 65.96 |
| 5 | Bengkulu | 5.60 | 1.53 |
| … | … | … | … |
| … | … | … | … |
| 37 | South Papua | 0 | 0 |
| 38 | Southwest Papua | 89.60 | 2451 |
| | Total | 2.367.28 | 675.05 |

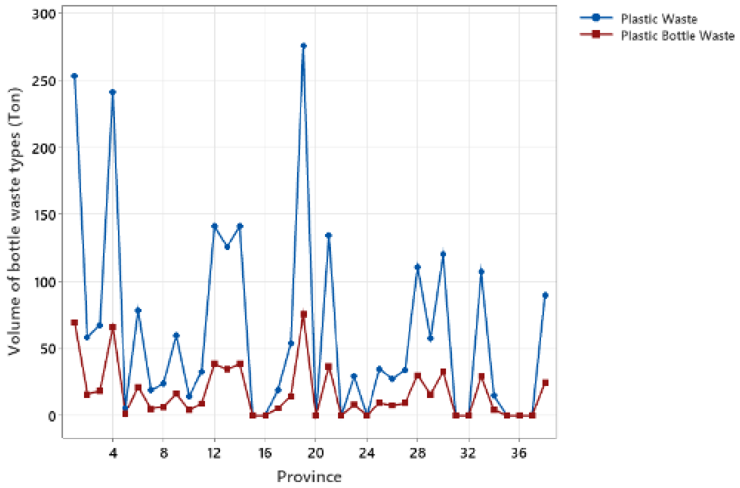


Figure 3. Total volume of bottle waste types in Indonesia by province, 2023

### 3.2. Convex hull

Convex hull (CH) is a classic problem in computational geometry, the problem is described simply in two-dimensional space (plane) as finding a subset of the set of points on the plane such that if the points are made into polygon it will form a convex polygon [13]. A polygon is said to be convex if a line connecting the points is drawn then there is no line that intersects the line which is the outer boundary of the polygon. Another definition of convex hull is a polygon composed of a subset of points such that no point from the initial set is outside the polygon all points are on the outer boundary or inside the area enclosed by the polygon [14]. The CH of a set of points is the smallest convex set that contains those points. In two dimensions this is a convex polygon, a simple polygon is a two-dimensional shape that has many angles where there is no intersection between the angles. Each simple polygon has an inner region and an outer region [15]. A simple polygon is said to be convex if the magnitude of the inner degree formed for each angle is smaller than 180 degrees, the convex hull of a polygon P is the smallest region of the convex polygon which surrounds the polygon P. It can also be said to be a rubber band that covers around P. The convex hull of a convex polygon P is P itself [16].

#### 3.2.1. Identification and treatment of the positional relationships between the recycled plastic bottles

How to arrange recycled bottles several pneumatic nozzles on a pneumatic jet separator sort the recycled plastic bottles. Therefore, the centroid of each bottle must be obtained through image processing in order to identify the pneumatic valve identifiers that should be activated and when these pneumatic valves should be triggered. We carried out a straightforward experimental investigation prior to undertaking the theoretical investigation of this subject [17]. According to experiments, when a plastic bottle is positioned at random on a conveyor belt, there are three possible outcomes: disjunct, neighboring, and overlapping. Bottles that are not in contact with one another are referred to as disjoint bottles. Adjacent bottles are those that come into contact with one another without being covered. Additionally, if the bottles overlap, it indicates that, according to these real circumstances, one bottle is covered by the other [18].

#### 3.2.2. Identification of the positional relationship of plastic bottles

To identify the positional relationships of plastic bottles, one must first distinguish between the three scenarios. To identify discontinuous plastic bottles, one must first get their outlines and convex hulls of targets on the conveyer belt. The convex hull H of an arbitrary set S is the smallest convex set that contains S; the convex defect is the difference between H and S. In this paper, the convex hull of the contour of each plastic bottle is obtained using the Jarvis stepping convex hull algorithm [19].

#### 3.2.3. Separation of adjacent plastic bottles

While determining the centroid of each bottle is difficult for overlapping bottles, it is still possible to determine the centroid of each bottle by image processing, as shown by the binary image of adjacent plastic bottles. When the two red dots are connected, it is clear that the nearby target can be divided into two discontinuous targets. After that, their centroids can be acquired independently. The two concave spots in this work have been found using the convex hull and the convex defects of the contour. The picture of nearby plastic bottles [20].

**3.2.4. Analysis result of convex hull**

In order to distinguish the color of plastic bottles and use it as a feature, the aggregate accuracy combined with the color of plastic bottles is simply separated into three groups: colorless, blue, and green bottles. Seven color-based categories can be used to classify plastic bottles: light blue, light purple, brown, blue, light green, dark green, and colorless. Naturally, a more accurate color classification for plastic bottles will make it more difficult to analyze such images, Figure 4, shows the process of identifying pile of plastic bottles waste. Figure 4(a) shows waste pile used as an object for analysis for random pile of plastic bottle waste. Figure 4(b) shows analysis of waste pile with object marking with random pile of plastic bottle waste based on detected area. Figure 4(c) shows analysis result based on selected pile of plastic bottle waste.

(a) (b) (c)

Figure 4. Pile of plastic bottle waste: (a) waste pile used as an object for analysis for random pile of plastic bottle waste, (b) analysis of waste pile with object marking with random pile of plastic bottle waste based on detected area, and (c) analysis result based on selected pile of plastic bottle waste

Figure 5 is the result of analyzing the graph of the image capture process of the random waste selection process with the process of plastic bottle waste types in packaging that are still mixed with other plastic bottles. Furthermore, the results of the image analysis to obtain the plastic bottle garbage image results can be used as polygon data for image detection and the final result is an accurate adaptive vortex edgeless area extraction. A retrieval method that pays attention to the three characteristics of the preprocessing image and to close the gap, the first task is to accurately retrieve the vortex edge accurately to accurate adaptive vortex edge-less area extraction for the retrieval method.

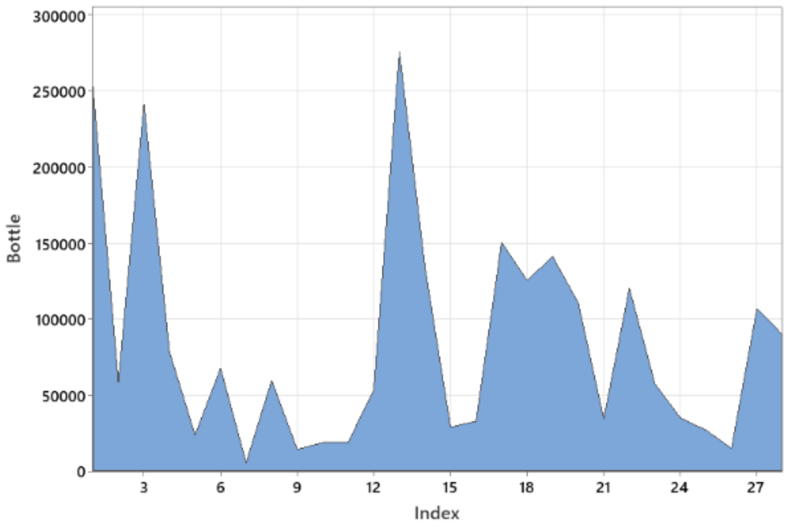


Figure 5. Convex hull image group based on detected image

From the convex hull image point set, the point known as the pole is chosen and joined to create a convex hull dividing line. This is achieved by sorting and scanning the points inside the convex hull that are the farthest away in respect to the vortex edge image's edge noise points characteristics using cyclical recursion. After then, a new mast is attached via scanning at the dividing line's furthest point. The convex hull is determined recursively until the algorithm is unable to generate more poles. The convex hull method to extract isolated poles from the vortex image is straightforward [21]. A coordinate system is established with the origin in the lower left corner. Following the assignment of a linking label to each isolated point on the positioned image, the procedure is continued until the convex hull corresponding to the two polar points cannot be located and the convex hull point or convex polygon [22] is the farthest point, as seen in Figure 6.

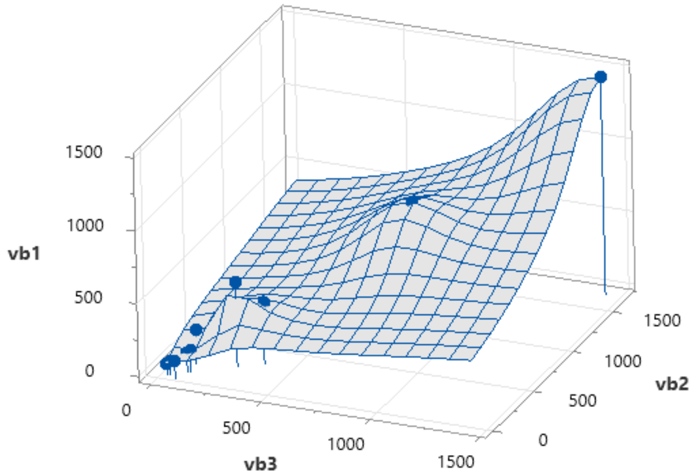


Figure 6. Group of convex hull images based on detected area type

It is possible to determine the centroid of each bottle which is still overlapping but adjacent to other plastic bottles by using image processing. This allows for the presentation of a binary image of adjacent plastic bottles, making it clear that, once connected, the two red dots on adjacent targets can be distinguished as two distinct targets. It is thus possible to determine their center points independently. Two concave locations have been found in this paper using the contour's convex hull and convex defect. Figure 7, analysis of the transformation process using the convex hull algorithm for plastic waste bottles. Figure 7(a) shows convex hull analysis of a discontinuous target based on color histogram transformation. Figure 7(b) shows convex hull analysis of adjacent targets based on color histogram transformation. Figure 7(c) shows convex analysis of overlapping targets based on color histogram transformation.

(a) (b) (c)

Figure 7. The convex hull transformation: (a) convex hull analysis of a discontinuous target based on color histogram transformation, (b) convex hull analysis of adjacent targets based on color histogram transformation, and (c) convex analysis of overlapping targets based on color histogram transformation

The contour area and the convex hull are shown as the area surrounded by the blue curve and the area surrounded by the green curve and the ratio of the two on the gray color curve. So that the area difference in the convex defect is judged to be significantly different. With a number of images with three kinds of position relationships collected as the description of such curves as the convex hull of the disjoint target, the convex hull of the adjacent target and the convex hull of the overlapping target, as shown in Figure 8.

A plastic bottle sorting system based on machine vision can distinguish between seven different colors of plastic bottles on the market. In one round of sorting, the system should be able to recognize plastic bottles in one of the seven colors, as shown in Figure 9. In Table 3, the relationship matrix obtained from the training set and test set are the colors light blue, purple, brown, blue, light green, dark green, and colorless bottles labeled 1 to 7 respectively by giving a value to the matrix, the image process used will be visible.

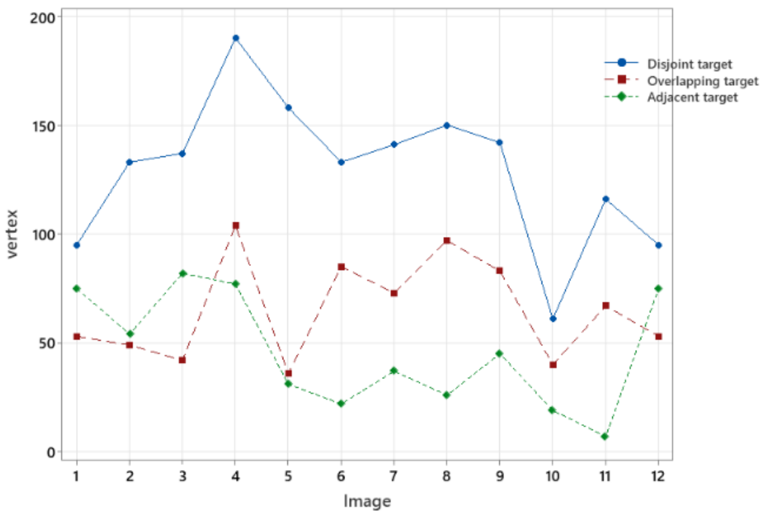


Figure 8. Relationship of convex hull curve of object image process

Figure 9. Analysis results with bottle sorting system based on bottle color, bottle color sorting results through histogram model process to cyan/magenta/yellow/key (CMYK) model including blue light, brown light, green, white, brown, blue and colorless as the basis for identification based on Chen and Han (CH) algorithm

Table 3. Confusion matric of training set

| | | Predicted category | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Actual category | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | 180 | 20 | 0 | 3 | 0 | 10 | 0 |
| | 2 | 20 | 180 | 0 | 8 | 0 | 0 | 0 |
| | 3 | 0 | 0 | 210 | 0 | 0 | 0 | 0 |
| | 4 | 3 | 6 | 0 | 198 | 8 | 0 | 0 |
| | 5 | 0 | 0 | 0 | 0 | 196 | 0 | 0 |
| | 6 | 0 | 0 | 0 | 8 | 0 | 193 | 0 |
| | 7 | 10 | 0 | 0 | 0 | 0 | 0 | 194 |

4 colorless plastic bottles were misidentified as light blue bottles, 7 light blue bottles as purple bottles, and 7 purple bottles as light blue bottles. The phenomena of mutual misjudgment are demonstrated by these three-colored plastic bottles. Only 2 blue bottles are mistaken for purple bottles, and 2 dark green bottles are mistaken for light green bottles. This indicates that the accuracy of identifying plastic bottles of different colors is fairly high, and the photos of brown and light green plastic bottles are all accurately identified.

Based on Table 4, through observation, the colors of the light blue, light purple, and colorless bottles are relatively similar, which determines that it may be relatively difficult to identify them accurately. On the contrary, its difference from the other four colors is relatively clear, which determines that it may be easy to identify it accurately, so, the test results have come in according to expectations. The vortex hull analysis is to identify the relationship between the position of the plastic bottle and the color recognition scheme described in the experiment, so the experimental platform needs to be built before the illumination conditions have been simulated and analyzed, as in Table 5.

Table 4. Confusion matric of the test set

| | Predicted category | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Actual Category | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | 85 | 13 | 0 | 4 | 0 | 0 | 8 |
| | 2 | 15 | 20 | 0 | 0 | 0 | 0 | 0 |
| | 3 | 0 | 100 | 110 | 0 | 0 | 0 | 0 |
| | 4 | 0 | 4 | 0 | 98 | 0 | 0 | 0 |
| | 5 | 0 | 0 | 0 | 0 | 110 | 0 | 0 |
| | 6 | 0 | 0 | 0 | 0 | 0 | 100 | 0 |
| | 7 | 6 | 0 | 0 | 0 | 0 | 0 | 98 |

Table 5. Experimental results of the discrimination of the position relationships between plastic bottles

| Position relationships | Convex hull | | |
|---|---|---|---|
| | Disjoint targets | Adjacent targets | Overlapping targets |
| Quantity | 40 | 40 | 40 |
| Quantity with correct judgment | 40 | 30 | 40 |
| Accuracy | 100% | 90,20% | 100% |
| Total accuracy | 98.60% | | |

Based on the test findings, the classification accuracy tends to settle when the number of characteristics reaches 8. This demonstrates that certain candidate traits with lower weights are not important, allowing for feature limitation. When it comes to plastic bottle color recognition, the elements that weigh the most are chosen as color features. Classification models with varying training set sizes are trained and tested with test sets in order to examine the impact of training set size on color identification based on the system's actual operating environment and the eight color features that were chosen. Each color of plastic bottle has the same quantity in both the test and training sets.

Numerous factors, including lighting conditions, color features, and the general scheme of recognition algorithms for color recognition problems, can influence the size of the training set. For example, the accuracy of the test set's results increases significantly as the number of training set samples increases for color recognition of plastic bottles. To get the greatest results, these elements can only be changed based on the actual application conditions, as Figures 10 and 11 illustrate.

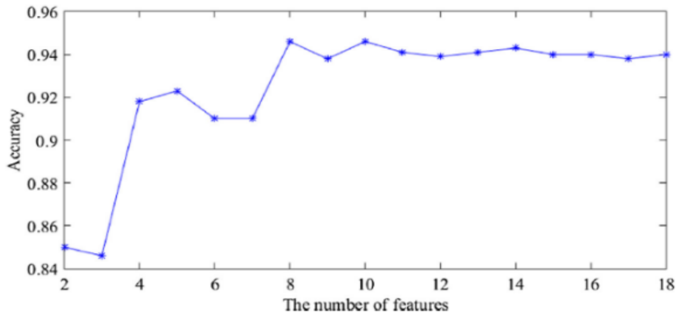


Figure 10. Accuracy rate with different number of features

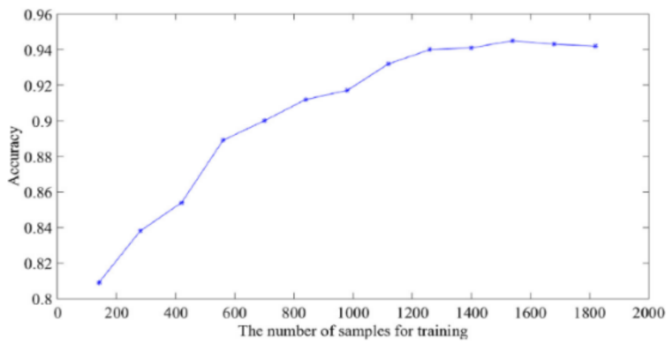


Figure 11. The relationship between the number of samples for training and the accuracy of the test set

### 3.3. Autoregressive integrated moving average

The autoregressive integrated moving average (ARIMA) method is a forecasting method that does not use theory or influence between variables as in regression models, thus the ARIMA method does not require an explanation of which variables are dependent and independent. This method does not require breaking patterns into trend, seasonal, cyclical components as in time series data in general [23]. This technique, which is commonly referred to as the Box-Jenkins approach because it was created in 1970 by two American statisticians, G.E.P. Box and G.M. Jenkins, solely uses past data to produce predictions. Finding a strong statistical correlation between the variable's historical value and its expected value is the aim of ARIMA modeling, which enables forecasting using the model. When applying the ARIMA approach, stationary data is required; if not, a data stationary test must be performed. ARIMA models are capable of making future predictions based solely on historical data [24].

The ARIMA forecasting method's benefits include its flexibility (following data patterns), a reasonably high forecasting accuracy, and the ability to forecast a variety of variables quickly, easily, accurately, and affordably because it solely needs historical data. The ARIMA forecasting method's disadvantage is that it makes the assumption that the model is linear. As a result, non-linear patterns that are typical in time series are not captured by the ARIMA model. Consequently, a model that can capture non-linear patterns is needed [25].

On the pertinent details required to comprehend and apply ARIMA models for univariate time series, Box and Jenkins have successfully come to a consensus. There are multiple steps in the process of creating an ARIMA model. Model identification, parameter estimates, diagnostic checking, choosing the optimal model, and forecasting are the steps in the process. Both seasonal and non-seasonal models are included in the Box-Jenkins model. While the ARIMA $(p, d, q)$ model is a type of non-stationary model, the non-seasonal stationary models include autoregressive (AR)($p$), moving average (MA)($q$), and autoregressive moving average (ARMA)($p, q$) [26].

#### 3.3.1. Equation formulas

AR is a model of regression results with itself at the previous time. The general form of the Autoregressive model with the $p^{th}$ order, namely $AR$ ($p$) or ARIMA ($p$, 0,0) model is written as with the (1):

$$Zt \ = \ \Phi 1Zt - 1 \ + \ \dots + \ \Phi pZt - p \ + \ at \ atau \ \Phi p(B)Zt \ = at \tag{1}$$

MA model, the general form of the $q^{th}$-order, $MA(q)$ or ARIMA $(0,0, q)$ is written as (2):

$$Zt \ = \ at - \ \theta 1at - 1 \ - \ \dots \ - \ \theta qat - q \ atau \ Zt \ = \ \theta q(B) \ at \tag{2}$$

ARIMA, the general form of both $AR(p)$ and $MA(q)$ models, namely ARIMA $(p, 0, q)$ with the (3):

$$\Phi p(B)Zt \ = \ \theta q(B)at \tag{3}$$

If non stationarity is added to the ARMA process, then the ARIMA $(p, d, q)$ model with d differencing is written with the (4);

$$\Phi p(B)(1 - B)dZt \ = \ \theta q(B)at \tag{4}$$

#### 3.3.2. Autocorrelation function and partial autocorrelation function

In a time series, the autocorrelation function (ACF) is the linear relationship between $Zt$ and $Zt + k$. When data is steady, the mean μ and variance σ2 remain constant. ACF confirms that the mean is stationary using the (5):

$$pk\frac{\sum_{t=1}^{n-k} (Z_t - Z_t)(Z_{t+k} - Z_{t+k})}{\sum_{t=1}^{n} (Z_t - Z_t)2}; k = 0,1,2,3 \tag{5}$$

#### 3.3.3. Analysis result of ARIMA

The study's variables include the total amount of waste generated in Indonesia by province and the kind of plastic bottle waste generated in 2023. The data for analysis is separated into two sections: training data and testing data. As shown in Figure 12, testing data is used for comparison with forecasting outcomes, while training data is used for modeling. Figure 13 shows the stationarity test, which eliminates the necessity for differencing by allowing stationary data to be known formally or visually. The formal test can be performed using the augmented Dickey-Fuller (ADF) test, while the visual test is performed by examining the time series data plot. Using the ACF to estimate AR and MA order for ARIMA modeling. The results of the ACF analysis for plastic bottle waste still have a very low linearity that needs further analysis.

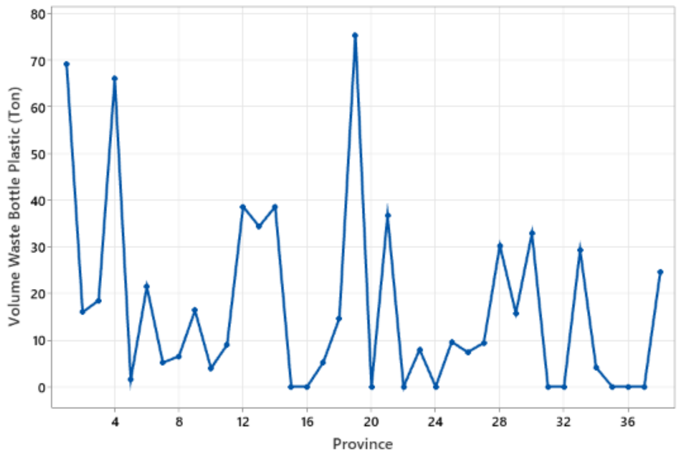


Figure 12. Waste volume in Indonesia by province and plastic bottle waste type in 2023

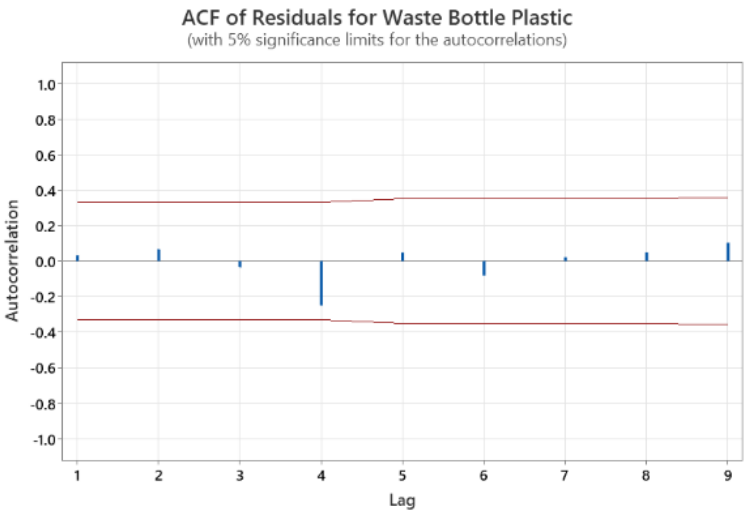


Figure 13. Autocorrelation function test

Figure 14 plot analysis of partial auto correlation functions (PACFs). Ten temporary models and ARIMA (1,0,1), the best model, are produced using the ACF and PACF plots. The significance, residual normality, independence, autoregressive conditional heteroscedasticity-Lagrange multiplier (ARCH-LM), and linearity tests are then conducted. The PACF analytical results for plastic bottle trash are considered absolute since they make reference to linearity. Decomposition is a forecasting technique that aims to isolate three distinct elements from the underlying patterns that typically define business and economic data sets. Seasonal, cyclical, and trend variables are these constituents. The decomposition method or often also called the time series method is one of the forecasting methods based on the fact that usually what has happened will repeat or reoccur with the same pattern [27]. In this study, the decomposition of plastic waste based on the type of waste is the highest is food waste, so that an analysis can be carried out which is divided into several wastes, and the type of plastic waste is a national contributor. Decomposition of waste types in Indonesia as shown in Figure 15.

In Figure 16, the waste decomposition is broken down into several parts where the plastic bottle waste has a fluctuating value from and refers to the decomposition data, the model is reduced data is the original data of the analysis results, namely original data which is the result of real data analysis, reduced data is reduced according to the season and seasonally adjusted and detected data which is adjusted by seasonal data. These four variables can be used as predictive data for the next year's waste runoff, as decision makers and as accurate analysis data [28]. The results of the original data analysis according to the results of the highest analysis are waste in the province of Center Java compared to other provinces, the results of the analysis of the highest reduced data are from the province of West Java, the province of West Java is the outcome of the analysis of seasonally adjusted and detected data, and the province of West Sumatera is the outcome of the analysis of seasonally adjusted data.

The final result for prediction using ARIMA with the object of plastic bottle waste is based on the analysis that has been done that the data pattern is not stationary, based on the ADF test it can be concluded that the p-value is 0.49>0.05 (α) so that the decision fails to reject H0 so it can be concluded that the data is not stationary. Based on the ACF and PACF plots, it is also concluded that the data is not stationary because there is a lot of data that comes out of the lag limit. After the data is differentiated, the data pattern shows stationary [29].

The ADF test returned a p-value of 0.01<0.05 (α) for the differentiated data, indicating that H0 was rejected and the data should be regarded as stable. The significant coefficients obtained from the overfitting results are the ARIMA (2,1,0) and ARIMA (0,1,1) models. The results of the diagnostic test between the ARIMA (2,1,0) and ARIMA (0,1,1) models indicate that the latter is the best model because it has the minimum AIC value of 2531, which makes it possible to use it for predicting [30], as shown in Figure 17.

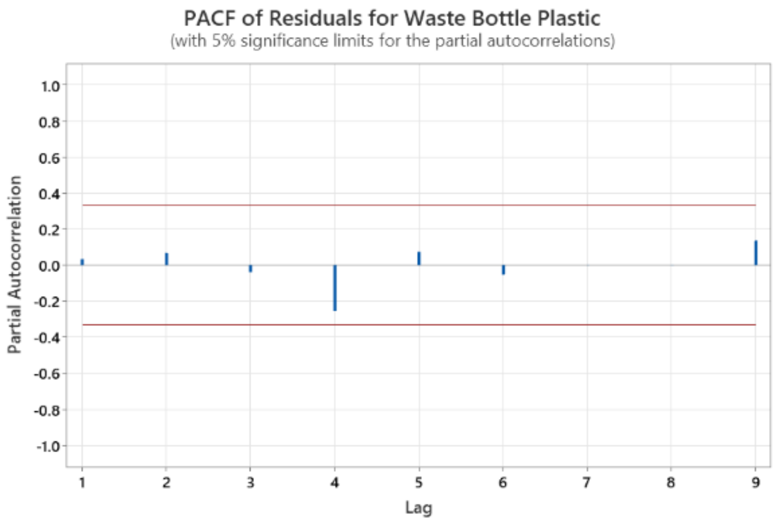


Figure 14. Partial autocorrelation function test

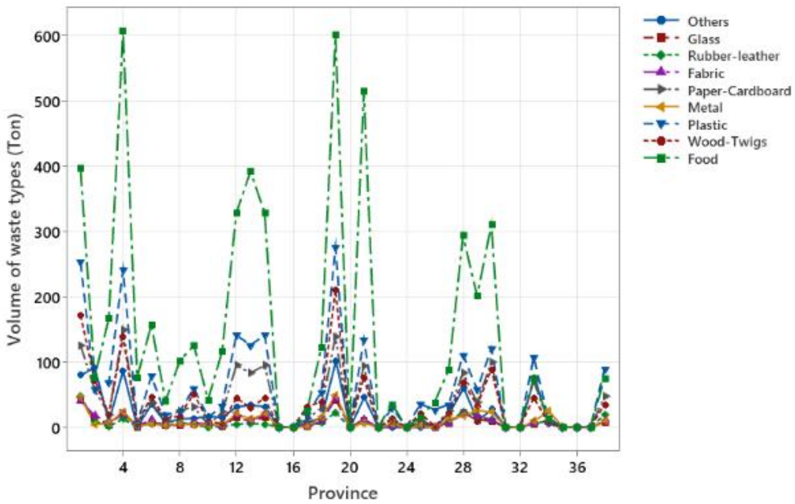


Figure 15. Decomposition plastic bottle waste by type

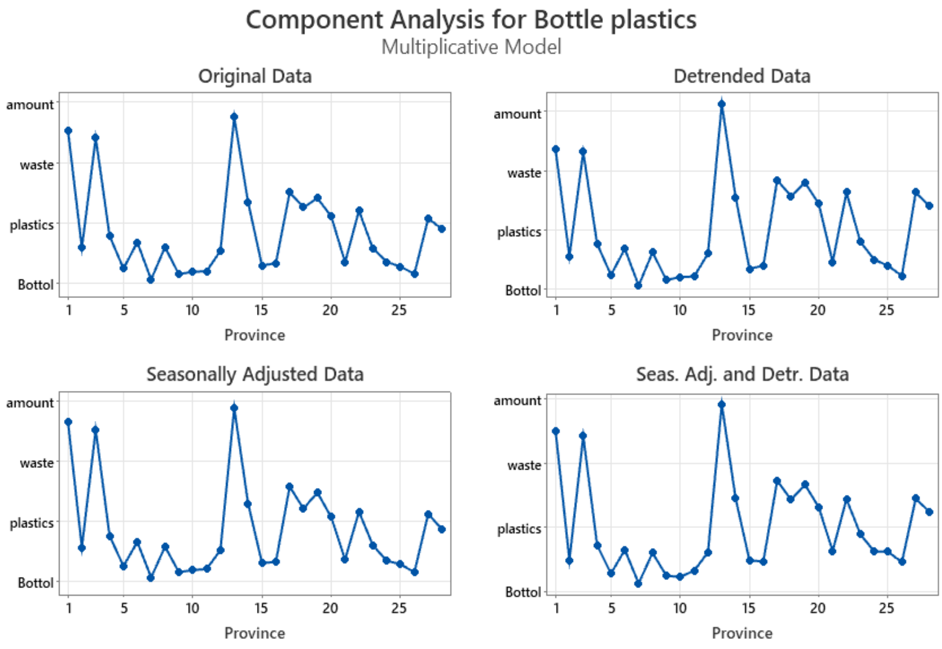


Figure 16. Decomposition of plastic bottle waste by season

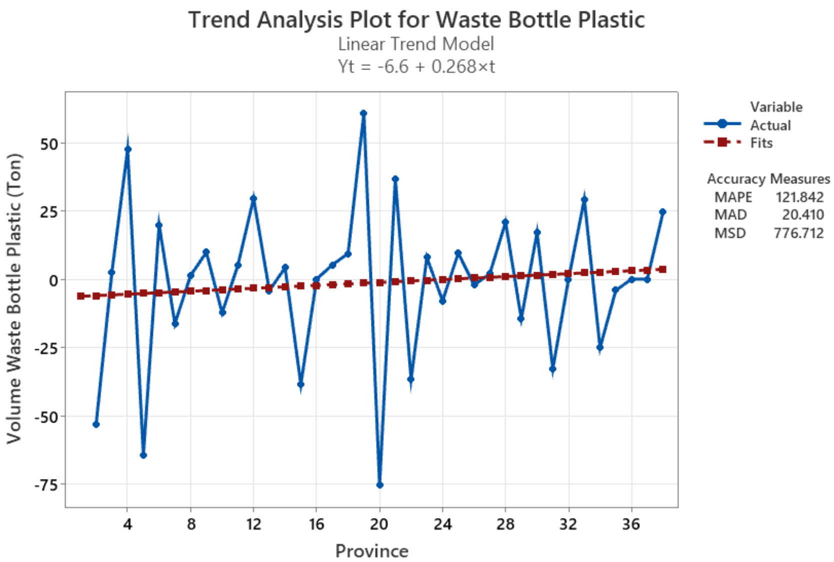


Figure 17. Trend analysis for waste bottle plastic

## 4. CONCLUSION

The analysis's findings were obtained by comparing 50 sets of vortex images with varying forms and vortex regions as experimental objects to the reference, which consisted of manually derived contour images. The results indicate that the extracted area calculated by the method described in this paper is more reliable and closer to the true values than the manual extraction method, with a mean error of 2.640%, a correlation coefficient of 0.9967, and a root mean square error of 0.301. Consequently, the conventional procedure for researching cooling parameters (manual testing) can be replaced by the suggested approach. With measurement values mean absolute percentage error (MAPE)=121,842, mean absolute deviation (MAD)=20,140, and mean squared deviation (MSD)=776,712, the trend analysis of plastic bottles for ARIMA modeling leads to the conclusion that the waste from plastic bottles will continue to rise annually and that efforts must be made to address this trend with knowledge and waste recycling technology. plastic with applications in both industry and society.

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