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SVM-CNN Hybrid Classification for Waste Image Using Morphology and HSV Color Model Image Processing

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ABSTRACT

Waste is a significant problem that is around us. The problem occurs because waste volume speed could be faster. This problem can be solved by implementing machine learning in the waste sorting process based on two categories which are organic and inorganic. Knowing the most efficient image processing and classification machine learning model is necessary. This research uses the Support Vector Machine classification model hybridized with the Convolutional Neural Network, image processing morphology, and the HSV color model. The dataset is collected from the images available on the Kaggle website and executed using Python. The data used amounted to 25,077 with a training and test data ratio of 85:15. The data is processed using the proposed method, namely the morphology and HSV color model, to determine the performance between using the image process and those that do not. The data that has been processed is classified using the SVM-CNN Hybrid classification model. The performance results are an accuracy rate of 99.34% and a loss of 1.67% without overfitting.

1. INTRODUCTION

Statistics conducted by the Ministry of Environment and Forestry of Indonesia (KLHK) show that one resident of Indonesia produces 0.7 kg of waste per day. There are 55.87% of the waste managed annually. This statistic shows that much trash needs to be addressed. Based on interviews with the manager of the nearest waste bank of Guwosari Training Center (GSTC) Yogyakarta, Indonesia, the main problem in managing waste is sorting waste based on its type, which is organic and inorganic. Employee complaints regarding the uncomfortable with the smell of organic waste, so sorting performance slows down. This problem can be handled by implementing machine learning to separate waste based on its type [1].

Implementing machine learning for waste sorting will solve employee complaints about garbage odors because machines have a tolerance for odors. Implementing machine learning for sorting waste will make employees more focused on handling waste based on its type rather than the sorting process.

The methods to produce the desired machine learning are obtaining the dataset, preprocessing the images in the dataset, implementing a classification model, and evaluating the research results [2]. The research was carried out coherently and used a classification model and image processing that had been done before.

Many previous studies have succeeded in creating machine learning as a machine that can sort types of waste. One such study is the study by Guo et al. [3]. The study explained that machine learning had been successfully used to sort waste. It was also explained that many classification models had been implemented in machine learning.

Many previous studies explain the classification model for waste sorting. For the Convolutional Neural Network (CNN) classification model, one of the studies was conducted by Gyawali et al. [4]. The highest accuracy performance achieved in this research using the CNN model is 87%.

Another previous research is waste sorting using the Support Vector Machine (SVM) classification model conducted by Puspaningrum et al. [5]. The research resulted in an accuracy rate of 62% using SIFT-PCA as the feature extraction.

Based on the image processing that occurs, many ways of image processing are carried out, including morphology and the HSV color model. One of the studies using morphology as image processing is the research conducted by Saputra et al. [6]. In this study, morphology was successfully carried out as an effort for image processing in the case of identifying fish freshness based on fish eye images.

One of the previous studies that used the HSV color model as the basis for the color scale used for training data was conducted by Musliman et al. [7]. The study explained that the HSV color model could also be carried out without problems as an image processing step to identify white blood cells.

This study aims to obtain machine learning performance results based on the percentage of accuracy and loss in the SVM classification model combined with CNN. Image processing is also carried out to achieve these accurate results, namely morphology while using the HSV color model on each training data image. The most important innovation in this research is comparing models with predefined control variables and experimental variables in the form of a hybridized SVM-CNN classification model and implementation of image processing HSV color model and morphology compared to default image processing and other model classification in the case of waste datasets. As far as we know, no SVM-CNN hybrid method is used for different waste images. Even if there is research using the same method, the point of this research is to compare model classification and image processing to get the most efficient way to create a better machine learning system before implementing it into hardware for waste sorting management.

2. BASIC CONCEPT

2.1 Waste

Waste has three types, namely organic, inorganic, and B3 waste [8]. Household waste usually has organic and inorganic types, and B3 is limited to industrial waste [9]. Waste with B3 type is usually individually managed directly by the industrial factory [10]. In contrast, household waste is a collection from many households into the same place managed by some organization. Therefore, this research only focuses on the organic and inorganic waste types [11].

Organic and inorganic waste have different waste management. Organic waste is managed into compost and used for agriculture or reforestation [12, 13]. Inorganic waste is usually recycled to be used again or made into other products [14]. This different waste management makes waste sorting vital before it is managed.

2.2 Support Vector Machine

Support Vector Machine (SVM) is a classification model that uses a hyperplane as an intermediary for each category as a differentiator for each category [15]. Usually, SVM is used for two categories, but it is possible to use it for more than two categories [16, 17]. The hyperplane in SVM is determined from the midpoint of calculating the maximum margin for each category [18]. The maximum margin is determined from the adjacent points between categories [19]. Here is the hyperplane determination formula.

$$f(x) = w.x + b \tag{1}$$

or

$$f(x) = \sum_{i=1}^{m} a_i y_i \, K(x, x_i) b \tag{2}$$

$f(x)$ is a function to find out the value of the hyperplane located. Variables that affect the existence of a training data point in the hyperplane (x) multiplied by the weight of each point (w) are added to the bias value (b). The $f(x)$ must be equal to zero to be called original hyperplane.

SVM can be used for supervised machine learning or unsupervised machine learning [20]. This study focuses on SVM as a supervised machine learning classification model because the category of waste types has been determined before the data is trained.

2.3 Convolutional Neural Network

Convolutional Neural Network (CNN) is a classification model that uses a neural network as machine learning to classify the tested object [21]. CNN has a convolution layer as a mechanical way to assess objects and extract features in an image [22]. As with SVM, CNN also looks for each object's weight and bias values and enters them in a matrix [23]. In the collected matrix, *pooling* is carried out on the matrix to summarize the data by taking the essential value. If the most critical value is the highest, then the pooling layer is called max-pooling [24].

In this study, feature extraction on objects is more focused on using CNN than the others and hybridizing with SVM by adding CNN models before SVM classification is carried out. So, what becomes feature extraction is the convolution layer to the fully-connected layer, but hyperplane is used to classify it; thus, the SVM-CNN hybrid is created.

2.4 Image processing

Image processing is an effort to make the image more readable for the machine so that the machine learns more easily when data training is carried out [25]. Image processing can include adding or reducing noise, cropping, transformation, and others [26]. There are many kinds of image processing, but this research is limited to using the morphology method and the HSV color model as feature extraction based on color.

The morphology and HSV color models are expected to change the image on the training data to make the machine more accurate in studying it and assessing the weight and bias of each object in the image.

3. RESEARCH METHOD

The research method that was carried out began with data collection, preprocessing, implementation of the classification model, and research evaluation. The following Figure 1 are the stages that occur in detail.

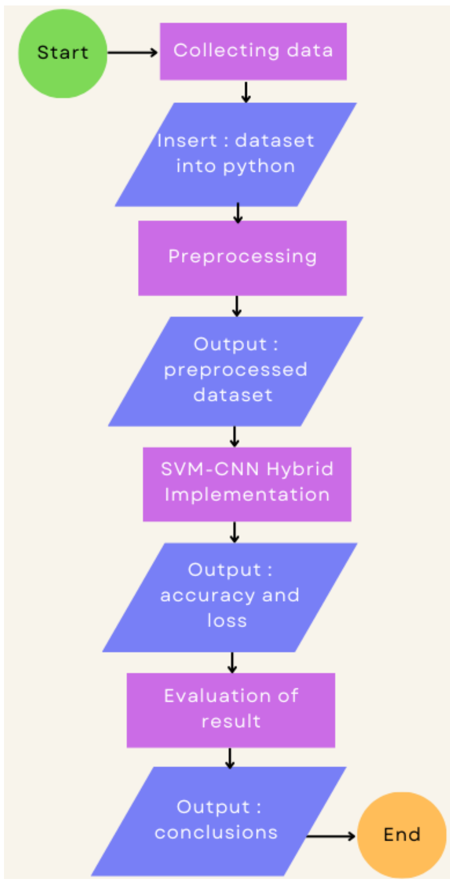

Figure 1. Research flowchart

3.1 Dataset

Data collection is carried out to form a dataset. The dataset was obtained from the Kaggle website [27]. The existing data includes 85% training data and 15% test data from 25,077. The dataset also consists of two categories commonly referred to as binary categories, namely the organic and inorganic categories, the same as the limitations of the problem carried out in this study.

3.2 Preprocessing

Image processing changes its original color model into the HSV color model, after which the image morphology is carried out. The HSV color model uses a color scale based on Hue, Saturation, and Value [28]. HSV is also a color close to the color usually captured by the human senses because there are more exact values than the RGB color model [29]. In contrast to the RGB color model, which is a mixture of primary colors without regard to the color depth variable [30]. The way to convert RGB to an HSV color model is with the following equation.

$$H = \tan\left(\frac{3(G-B)}{(R-G)+(R-B)}\right) \tag{3}$$

$$S = 1 - \frac{\min(R,G,B)}{v} \tag{4}$$

$$V = \frac{R+G+B}{3} \tag{5}$$

The variable values that occur in RGB will determine the value of each HSV parameter [31]. After finding the HSV parameter value from the original image that has an RGB color model, further image processing is carried out, namely morphology [32].

Morphology is image processing that uses a mathematical formula to transform an image into another image with more prominent features than other images [33]. Morphology aims to focus the image on the main object and remove unnecessary objects, such as the background.

Figure 2. Original image

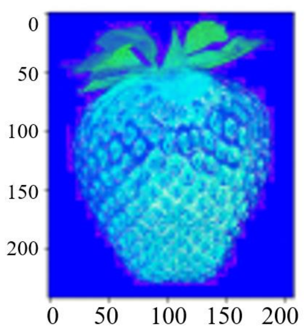

Figure 3. HSV color model

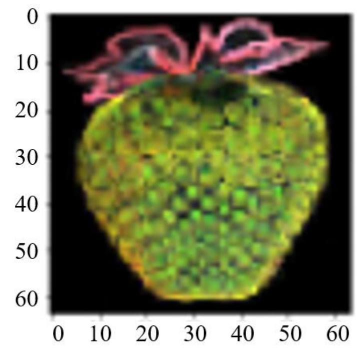

Figure 4. Morphology and resize

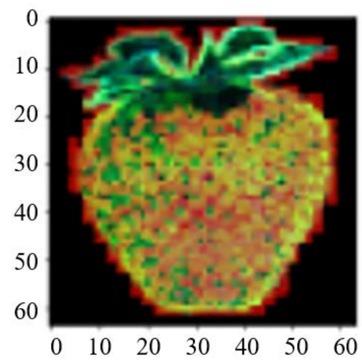

Figure 5. HSV color model, morphology, and resize

After that, change the size of the data image used as training data with a uniform size. The size used for this research is 64×64 pixels. From the preprocessing that occurs, the input shape that is formed is 64×64×3.

Figures 2, 3, 4, and 5 are image processing used in this study by implementing the HSV model, morphology, and resizing on the original image.

Table 1. SVM scheme merged with CNN

Parameter	Value
#First layer	
Conv 2D filter	32
Conv 2D kernel	3×3
Input Shape	64, 64, 3
Activation	relu
MaxPooling2D kernel	2×2
MaxPooling2D Strides	2
#Second layer	
Conv 2D filter	32
Conv 2D kernel	3×3
Input Shape	64, 64, 3
Activation	relu
MaxPooling2D kernel	2×2
MaxPooling2D Strides	2
#Data normalization	
Flatten	
#Fully-connected layer	
Dense unit	128
Activation	relu
#Output Layer	
Dense unit	1
Kernel Regularisasi	L2
Optimizer	Adam
Loss	hinge
Metrics	accuracy

3.3 Implementing SVM-CNN model classification

SVM-CNN model classification is a model that mixes SVM and CNN model architecture to classify the waste image based on its type [34]. The convolution layer, pooling layer, data normalization, and fully-connected layer are used for feature extraction from the image and to simplify the image so that the machine can learn based on the image [21]. After using the CNN model, the SVM hyperplane is used to classify the image based on its type [35]. Table 1 explains the architecture of the SVM-CNN model architecture.

Based on Table 1, CNN is used as a deep neural network layer for classifying an image. The layers are formed by two layers that function as input: the convolution layer and the pooling layer. After that, a normalized data layer uses a flatten layer to make the data dimensions uniform and one-dimensional.

The fully connected layer functions to combine each unit into one dense unit and can be used as output material. The dense unit that is formed is reduced to one unit because of its classification into two categories or binary categories.

For the output layer, SVM being implemented by using in the loss function, the hinge is used to form a decision boundary which can be a requirement that it is an SVM hyperplane.

3.4 Evaluation

Evaluation is done by analyzing the graphical results of the classification model performance on the processed images. The performance results analyzed are the percentage of accuracy and loss. Best accuracy and loss can be analyzed from training data that is not overfitting or underfitting [36].

4. RESULT AND DISCUSSION

The data used is the image of trash from Kaggle, totaling 25,077 data. The training and test data ratio is 85:15. After all the images have been processed to become like Figure 5, training is carried out on the image data using the SVM-CNN hybrid classification model. Figure 6 is a graph of the accuracy that occurs in each epoch.

Based on Figure 6, data training is not overfitting or underfitting because data training and validation are improving every epoch with the value of the difference between validation and training data less than 5%. Once it is known that no problem occurs in the training data compared to data validation, then proceed to analyze the results of machine learning that has been trained on test data. When tested with test data, accuracy results show the overall accuracy performance is 99.34%, with a loss of 1.67%. Figure 7 is the result of the evaluation using test data.

Research using the morphology process and the HSV color model has been successful without experiencing errors, overfitting, or underfitting. The HSV color model is applied to RGB images and produces new images with a different noise. Changes in the color scale can change the value of the weight and bias of an object to be studied by a machine. The HSV color model is only carried out on training data as a feature extraction method based on the color scale so that it can be compared with the original color scale, namely RGB. Morphology in this study clarifies the main object's shape. It ignores unimportant objects so that the convolution layer can assess the main object's weight and bias accurately on each training data.

Figure 6. Accuracy result

```
67/67 [==============================] - 1s 9ms/step -
    loss: 0.0167 - accuracy: 0.9934
```

Figure 7. Overall performance on test data

Unlike the research conducted by Gyawali et al., this study used SVM combined with CNN, while Gyawali et al. used only CNN [4]. Accuracy results are also different, for the accuracy of the image processing HSV color model and morphology is better than using only CNN alone. Several possibilities make this research have better results than its predecessors; this research uses SVM combined with CNN with a simple model, but there is image processing which causes the resulting accuracy to increase. The next possibility is that the dataset used is different, so the classification model and image processing do not affect accuracy. However, a good dataset affects the accuracy of the results obtained.

The difference between the research and the Puspaningrum et al. is a different model, i.e., SVM with SVM-CNN hybridization and a different dataset [5]. The accuracy results are much better using hybridized SVM-CNN compared to SVM with SIFT-PCA as its feature extraction. In this study, the dataset with more than two categories makes the difference striking. It is suspected that the existence of more categories causes the accuracy to weaken. However, this does not rule out the possibility that different classification models and image processing are also a factor in the accuracy values that are far adrift.

Table 2. Comparison of previous research using similar model classification

Model Classification	Image Processing	Same Dataset	Accuracy	Source
CNN	Not using HSV color model or Morphology	No	87%	[4]
SVM	Not using HSV color model or Morphology	No	62%	[5]
SVM	Not using HSV color model or Morphology	Yes	83.61%	Independent research
CNN	Not using HSV color model or Morphology	Yes	98.92%	Independent research
SVM-CNN	Not using HSV color model or Morphology	Yes	96.16%	Independent research
SVM-CNN	Using both the HSV color model and Morphology	Yes	99.34%	This research

Compared to studies using morphology and the HSV color model, research in this paper has also succeeded in classifying images using training data from the Kaggle dataset. So the image processing combined is working fine.

Compared with independent research with the same dataset using only SVM without the HSV color model and morphology, it produces an accuracy of 83.61%. If only using CNN without the HSV color model and morphology, it would have an accuracy of 98.92% and a loss of 4.3%. The result proves that the difference in model accuracy results between SVM and CNN is very different, around 15.31%. CNN proved to be a better model than SVM. If using the SVM-CNN hybrid model without the HSV color model and morphology image processing, the accuracy result obtained is 96.16%, and the difference in accuracy is 2.76%, with CNN only model being superior. The result of the SVM-CNN hybrid model without the HSV color model and morphology compared to the SVM model using the HSV color model and morphology is SVM-CNN hybrid model is better than the SVM-CNN hybrid model without the HSV color model and morphology with an accuracy of 99.34%. Table 2 is the conclusion from the comparison of each study conducted.

Table 2 can also be analyzed that different models and image processing can produce different accuracy even though the dataset is the same and the changes are not too much. It also explains that differences in datasets in previous research can cause differences in performance based on accuracy. Further experiment regarding the dataset and adding data is conducted. The first experiment used a different dataset but the same topic: the waste image. The effect results from far greater accuracy even though the image processing and classification model are identical. Under these conditions, the image processing and classification models were used as control variables. The differences in datasets and the number of categories were used as experiment variables resulting in much lesser accuracy, around 30% less. The central hypothesis that causes this to happen is that the number of categories in other datasets is so large that the machine has to use categorical cross-entropy, it takes a long time, and the accuracy reduces drastically. However, if only a tiny number of images is added, like adding images using a camera, the effect on accuracy and training time is similar. The difference is still in the margin of error percentage. Furthermore, adding many images using data augmentation improves the result and avoids overfitting.

The advantage over using SVM and CNN separately is the accuracy results explained in the comparison results table (Table 2). SVM alone, if done without CNN, will yield lower yields than hybridization. Whereas for CNN itself, we still need to learn the difference between CNN and SVM-CNN hybrid using the same image processing. SVM-CNN is also superior in maximum capabilities with a simple architecture. CNN is used as an SVM assistant to perform feature extraction more efficiently and faster than regular feature extraction. As a whole layer, CNN trains data so that a deep neural network is formed to determine the distinguishing features between objects. The role of SVM in SVM-CNN hybridization is as a classifier using a hyperplane. SVM is used because it is simple to implement and works well with CNN layers. In conclusion, the SVM-CNN hybrid is simpler and more efficient to build than the SVM or CNN standalone.

After comparing with similar model classifications to know the difference between SVM, CNN, and SVM-CNN hybrid, comparing with various model classifications needs to examine whether SVM-CNN hybrid is still better than various model classifications based on previous research. Table 3 is a comparison table between various model classifications based on accuracy for the waste dataset.

Table 3. Comparison of previous research using various model classification

Model Classification	Accuracy	Source
Random Forest	97.49%	[37]
Gaussian Naïve bayes	81.46%	[37]
Multi-Layer Percept	96.44%	[37]
VGG16	97.00%	[38]
FastAi (resnet26)	92.56%	[39]
SVM-CNN Hybrid	99.34%	This research

Based on Table 3, various model classifications have been done in the previous research. The research can be compared based on the accuracy of each model classification, and it can be concluded that the SVM-CNN hybrid is still superior to various model classifications.

5. CONCLUSION

This study concludes that a suitable dataset, classification model, and image processing that complement the dataset produce good accuracy when tested with test data.

SVM-CNN using image processing in the form of the HSV color model and morphology was successfully carried out with an accuracy rate of 99.34% and a loss of 1.67% without overfitting or underfitting. If the accuracy and image processing models performed are compared with previous studies, the classification models and image processing carried out in this study succeeded in outperforming them.

Suggestions for further research are machine learning for the same case study but using the CNN classification model, the morphology, and the HSV color model. This research can be examined more deeply because the comparison table with independent research using CNN is superior to SVM-CNN when not using image processing HSV color models and morphology. CNN with morphology and HSV color model may outperform SVM-CNN hybridization. The next suggestion is to use the same image processing and model classification on different datasets or data such as signal, text, speech, pattern, or any kind of data. We further suggest building machine learning using SVM-CNN hybridization, HSV color model, and morphology image processing for practical purposes using Internet of Things (IoT) technology.

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