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Article

Classification for Waste Image in Convolutional Neural Network Using Morph-HSV Color Model

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Abstract: Waste management is essential in preserving nature to be cleaner and more well-maintained. Waste management runs slower than the speed of waste accumulation. One reason is slow waste sorting. This problem can be overcome by building a learning machine that can sort the types of waste. The type of waste often separated in the first sorting is waste based on its type, namely organic and inorganic. The classification model used is the CNN with image processing Morph-HSV color model. The data obtained from Kaggle is collected and processed using Python. The processed image is trained using a CNN classification model. The results of this study are an accuracy of 99.58% and a loss of 1.57%. With this research, it is hoped that it can accelerate waste sorting performance using the most efficient ML based on image processing and its classification model.

Keywords: Image Processing; Waste Management; CNN; HSV color model; Morphology; Machine Learning

1. Introduction

Waste management is an effort to deal with the problem of waste accumulation. Waste in Indonesia is collected in one place and separated by type. Separation of waste by type is a process that takes a long time [1]. Waste separation takes a long time, especially for organic waste, because the workers at landfills do not like the smell of it. This problem can be solved using machine learning (ML) to sort waste by type [2]. In Indonesia, waste types are divided into organic, inorganic, and B3 [3]. This study only focuses on two types of waste, organic and inorganic, because household waste often produces these wastes [4]. At the same time, B3 waste is produced by an industrial factory or hospital, which must handle this waste by the waste producer itself. In contrast, the government manages the waste households in each region [5].

Implementing ML can help speed up waste management, especially when sorting waste types [6]. The machine has immunity to unpleasant odors and does not care about the smell produced by the waste it manages. That way, workers can focus on the next step in waste management based on its type. If the waste is organic, composting will be carried out; if the waste is inorganic, then recycling is carried out according to the needs of the raw materials produced by the inorganic waste [7].

One way to know what kind of ML effectively handles waste datasets is to compare image processing (IP) and classification models [8-11]. Many previous studies have used ML as a breakthrough in solving problems regarding waste sorting. Previous research can be used to reference and compare which IP and classification models are adequate for waste datasets.

In this research, the classification model chosen is the Convolutional Neural Network (CNN), which is paired with IP techniques using the Morphology and HSV color model (morph-HSV). The effectiveness of this model and processing method will be assessed and compared to earlier studies, based on their parameter values.

CNN classification model with the HSV and morphological IP was conducted by Kangune et al. [12]. This study has the same classification model and IP but different case studies. The case study raised is the maturity of the grapes with an accuracy of 79.49% using the CNN classification model and 69% with the Support Vector Machine (SVM) classification approach.

Hu et al. [13] describe the application of open-source ML that was created using the CNN classification model in a waste case study. The difference occurs in IP, where this study only uses IP morphology. However, this study focuses more on applying the method to automatic waste, so it needs to explain how much accuracy is produced. This study explains that the resulting source code can be implemented in a tool that sorts waste based on its type.

The following research focuses more on feature extraction based on color. Ganesh et al. [14] compare ML efficiency based on precision, recall, and f1-score values from IP feature extraction based on RGB, HSV only, and RGB+HSV. From the overall results, it can be concluded that RGB+HSV is superior to RGB-only and HSV-only color feature extraction.

The following previous research is research in making a fundamental tool that implements IP. The tool only relies on visual perception to identify objects, so the morphological role is needed to determine the main object to be targeted. Min et al. successfully carried out evidence that the tools built can distinguish garbage objects from other objects for further management. This tool uses the same classification model, namely CNN, and the same IP, namely the Morph-HSV, but does not show accurate performance results. This research only shows that a ML system with the CNN classification model, IP color model, and morphology can be implemented in a tool that can sort waste.

The next research is from a gesture recognition review conducted by Neiva et al. [15]. The results of this review explain in detail how gesture recognition can be built with different classification and IP models. One of the classification models used is CNN, and the IP used is the Morph-HSV. Different classification models and IP can produce different accuracy values. So, it is necessary to do research with various classification models and IP to find which is the most efficient for waste case studies.

Several previous studies conclude that we need to find efficient model classification and IP; thus, this research aims can be fulfilled by comparing classification models and IP. An efficient system is expected to expedite the waste management process so that the accumulation of waste is reduced.

2. Basic Concept

2.1. CNN

CNN is a ML commonly referred to as deep learning [16]. CNN is considered deep learning if it has a neural network with the same or more than two layers [17]. CNN is often used because of the efficiency of the classification model for images [18]. Many images classification studies state that CNN can outperform other classification models. CNN consists of different layers according to their functions and roles. Beginning with the convolutional layer, followed by the pooling layer, data normalization (via the flatten layer), and concluding with the fully connected layer [19]. These layers are arranged and linked sequentially to classify a machine based on what the machine learns from the training data.

2.2. Image Processing (IP)

IP is a step performed on training data images to become more efficient data for ML [20]. Machines cannot read images the way humans can read images. The machine can only read numbers, so each object in each image pixel is assessed for weight and bias to determine which object is the target that must be studied [21].

IP helps the machine focus on the image's main object. IP used in this research is the Morph-HSV [22, 23]. The Morph-HSV are expected to make it easier for the machine to recognize the main object in the image so that the weight and bias values are more accurate for the main object.

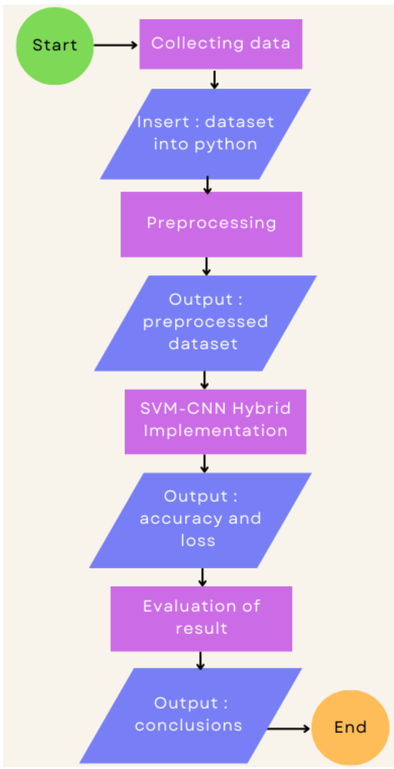

Figure 1. Research flowchart

3. Research Methodology

The research process started with gathering data, followed by preprocessing, applying the classification model, and concluding with evaluation. A detailed overview of these stages is shown in Figure 1.

3.1. Dataset

Datasets are created by collecting data. The Kaggle website provides datasets for free [24]. The dataset contains 25,077 samples, which are split into 85% for training and 15% for testing. It is composed of two binary categories: organic and inorganic. The limitation occurs because the only category that matter is household waste which is organic and inorganic waste.

3.2. Preprocessing

The preprocessing involves changing the feature extraction from the original RGB color space to HSV. Once converted to HSV, the image undergoes morphological processing. Morphology helps minimize the weight and bias associated with irrelevant objects, such as backgrounds. As suggested by its name, the HSV color model consists of hue, saturation, and value, which are calculated using equations 1, 2, and 3, with RGB values derived from the original image [25]. The HSV represents the color that a machine can read closer to the color scale accepted by the human eyes naturally rather than using the RGB color scale [26]. This occurrence happens because RGB only relies on primary colors and their mixtures without regard to other variables, such as color depth [27]. Converting RGB to an HSV can be done using the Equation 1-3.

$$H = \tan\left(\frac{3(G-B)}{(R-G)+(R-B)}\right) \quad (1)$$

$$S = 1 - \frac{\min(R,G,B)}{v} \quad (2)$$

$$V = \frac{R+G+B}{3} \quad (3)$$

The RGB value serves as the primary variable for calculating the HSV value, as the original image is represented in the RGB color scale [23]. The HSV values generated using equations 1, 2, and 3 will be processed again using IP morphology [28].

Morphology is a technique that uses mathematical formulas to transform an image, making the main object more prominent. This method typically emphasizes the shape of the primary object while eliminating irrelevant noise, such as the background, allowing the machine to focus solely on the main object for tasks like weight and bias assessment, without being influenced by other elements. [29].

To reduce the training data processing time, resize the existing images to be uniform and smaller. The specified size is 64x64 pixels for all data to be trained. Figures 2, 3, 4, and 5 are original and image data produced using the HSV, morphology, and resized into 64x64 pixels.

Figure 2. Initial image (original)

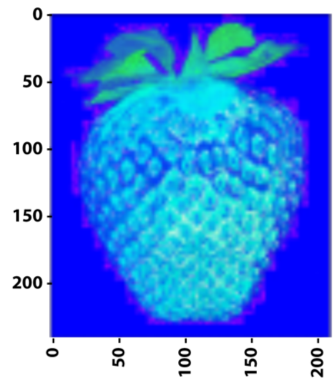

Figure 3. Application of HSV

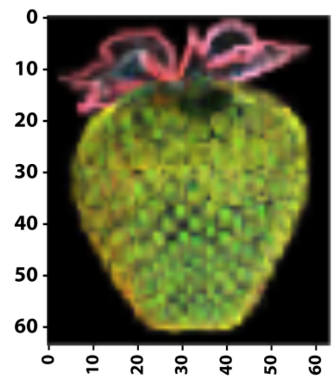

Figure 4. Morphological Processing and Resizing

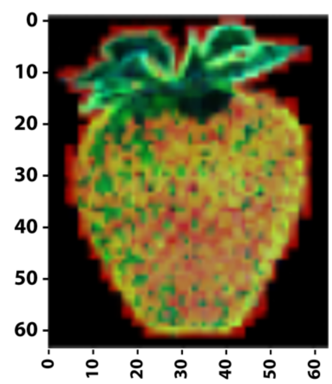

Figure 5. Combined HSV Model, Morphology, and Resizing

Table 1. CNN scheme

Parameter	Value
#**First layer**	
• 2D Convolutional Filters	64
• Kernel Size for 2D Convolution	3x3
• Shape of the Input	64, 64, 3
• Activation Function	ReLu
• Kernel Size for Max Pooling	2x2
• Strides for Max Pooling	2
#**Second layer**	
• 2D Convolutional Filters	64
• Kernel Size for 2D Convolution	3x3
• Shape of the Input	64, 64, 3
• Activation Function	ReLu
• Kernel Size for Max Pooling	2x2
• Strides for Max Pooling	2
#**Data normalization**	
• Flatten Layer	
#**Fully-connected layer**	
• Number of Units in Dense Layer	64
• Activation Function	ReLu
#**Output Layer**	
• Number of Units in Dense Layer	1
• Activation Function	Sigmoid
• Optimizer Method	Adam
• Loss Function	Binary cross-entropy
• Evaluation Metrics	Accuracy

Figures 2, 3, 4, and 5 shows that the process produces images with different color scales and the clarity of the main object by blackening out irrelevant objects.

3.3. Implementing CNN model classification

3.3.1. Convolution layer

CNN classification model is a model that has its feature extraction, which is commonly called the convolution layer [30]. The convolution layer is a layer that determines the weight and bias values of images so that a set of numbers is entered into a matrix [10]. The matrices in this study are 3x3 in size with a stride value of 1. This condition indicates that for every 3x3 pixels, the convolution layer will assess the weight and bias and shift one pixel to the right to input the new weight and bias values.

The equation that describes the convolution layer is if the input has a value of W1 x H1 x D1, and the convolution layer will produce W2 x H2 x D2. More detailed equations explain as follows.

$$W2 = \frac{W1-F+2P}{S} + 1 = H2; D2 = K \tag{4}$$

The values of W1, H1, and D1 are already known in the resizing process carried out at the IP stage, namely 64x64x3. The D1 value is 3 because the image base used is not grayscale but RGB which has a value three times greater than grayscale. W2 and H2 have the same value. F is the spatial size of the filter, which is 3x3, P is the padding, and the value used in this study is the default value based on the TensorFlow default value. S is the stride which in this study is the default value. While K is the number of filters used, in this study, its value is 4.

3.3.2. Pooling layer

After the weight and bias values are collected, the matrix is processed again using the pooling layer [31]. In this study, max-pooling uses a 2x2 size of the kernel. The kernel will determine the highest value of the matrix generated by the convolution layer and accommodate it in the new matrix. For the stride, it has the same value as the kernel size, which is 2.

The equation used in the pooling layer is similar to the convolution layer, where if the input has a size of W1 x H1 x D1, then the pooling layer used has the Equation 5.

$$W2 = \frac{(W1-F)}{S} + 1 = H2; D2 = D1 \tag{5}$$

It is the same with the convolution layer. It is just that the pooling layer rarely has padding, and the value of D2 is often the same as D1.

3.3.3. Data Normalization

After the max-pooling result matrix is formed, the data will be normalized. One of the data normalizations is called flatten. Flatten will make the dimensions into a one-dimensional parameter [32].

3.3.4. Fully-connected layer

The neural network is merged from the input to the output layer in this layer. The neural network formed is connected to each other between layers and neurons [33]. Table 1 shows the parameters and values in the CNN formed in this study.

Based on Table 1, CNN is formed with two layers of convolution layer and max-pooling layer. After the max-pooling layer is formed, the data is normalized into one dimension with a flatten function. After that, every connected neuron is connected from input to output. The output layer uses sigmoid activation and loss binary cross-entropy because the specified category has only two categories. The metric that becomes the benchmark is accuracy.

3.4. Evaluation

Evaluation is done by analyzing the training data accuracy graph compared to the validation data formed by TensorFlow using matplotlib. The graph explains whether the training data is feasible for testing with test data. If the training data is overfitting or underfitting, then the training data is not viable to be tested with test data. However, if the data does not experience any error, it can be tested with test data [34].

4. Result and Discussion

A dataset of 25,077 data was collected and divided by the ratio of training data and test data of 85:15. After all images in the training data were processed with the Morph-HSV, the data were trained using the CNN classification model and compared with the validation data.

The validation data consists of 20% of the training data with a function to determine whether the machine can correctly classify garbage images. If the training and validation data experience performance changes in parallel, the training data has successfully classified garbage images correctly. However, the training data always increases in accuracy, while the validation data does not experience the same changes as the training data. In that case, the data will likely experience an error called overfitting. If the opposite applies, then underfitting will occur.

Therefore, it is essential to analyze the accuracy performance of the training data compared to the validation data to determine whether the training data can be used as learning material for ML with no signs of overfitting or underfitting. Figure 6 illustrates the accuracy results for both the training and validation data of garbage images, using the CNN classification model along with the HSV and IP techniques.

Based on Figure 6, training and validation data experience parallel performance changes; the difference is negligible. The training data's accuracy has improved performance and data validation in parallel, so it can be concluded that the training data is neither overfitting nor underfitting.

After knowing that the training data does not experience overfitting or underfitting when it becomes ML material, the system can continue testing with test data. The following is Figure 7, which shows the results of ML accuracy when tested using test data.

The research was completed successfully, achieving an accuracy of 99.58% and a loss of 1.57%. The research went according to expectations where the morph-HSV could be implemented on the garbage images in the CNN classification model without any errors in the form of overfitting or underfitting.

Many studies have used the CNN classification model and IP in the form of the Morph-HSV. One of them is the research by Kangune et al. [12]. This study succeeded in classifying grape ripeness with an accuracy of 79.49% using the CNN classification model. The difference with our research is only in the case study objects studied.

Next is a comparison with previous research conducted by Gyawali et al. [8]. In this study, in-depth research was conducted on CNN with various parameters. The maximum accuracy result obtained is 87%. The dataset and IP are done differently, so the resulting accuracy is also different.

The next difference is with a different model, namely the SVM model by Puspaningrum et al. [35]. SVM is a simpler classification model than CNN. CNN has more complexity because CNN is a deep neural network that has many neurons to categorize an object, in contrast to SVM, which only relies on decision boundaries to categorize an object. The accuracy produced in this research is due to two main things: datasets with more categories, different IP, and different classification models. The accuracy of the results is 62%, a vast difference compared to the accuracy in our study, which is 99.58%.

Compared with research using IP Morph-HSV, this research has successfully used processed images to classify [22, 23, 25-29]. When compared with independent research, the results have an impact on accuracy. CNN without IP Morph-HSV produces 98.92% compared to CNN using the Morph-HSV, which has an accuracy of 99.58%, an increase of 0.66%.

Other independent research in which classification models and IP are efficient for waste case studies are SVM without Morph-HSV, SVM-CNN hybrid without Morph-HSV, and SVM-CNN hybrid using Morph-HSV. Table 2 is a summary comparison with previous research and other independent research.

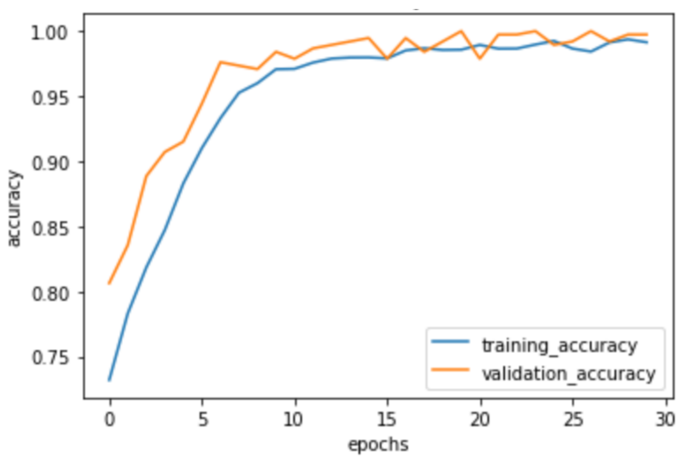

Figure 6. Accuracy result

67/67 [==============================] - 3s 46ms/step - loss: 0.0157 - accuracy: 0.9958

Figure 7. Overall performance on test data

Table 2. Comparison with Earlier Work

Model	IP	Same dataset	Accuracy (%)	Source
CNN	Without Morph or HSV	No	87.00	[8]
SVM	Without Morph or HSV	No	62.00	[35]
SVM	Without Morph or HSV	Yes	83.61	Own research
CNN	Without Morph or HSV	Yes	98.92	Own research
SVM-CNN	Without Morph or HSV	Yes	96.16	Own research
SVM-CNN	With both Morph-HSV	Yes	99.34	Own research
CNN	With both Morph-HSV	Yes	99.58	This research

Table 2 shows that CNN using image data that has undergone IP of the Morph-HSV has outperformed in accuracy metrics. The slight difference with SVM-CNN amounts to 0.24%. This difference indicates two possibilities: first, CNN is superior to SVM-CNN if IP is performed using Morph-HSV on the same dataset. The second possibility is that because of the slight difference, the changes that occur within the margin of error range. There is no significant change because the accuracy results are dynamic. The error margin can happen due to the instability of TensorFlow and Python in calculating the accuracy and doing the classification. When viewed from CNN without using the Morph-HSV with SVM-CNN without using the Morph-HSV, CNN is superior with the difference accuracy above the margin error value. However, this cannot be analogous to the accuracy results using images that have undergone IP Morph-HSV. There is no significant difference between SVM-CNN and CNN when using the Morph-HSV IP.

Table 2 also shows that differences in datasets, dataset categorization, IP, and model classification affect the resulting accuracy. Each dataset has a different classification and IP model to achieve the best efficiency level.

4. Conclusion

Dataset, dataset categorization, classification model, and IP are parameters that must be in harmony with each other to achieve the desired efficiency level. The more suitable a classification model or IP is for the dataset, the better the resulting accuracy. Between SVM-CNN hybrid using IP Morph-HSV and CNN using Morph-HSV has a slight difference. It can be included in the margin of error due to the instability of TensorFlow and Python in calculating the accuracy.

Future research could explore ML techniques on the same dataset, utilizing different classification models or IP to find which classification and IP models are suitable for the garbage dataset from Kaggle. Another suggestion is the creation of a ML to hardware and IoT that is formed to expedite waste management.

5. Conflicts of Interest

The authors declare no conflicts of interest.

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