1st International Conference on Science and Technology Innovation (ICoSTEC)
February, 26 2022. Yogyakarta, Indonesia
ISBN: 978-623-331-338-4

Waste Classification using CNN Algorithm

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Abstract— **One of the cornerstones to efficient waste management is proper and accurate waste classification. However, people find it challenging to categorize such a big and diverse amount of waste. As a result, we employ deep learning to classify waste efficiently. This paper uses the CNN algorithm to provide a problem-solving strategy to waste classification. The model achieves an accuracy of 0.9969 and a loss of 0.0205. As a result, we argue that employing CNN algorithms to categorize waste yields better results and reduces losses efficiently.**

***Index Terms*— Deep Learning, Waste, Classification, CNN.**

I. INTRODUCTION

Waste classification is part of the primary strategy in waste management, which plays a vital role in sustainable management. Due to the increasing population, it will impact increasing the amount of public consumption. It also causes an increase in the amount of waste. The waste usually comes from domestic activities or industrial process waste. Accurate classification and proper treatment of various types of waste help protect the environment and provide economic benefits. In addition, waste classification also plays a vital role in avoiding wasting resources and protecting the entire ecological environment [1].

One strategy to process and benefit from waste categories is turning it into fertilizer, recycling it, and using it as raw material. Organic waste is turned into fertilizer. Cans, plastic, bottles, paper, and other recyclable materials are commonly found in recycling waste. For the time being, several parties are working hard to improve waste recycling technologies since they believe it is one of the most effective ways to make a beneficial influence. There will be less trash to create, and the resource will last longer and be more sustainable as a result [2]. Furthermore, waste recycling can result in a variety of handicraft goods and a valuable business opportunity.

More than a hundred countries recognize the importance of waste classification and have regulations in place to address it [3]. Because countries that value waste classification recognize how hazardous waste is to the environment and persons. China is one of the world's leading producers of trash. Waste classification is incorporated into waste disposal regulations in Shanghai, China, to emphasize the need for waste classification [4].

One of the challenges in implementing regulations is awareness of classification. As a result, it is critical to educate on the importance of understanding the dangers of trash and being aware of how to dispose of current waste properly. According to a study, if kitchen garbage is mixed with other debris in significant amounts, such as plastic bags, the environment will be severely polluted. Surface water pollution, groundwater contamination, soil pollution, greenhouse gas emissions, and reduced crop yields are all risks connected with the dumping of unsegregated waste [5].

As a result, garbage should be classified as soon as possible to ensure the amount of recyclable waste and decrease the chance of it mixed with other litter. The main hurdles to waste classification are described in a study. The first barrier is government planning and budgeting, which lacks waste management legislation and finances. The lack of appropriate waste classification technologies is the next roadblock. The most common stumbling block for most families is their lack of understanding of the significance of independent waste sorting. The high cost of manual waste classification is the final stumbling block [6].

Rapid automatic detection and recognition of waste from photos to replace human sorting is becoming increasingly achievable because of advances in artificial intelligence. One of the aspects of computer vision technology is image classification. This technology can teach a machine how to learn visuals visually. The CNN algorithm is an image categorization technology. Deep Learning approaches, particularly CNN, have emerged as a valuable tool for studying accurate data representation [7].

CNN-based applications have grown in prominence in recent years due to their high accuracy in identifying images and increased training speed [8]. So there's no harm in developing a model using the CNN algorithm in the hopes of getting good waste classification results.

The development and study of the CNN algorithm necessitate a large number of trials to acquire the best results. The current research focuses on improving accuracy, minimizing errors, and reducing the number of resources used by the CNN algorithm. The most popular models employ CNN to classify waste, such as Faster-RCNN [9], YOLOv4, and DSSD [6], all of which have significant advantages in terms of accuracy, size, and speed.

We present a waste classification approach that uses a deep learning algorithm to categorize organic and recycled waste in this study to address this issue. This research also aims to get the highest levels of accuracy by testing using waste currently in the library. As a result, the following is a summary of the primary contributions that we will make in this project, with a focus on waste classification:

1. We present a waste classification approach based on deep learning, a popular method. The CNN method is used in this experiment to create a classification model that divides waste into organic and recyclable waste. We show that using the CNN algorithm improves accuracy and reduces loss compared to machine learning.
2. We use a dataset of 2000 images to build the model, with 80% of them being used for training and 20% for testing. We also use callbacks to decrease loss validation and use validation split 0.2 and epoch 50.
3. This work uses three distinct architectures to evaluate the model: ReLU, Tanh, and Sigmoid. Using various activation functions will result in a model that performs better. Then, using graphs and confusion measures, they present the test results. ACCORDING TO THE MODEL TEST, the CNN algorithm can efficiently classify recycling and organic waste.

Organization: Part I explains the problem of waste classification and contributes. Part II describes the problem of waste classification and contributes. Work-related information is presented in Part II. The context of this study is discussed in Part III. The proposed model is presented in Part IV. Part V examines the experimental setup. The research findings and analyzes are presented in Part VI. In section VII, we give our conclusions and plans for the future.

II. Related Work

Traditional waste classification relied solely on manual selection at first. We can considerably minimize the health hazards of municipal workers by avoiding the transmission and spread of infectious diseases by modifying this strategy [10].

Waste Recognition-Retrieval (W2R) uses computer vision to classify household waste in two stages (RegM and RevM). The model will be trained using ClfM and manual sorting (MS) as a comparison [11]. Furthermore, there are several approaches to solving this problem, including thermal imaging in the 8-15m long-wave infrared range (LWIR) [12], neural network technology, the LoRaWAN protocol, and recording devices [13].

Another study used the Support Vector Machine (SVM) classification method with SIFT-PCA feature extraction to classify waste images into six categories (cardboard, glass, metal, plastic, paper, and garbage). The accuracy of SIFT feature extraction, on the other hand, was 62 percent [14]. The accuracy of another study that employed the SVM approach to classifying fruit waste recycling was 90 percent to 100 percent [15].

Another study classified waste containers using CMYK colors using the K-Means clustering approach. On the other hand, the K-Means technique was not acceptable for this situation because it only yielded less than 70% [16].

The machine learning method used the K-Nearest Neighbors and Multinomial Regression algorithms for can classification. The cans classification utilizing the Multinomial Regression approach had a lower success rate than the K-Nearest Neighbors method [17].

In addition to the one mentioned above, several studies combined four machine learning methods (Decision Tree, K-Nearest Neighbors, Logistic Regression, and Support Vector Machine). In addition, the study used visual and physical aspects of objects [18].

Although waste sorting has progressed through efficient machine learning methods, the value of classification accuracy still has to be improved, necessitating the use of more current approaches. Amount of research that used deep learning to detect it automatically got considerably better results. In waste classification, CNN is one of the deep learning approaches [7].

The accuracy of waste categorization research using the CNN approach and the AutoEncoder Network was 99.95 percent [19]. Another paper used the CNN algorithm implemented in the Raspberry Pi and recording device for real-time monitoring for domestic waste classification [20].

The study used a multi-tasking learning architecture based on the CNN principle to identify the type of trash image and attained an F1 score on the waste classification test of over 95.50 percent, with an average precision score of above 81.50 percent [7].

A trash classification system was proposed in an article that used the CNN algorithm and tested a five-layer model. On the other hand, the fourth layer had the maximum accuracy of 83 percent [21]. However, testing the CNN approach for plastic waste categorization research on layer 15 and layer 23 yielded different results. The study achieved the best accuracy of 99.92 percent utilizing photos with a dimension of 120x120px and 227x227px [22].

In an experiment, the classification of recyclables using a genetic algorithm yielded the best results on the

DenseNet121 architecture's optimum performance and had the highest accuracy of 99.6% [23]. The garbage picture classification system based on the DenseNet169 architecture achieved an accuracy of more than 82 percent [24].

Several studies used three CNN architectures for classification: MobileNetV2 had a classification accuracy of 96.27 percent, ResNet34 96.273 percent, DenseNet121 96.42 percent [25] , VGG-19 86.19 percent, ResNet50 79.63 percent, and Inception-V3 81.15 percent [26].

This study aims to improve the accuracy of the CNN algorithm, a deep learning approach, by using three activation functions in trash classification to create a model that performs better. As a result of this research, an effective waste categorization model will be developed, which will aid in efficient waste sorting.

III. Background

This section gives a formal specification of the experimental definition and discusses how this study came to be.

A. Problem Definition

This study builds a waste classification model by utilizing data in images. This classification has a potential solution to support the waste sorting process work more efficiently. Instead of practicing manual classification methods and machine learning methods with this method, we propose developing deep learning as a waste classification method to improve model performance. This study shows how to use deep learning as a classification solution to overcome waste sorting with a learning model.

This article uses data collection containing waste images, domestic and other waste, as materials for building and testing models. We use three activation functions: ReLU, Tanh, and Sigmoid. Our experiment divides the existing data with 80% for building the model and 20% for evaluating the model.

B. The proposed method

With precise waste classification, deep learning can distinguish tasks [7]. For instance, several studies have examined deep learning classification models based on CNN for domestic waste classification [20] and FasteR-RCNN for solid waste classification [9].

We describe a CNN algorithm for categorizing waste into two types: organic and recyclable, based on hundreds of data sets. Our research employs deep learning techniques to develop a model for waste classification that is more performant. CNN is a subset of neural networks with similar needs and can evaluate visual pictures because CNN is identical to the human brain in its operation. The model is capable of classifying objects according to their characteristics. We apply CNN to comprehend and evaluate image data [10]. Four layers comprise CNN: an input layer, a hidden layer, and an output layer.

In this article, we examine deep learning from two perspectives. CNN develops a classification algorithm based on images from a waste dataset. The convolution layer is one of the phases of the CNN architecture. The convolution layer repositions the filter on top of the input image, resulting in new features. These new values relate to the image used as the input for the subsequent layer. It generates an activation map from the feature extraction output, then used to process the convolution layer. The activation map depicted in Figure [19] illustrates the different characteristics identified in that region. The filter is applied to each convolution layer. Each shift will perform a " dot " operation between the input and the filter value used to generate the output.

$$Y_k = f(W_k * x) \qquad (1)$$

Table 1: Mathematic notation

Notation	Description
$\mathbf{Y}_k$	Output feature map
x	Input image
$\mathbf{W}_k$	Convolutional filter
$f(.)$	Nonlinear activation function

The pooling layer is the next in the CNN. This layer helps reduce the total number of parameters and computational memory required and the spatial length and size of the representation [10]. We employ the max-pooling method, which uses the largest value in the 2x2 area, and the average pooling method, which uses the average values in each feature map.

$$(n_h - f + 1)/ s * (n_w - f + 1)/s * n_c \qquad (2)$$

Table 2: Mathematic notation

Notation	Description
n_h	Height of the feature map
n_w	Width of the feature map
n_c	Number of channels in the feature map
f	Size of filter
s	Stride length

Layers that are fully connected perform multiple operations in unison. They flatten features from previous layers and update weight parameters to facilitate feature classification in vectors [19]. Then, for the classification step, they label each remaining possible value. The extraction of features from fully connected layers yields the probability value for each label using Equation (3).

$$FC(W, x)_{(ij)} = \sum_{k}^{K} W_k . (r . x_{(ij)}) + b \quad (3)$$

Table 3: Mathematic notation

Notation	Description
FC	Fully connected
W	Matrix of convolutional kernels
x	Input feature map
i,j	Embodies a receptive field around the position
k	Dimensions convolutional kernel
W_k	Convolutional filter
r	variable
b	Trainable

IV. EXPERIMENTAL SETUP

A. Main Idea

The primary objective is to develop a classification model for organic and recyclable waste using the CNN algorithm. This method aims to generate a model that performs better at waste classification.

B. Dataset

For this study, we collected a dataset from Kaggle. This dataset contains 22564 images divided into two categories: organic and recycled. The images feature a variety of objects shot from various camera angles and under a variety of lighting conditions. Before training the model, the image is resized to 225 x 225 pixels. We divided the dataset into two sections to train our model: training and testing. The training data is used to construct the classification model, while the test data is used to evaluate the classification model's performance. The model is trained during epoch 50, with a validation split of 0.2, and makes use of callbacks that focus on maximum accuracy validation. The performance metric, as shown below, is 0.7937 for model accuracy and 0.5527 for loss after 50 epochs.

Table 4: Dataset description

Dataset Labe	Waste Feature	
	Training	Testing
Organic	800	200
Recycle	800	200

C. Data Pre-processing

At this point, we furnish a waste dataset extracted from Kaggle. Since the dataset is raw data, it has a low accuracy when applied to any classification system. Our objective is to produce a model with improved performance using several preprocessing techniques, including data selection and deletion, image size equalization, and data normalization. Numerous methods are employed to convert any information contained in the data set into a vector that the model can comprehend.

D. Classification Method

After preprocessing, we train a model that extracts features to create a waste classification model. We develop a deep learning model and train it on the organic and recyclable waste dataset. We employ three distinct activation functions on CNN to optimize the model and the training accuracy value.

We perform preprocessing during the training process. The raw dataset is converted to vectors using preprocessing techniques. We employ several preprocessing techniques, including data selection and deletion, image equalization, and data normalization.

During the testing phase, we use vectors as inputs for feature extraction. The dataset comprises two components: a training set and a testing set. Then, we perform model testing on the training data from our classification to ensure that we are getting the best results.

V. RESULT AND ANALYSIS

Our approach can produce a classification model using the CNN method during the classification process. We examine the data set using three different activation functions during training: ReLU, Sigmoid, and Tanh. Additionally, we use loss functions to estimate losses, compare, and quantify the results of successful or unsuccessful classification. As a result, the model's interconnection weights will be gradually adjusted until satisfactory results are obtained. We train our model in this study by adjusting several parameters to achieve the highest accuracy possible. We use epochs of 50, a validation split of 0.2, and callbacks that focus on minimum loss validation during the training and testing phases.

Table 5: Accuracy of classification model

Hyperparameter	Activation Function	Accuracy	Validation Accuracy
Epoch = 50	ReLU	**0.9969**	**0.8156**
LR = 0.001	Tanh	0.5078	0.6961
	Sigmoid	0.4836	0.5250

Table 6: Loss of classification model

Hyperparameter	Activation Function	Loss	Validation Loss
Epoch = 50	ReLU	**0.0205**	**0.5303**
LR = 0.001	Tanh	0.6934	0.6923
	Sigmoid	0.6951	0.6968

Table 5 summarizes the accuracy of the CNN model's performance, particularly during training and testing. The three activation functions ReLU, Tanh, and Sigmoid, are used to determine the model's accuracy. We used the ReLU activation function to test the training data and obtained an accuracy of 0.9969 and a validation accuracy of 0.8156. The Tanh activation function was then tested, yielding an accuracy of 0.5078 and a validation accuracy of 0.6961. Then, using the Sigmoid activation function, we obtained an accuracy of 0.4836 and a validation accuracy of 0.5250.

The results of the performance loss on the CNN model when three activation functions are used are shown in Table 6. The first test employs the ReLU activation function and achieves an accuracy of 0.0205 and a validation accuracy of 0.5303. We obtained an accuracy of 0.6934 and a validation accuracy of 0.6923 using Tanh from the second test. The most recent test, which used the Sigmoid activation function, achieved an accuracy of 0.6951 and a validation accuracy of 0.6968. Additionally, we compute the accuracy, precision, recall, F1, support, and confusion matrix to evaluate the model's performance on the evaluation metric. This study demonstrates the precision and accuracy of the overall waste data. Precision is a term that refers to the relationship between expected data and the model's prediction results. Recall quantifies the model's success in obtaining data. The F1 score can compare the average precision and recall weights to determine accuracy.

Table 7: Evaluation matrix

Classification Report	Precision	Recall	F1-Score	Support
Organic	0.80	0.94	0.87	200
Recycle	0.93	0.77	0.84	200
Micro avg	0.85	0.85	0.85	400
Macro avg	0.87	0.85	0.85	400
Weighted avg	0.87	0.85	0.85	400
Samples avg	0.85	0.85	0.85	400

Our proposed model can obtain the highest TP and TN scores based on the confusion matrix calculation. The confusion matrix obtained using the CNN algorithm has TP = 0.94 and TN = 0.77. The results obtained using the confusion matrix are more accurate and efficient in waste classification.

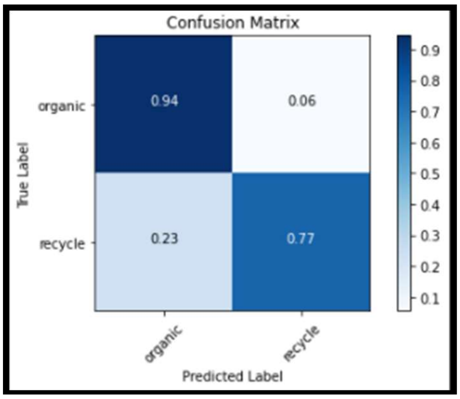

Fig 1: Confusion Matrix of the classification model.

VI. CONCLUSION

Waste classification is a popular area of research that is still developing. Numerous studies have proposed various approaches to this problem, including statistical, traditional, and machine learning approaches. However, this method is ineffective because it requires much time, cost, and effort to classify waste according to its type. This study employs CNN to develop a waste classification model with improved performance and accuracy while incurring the smallest possible errors. We use the CNN algorithm to classify waste based on the proposed model, and the CNN algorithm does not require much time or effort to determine the classification results.

We obtain the best performance results from the experimental data by adjusting the activation function used to optimize the model's performance. We set the epoch to 50, the validation split to 0.2, and the learning rate to 0.001, and then use callbacks to validate the minimum loss during the training and testing phases. The model can achieve an accuracy of 0.9969 and a loss of 0.0205 during the training process. The classification model may be a viable option for resolving the waste classification issue. Additionally, our proposed model is capable of obtaining TP = 0.94 and TN = 0.77.

Further research could make use of the classification of waste objects. The R-CNN or Faster R-CNN algorithms can be used to improve classification accuracy.

ACKNOWLEDGMENT

This study is conducted under the Department of Informatics. Universitas Respati Yogyakarta, Indonesia.

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