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Implementation of DenseNet121 Architecture for Waste Type Classification

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Abstract. The growing waste management problem in many parts of the world requires innovative solutions to ensure efficiency in sorting and recycling. One of the main challenges is accurate waste classification, which is often hampered by the variability in visual characteristics between waste types. As a solution, this research develops an image-based litter classification model using Deep Learning DenseNet architecture. The model is designed to address the need for automated waste sorting by classifying waste into ten different categories, using diverse training datasets. The results of this study showed that the model achieved an overall accuracy rate of 93%, with an excellent ability to identify and classify specific materials such as batteries, biological materials, and brown glass. Despite some challenges in metal and plastic classification, these results confirm the great potential of using Deep Learning technology in waste management systems to improve sorting processes and increase recycling efficiency.

Keywords: Classification, DenseNet, Deep Learning, Waste

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1. Introduction

Waste is one of the main problems that need to be addressed by the community and government. This is due to the increase in waste piles every year which is increasing, causing various disasters such as flooding, water pollution, environmental pollution and ecosystem damage. Based on data from the SIPSN KLHK website in 2023, from the results of input data that has been carried out by 111 cities / districts in Indonesia, there are around 11,998,481.07 tons / per year of waste. Of this amount, about 51.31% has been handled, 67.07% of waste has been managed and about 33.25% of waste is unmanaged. The process of classifying waste at the landfill centre is difficult because the waste is mixed [1]. The manual waste management process certainly requires a lot of time and effort. This is not ideal for handling the volume of waste that continues to increase every day. So effective waste management is needed to help classify waste based on its nature, namely the nature of organic waste and the nature of inorganic waste. Easily degradable waste such as vegetables and food scraps are organic waste [2]. While non-degradable waste such as plastic and glass is inorganic waste which takes a long time to disintegrate. In Indonesia, 75% of waste comes from residential areas, namely organic waste, the rest is inorganic waste. People usually utilize organic waste as material for making compost and biogas. However, there are still very few types of inorganic waste that manage it [3]. From the KLHK SIPSN data based on the source, the most waste is generated from households with a percentage of 37.9% and traditional markets with 22.7% data [4]. This is caused by people who do not know how to sort waste properly. People often mix waste without going through the sorting process first.

Along with the development of technology, the use of deep learning in waste management offers an innovative solution to the problem of effective waste sorting and management. Deep learning is a sub-field of machine learning that mimics the way the human brain processes data and makes decisions [4]. It uses artificial neural networks consisting of many layers to extract complex features from large, unstructured data, such as images, sound, and text [5]. With the ability to learn hierarchically, deep learning has revolutionized various fields, including image recognition, speech recognition, natural language processing, and game AI [6]. For example, in image recognition, deep learning can automatically recognize objects in photos with a high degree of accuracy. This is achieved through training neural network models using large amounts of labeled data and optimization algorithms such as gradient descent [7]. The power of deep learning lies in its ability to generalize from training data, allowing the system to adapt and perform complex tasks without significant human intervention [8]. Deep learning can be used to develop a system that can automatically identify and classify types of waste through image processing. Cameras installed at the disposal center can take pictures of incoming waste, and through deep learning algorithms, the system can distinguish between organic and inorganic waste, as well as other materials such as paper, plastic, glass, or metal. This not only improves efficiency in the waste sorting process, but also minimizes the need for large manual labor and reduces the risk of human error [9].

Deep learning models, such as Convolutional Neural Networks (CNN), have proven to be very effective in recognizing complex patterns in visual data [10]. With training using sufficient data, these models can achieve a high level of accuracy in classifying waste based on its composition [11]. In addition, this technology can be integrated with an intelligent waste management system that enables automatic monitoring and control over the waste sorting and management process. The implementation of this technology is expected to help the government and society in reducing unmanaged waste, supporting recycling efforts, and promoting environmental sustainability. DenseNet, which stands for Dense Convolutional Network, is a highly effective artificial neural network architecture in terms of performance and parameter efficiency. It was introduced by Huang et al. in 2017 and became popular due to its ability to minimize the vanishing gradient problem and improve feature efficiency through the use of dense connections between layers [12]. In the DenseNet architecture, each layer is directly connected to every other layer after it. Specifically, the output of each layer is combined with the input that will go to the next layer [13]. This is different from the ResNet architecture, where a layer is only connected to the next layer and the residual layer [14]. This uniqueness of DenseNet allows the network to utilize the features of all previous layers, increasing the efficiency of information usage and strengthening signal propagation into the network [15]. There are several main advantages of DenseNet:

1) Parameter Savings: Since each layer receives additional features from all previous layers, the network can use fewer units per layer without sacrificing accuracy.
2) Gradient Flow Improvement: Direct connection between layers facilitates gradient propagation during training, which reduces the vanishing gradient problem.
3) Feature Enhancement: Since each layer has direct access to the gradient and output of the previous layer, it helps in learning more varied and robust features.

DenseNet has shown excellent results on many computers vision tasks, such as image recognition and object segmentation. Its efficiency in managing resources and its ability to strengthen features through the use of old and new features make it a good choice for applications that require high-level image processing, including in automated waste sorting systems where it can help identify and classify different types of materials more accurately [16].

To perform the classification process in this study, researchers will use deep learning methods with DenseNet architecture which aims to develop a classification system for organic and inorganic waste.

This is expected to help the community and government in conducting more optimal waste management. DenseNet is one of several CNN architectures that are widely used to learn images [13]. Some types of DenseNet are such as DenseNet121, DenseNet169 and DenseNet201. Each type of DenseNet has its own size. The size for DenseNet121 is 33MB, DenseNet169 is 57MB, and DenseNet201 is 80MB [11]. In previous research that discussed the classification of organic and inorganic waste carried out using the Backpropagation artificial neural network method with an accuracy rate of 90% with an average prediction time of 49.9 ms [17].

Another study that discusses waste classification using DenseNet trained all types of DenseNet, namely DenseNet121, DenseNet169, DenseNet201. The test results of all types of DenseNet are able to produce good accuracy, precision, recall, and F1 value in classifying garbage. DenseNet121 achieved 93.1 accuracy, 94.08% precision, 94.00% recall, 94.03% F1 score and 1 minute 34 seconds training time as the best among other DenseNet types. Further research, also discussing waste classification with DenseNet architecture169 [3]. achieved superior results when dealing with unbalanced classes, showing a 1% increase in accuracy, reaching 91% compared to models using unbalanced data distribution. Further model refinements involved using an ensemble approach on five previously oversampled models using identical architectures in the training dataset. This technique produced noticeable improvements ranging from 3% to 5%, resulting in a final accuracy of 96% in the testing dataset. In Prakash et al's research obtained precise results in predicting liver lesions using CNN architecture, DenseNet. Resulting in 98.34% accuracy, 99.72% sensitivity, and 97.84% recall. Furthermore, a comparison conducted against alternative architectures revealed that DenseNet showed superior accuracy and performance compared to other architectures [18]. Therefore, for the classification of organic and inorganic waste with DenseNet offers the right solution for more optimal waste management with high accuracy. DenseNet can help people in overcoming waste problems

2. Methods

2.1. Proposed Stages

This research utilizes an experimental type of research. Utilizing the Convolutional Neural Network (CNN) algorithm in conjunction with the DenseNet architecture for the purpose of classifying Organic Waste and Inorganic Waste. Figure 1 illustrated the stages of this research method. In the first stage, a collection of types of organic and inorganic waste image datasets that will be classified. Second stage, image preprocessing is carried out as a preparatory step before entering the model training stage. The third stage, creating a CNN model using the DenseNet architecture. The fourth stage, model training using training data. The fifth stage evaluates the performance of the model by testing the model through testing data. Evaluating performance requires the utilization of metrics such as accuracy, precision, recall, and F1-score.

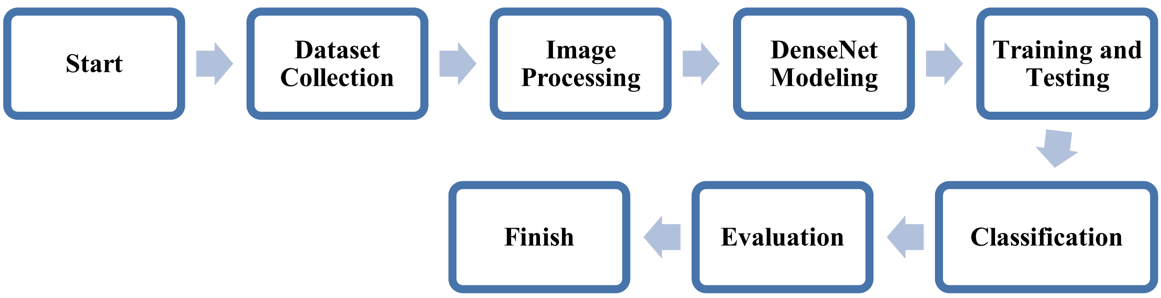

Figure 1. Research Flow

2.2. Dataset

The dataset used in this research is sourced from kaggle.com. This dataset is used to train the CNN model in litter classification. The CNN model will classify waste images based on their nature, the nature of organic waste and inorganic waste. In this study there are 10 classes including battery, biological, brown-glass, cardboard, green-glass, metal, paper, plastic, trash and white glass. The dataset has been divided into test data, train data and validation data. Train data and validation data are used during the training period. While the test data is used to test the model.

Figure 2. Sample of Dataset

2.3. Image Processing

Before image preprocessing, researchers first divided the data into training data and validation data. This research uses a dataset division scenario with a ratio of 80:20. Furthermore, the leaf image data augmentation process is carried out for the training process. Some techniques performed in the augmentation process are as follows.

Table 1. Techniques in the Data Augmentation Process

Parameter	Value	Description
Rescale	1./255	Serves to change the size of RGB image pixel data (0-255) into a number range (0-1) to facilitate the data training process.
Rotation	10°	Function to change the rotation of the image to the left and right by 10 °
Width Shift	20%	Serves to adjust the position of the image on the image width by 20%
Heigth Shift Range	20%	Serves to adjust the image position on the image height by 20%
Shear Range	10%	Function to stretch the image to the right and left by 10%
Zoom	10%	Function to increase the image size by 10%

2.4. CNN Modeling

After the preprocessing stage, the next stage is model building with the CNN algorithm and DenseNet architecture. The following is a flowchart of the training process. The first stage in training the model is to enter the leaf image data into the input layer, in this layer the image is converted into a three-dimensional matrix, with the size of length x width x 3 channels RGB (Red, Green, Blue). Next is convolution. The convolution process serves to extract the features (feature map) in the image using a filter. This research uses a filter size of 3x3 pixels, with stride 1 and no padding. To get the object in the image, it is necessary to separate the object with the background on the object. In this research, the ReLU activation function is used to determine whether or not the neurons in the neural networks are active so that only neurons related to the object are selected. The next stage is the pooling layer. Pooling layer serves to reduce the spatial size of the image and reduce the number of parameters and calculations in neural networks. This layer receives input from the feature map results from the convolution results in the convolution layer. This research uses max pooling 2x2 pooling size so that the resulting image is smaller. The next stage is the fully connected layer, the initial stage is to convert the 3-dimensional matrix data at the convolution stage into a one-dimensional vector (flatten). Output Layer is a layer that represents the final result of the classification process. The purpose of this layer is to predict the classification output in terms of probability value, where the largest class probability value is the class prediction output obtained. This research uses the Softmax activation function.

The study by Zhong and friends in 2020 utilized the DenseNet model for the classification of metastatic cancer images from small patches of digital pathology scans, demonstrating superior performance with higher AUC-ROC scores and accuracy compared to classical models such as VGG19 and ResNet34 through the use of data augmentation techniques [19]. Research by Wang and friends in 2021 developed an enhanced DenseNet algorithm with a residual attention mechanism for the classification of power equipment images, improving classification accuracy by up to 8.89% compared to previous methods[20]. Meanwhile, a study from the journal Scientific Reports in 2024 highlighted the application of DenseNet architecture for medical image classification, showing improvements in accuracy and efficiency through parameter reduction and the utilization of dense connectivity between network layers to address the vanishing gradient problem [21].

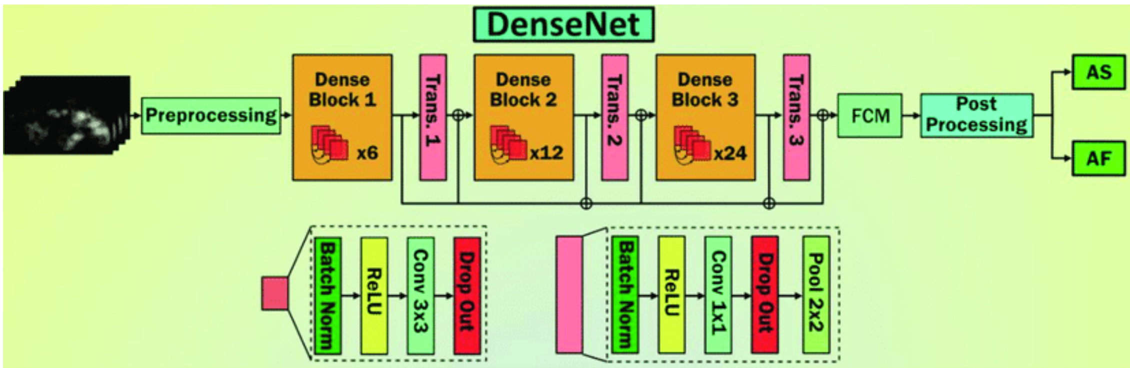

Figure 3. DenseNet Architecture

This architecture begins with a preprocessing stage, where the input image is prepared for the network. After preprocessing, the image passes through a series of dense blocks and transition layers as in Figure 3. Each dense block consists of several convolutional layers, where each layer receives input from all previous layers within the same block. This is indicated by the layers labeled Dense Block 1, Dense Block 2, and Dense Block 3, which contain 6, 12, and 24 convolutional layers, respectively. The transition layers between dense blocks are responsible for down-sampling feature maps using pooling operations. After passing through the dense blocks and transition layers, the feature maps are processed by a fully connected module (FCM), which prepares them for the final classification task. The output from this module then undergoes post-processing to enhance the final predictions. The DenseNet architecture leverages dense connections to promote feature reuse and mitigate the vanishing gradient problem, which enhances the training of deep networks.

2.5. Training

The training process was done with 20 epochs and Adam's optimizer. Researchers use early stopping which automatically saves the best model during the training period. Early stopping in this study uses patient = 5. If during the training period, the resulting loss does not increase for 5 iterations, then the training is stopped and the best model is saved. Adam's optimizer was chosen for this study due to its computational efficiency and low memory requirements. Adam, which stands for Adaptive Moment Estimation, is an optimization algorithm that combines the advantages of two other extensions of stochastic gradient descent, namely AdaGrad and RMSProp. It computes adaptive learning rates for each parameter by estimating the first and second moments of the gradients. The algorithm updates the weights iteratively based on these adaptive learning rates, which helps in dealing with sparse gradients on noisy problems. Adam is well-suited for problems with large datasets or parameters and has been widely used due to its robustness and effective performance in various machine learning applications [22].

2.6. Evaluation

After going through the entire training process, the next step is the model evaluation stage. Researchers use confusion matrix to conduct testing. Confusion matrix is a two-dimensional representation of the actual and predicted values of each class in a dataset [23]. This matrix is widely used in assessing the performance of classification algorithms because it summarizes the algorithm's correct and incorrect predictions [24]. True positive (TP) when the number of predictions (P) and actuals (A) in class 0 match, while true negative (TN) has a match between predictions and actuals in class 1. False positive (FP) when the number of images predicted as class 0 but included in class 1, while false negative (FN) when the number of images predicted as class 1 but included in class 0 [25].

3. Results and Discussion

After going through the stages of research that have been described in the previous chapter, the research results obtained from this study are that the model is able to identify 10 classes of waste with an accuracy of 93%. The details of the classification results have been visualized in the confusion matrix as follows in Table 2.

Table 2. The classification report based on confusion matrix

Classification Report				
	Precision	**Recall**	**F1-Score**	**Support**
Battery	0.97	0.97	0.97	95
Biological	0.98	0.94	0.96	118
Brown-glass	0.93	0.98	0.96	128
Cardboard	0.92	0.96	0.94	127
Green-glass	0.95	0.95	0.95	122
Metal	0.89	0.88	0.89	119
Paper	0.96	0.90	0.93	106
Plastic	0.89	0.88	0.88	136
Trash	0.97	0.93	0.95	84
White-glass	0.81	0.90	0.85	78
Accuracy			0.93	1113
Macro Avg	0.93	0.93	0.93	1113
Weighted Avg	0.93	0.93	0.93	1113

Figure 4 shown the performance of the developed classification model in identifying different types of waste. High diagonal values, such as for 'battery' (92), 'biological' (111), and 'brown-glass' (126), indicate a high degree of precision in the correct classification of these samples. However, some minor misclassifications, such as 'cardboard' being classified as 'battery' (2 times), indicate a shortcoming in the model to accurately distinguish between several similar categories. The misclassifications that occur can be a focal point for model improvement, by making adjustments to the training process or feature selection. The classification report shows the precision, recall, and F1 score for each class. The high precision and recall in categories such as 'battery' and 'biological' indicate that the model is very effective in identifying and classifying waste in these categories. However, categories such as 'metal' and 'plastic' had lower precision and recall, which could be due to similar visual characteristics between materials, or an insufficient amount of training data for these categories. This suggests the need for better strategies in data collection or advanced image processing techniques. The graphs of accuracy and validation values during the training process have been visualized as follows in Figure 5.

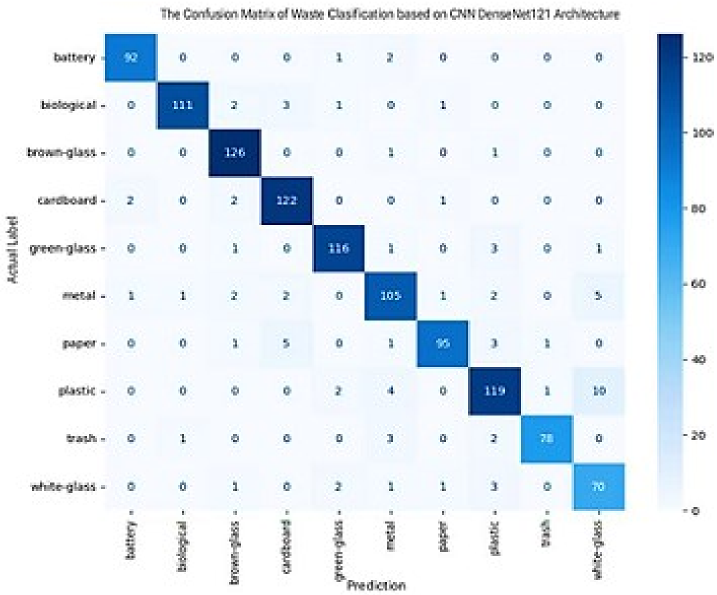

Figure 4. Confusion Matrix

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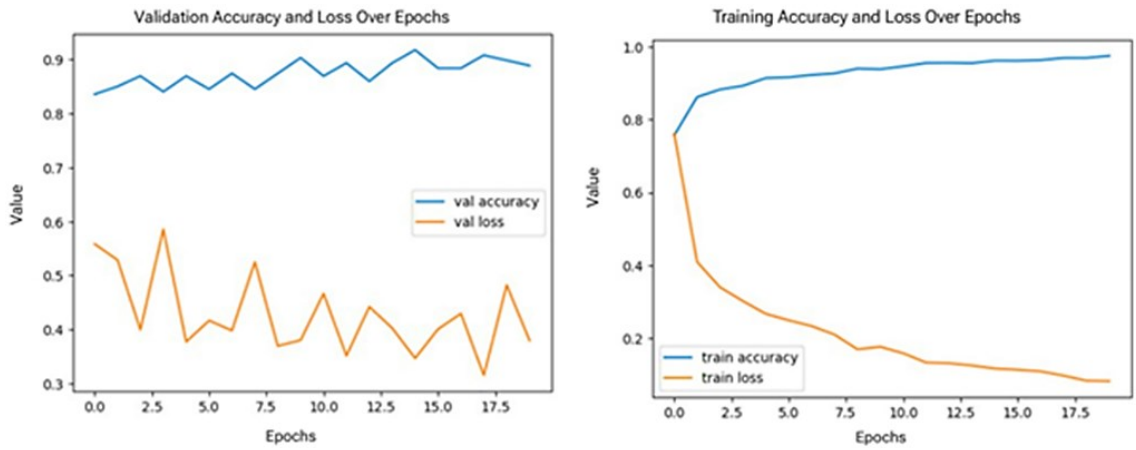

Figure 5 Result of Validation and Training : (a) Validation Accuracy, (b) Training Accuracy

Figure 5 (a) shown a trend of high validation accuracy stability (around 0.9) across epochs, while the validation loss shown greater variation. The variability in the validation loss graph indicates possible overfitting of the training data or the presence of noise in the validation data. This could require the application of further regularization techniques or a review of the data augmentation process to reduce variability and improve model stability. Figure 5 (b) shown a consistent increase in training accuracy, starting from around 0.4 in the first epoch and reaching almost 1.0 in the last epoch, while the training loss decreases sharply from around 0.6 down to around 0.2 in the same time. The significant decrease in loss and the steady increase in accuracy from 0.4 to almost 1.0 indicate that the model managed to learn from the training data effectively. This indicates that the model has a good performance in learning patterns from the given data.

4. Conclusion

This research successfully developed a litter classification model that identifies ten categories of litter with a high accuracy rate, reaching 93% overall. The model, which utilizes the DenseNet architecture, has shown excellent capability in recognizing and classifying various types of waste based on images. The performance of the model was especially good for categories such as batteries, biological materials, and brown glass, where the model achieved precision and recall above 90%. This demonstrates the potential for practical application of the model in automated waste management systems to improve waste sorting efficiency, which could greatly benefit recycling and waste reduction efforts. However, there are some challenges, such as the classification of metal and plastic categories that have lower precision and recall rates. This indicates the need for improvement in feature selection or the use of a more diverse and comprehensive training dataset. The misclassifications that occurred indicate that there is room for improvement in the accuracy of the model, especially in distinguishing between materials that have similar visual characteristics. Evaluation of the model through validation and training graphs shows that the model can learn stably without showing significant signs of overfitting, which indicates that the model is capable of good generalization. This stability is important for the practical application of the model in dynamic and diverse environments such as waste management facilities. Based on this study, it is suggested that further development could include exploring different DenseNet architectures or more advanced data augmentation techniques to overcome the limitations faced by the current model.

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