Modeling of Organic Waste Classification as Raw Materials for Briquettes using Machine Learning Approach

Norbertus Tri Suswanto Saptadi[1], Ansar Suyuti[2], Amil Ahmad Ilham[3]*, Ingrid Nurtanio[4]
Department of Electrical Engineering, Universitas Hasanuddin, Gowa, Indonesia[1, 2]
Department of Informatics, Universitas Hasanuddin, Gowa, Indonesia[3, 4]
Department of Informatics, University of Atma Jaya Makassar, Makassar, Indonesia[1]

***Abstract*—The existence of organic waste must be utilized by the community so that it does not only end up in landfills but can also be processed into something constructive so that it is useful and has high economic value. Organic waste can be converted into raw materials to manufacture of biomass briquettes. Machine learning techniques were developed for technological applications, object detection, and categorization. Methods with artificial reasoning networks that use a number of algorithms, such as the Naive Bayes Classifier, will work together in determining and identifying certain characteristics in a digital data set. The manufacturing method goes through several processes with a waste classification model as a source of learning data. The image data is based on five types: coconut shells, sawdust, corn cobs, rice husks, and plant leaves. The research aims to identify and classify types of waste both organically and non-organically so that it will make it easier to sort waste. The results of testing the organic waste application from digital images have an accuracy rate of 97%. The model design carried out in training data is useful for producing a data model.**

Keywords—Classification; organic waste; raw material; machine learning

I. INTRODUCTION

Waste that has not been treated optimally can damage the environment and make the water not clear, thus disrupting life and health around human habitation [1]. Household waste has dominated in generating waste in the city of Makassar, with an average of 900 tonnes per day sent to the Antang Final Disposal Site [2]. The Head of the Makassar City Environment Service said that high public consumption during the COVID-19 period, both before and during the implementation of the Large Scale Social Restrictions (LSSR) to Enforcement of Restrictions on Community Activities (ERCA), did not significantly decrease in the presence of waste ranging from 850-950 tons. The community must make use of the organic waste that already exists so that it doesn't just wind up in landfills but is also transformed into something productive with significant economic value [3].

Utilizing waste produced by the community and businesses, urban development aims to create urban areas with greater productivity, capacity, efficiency, creativity, competitiveness, innovation, and use of information technology [4]. The application of technology, object detection, and classification was developed using machine learning methods. Methods with artificial reasoning networks that use a number of algorithms will work together in determining and identifying certain characteristics in a digital data set [5]. Machine and deep learning are programmed with capabilities to learn, digest, and classify data [6] and have good skills in computer vision by classifying objects in digital images [7][8].

A method with a specialized approach that uses particular electronic systems or devices to detect an object is needed because a concentration of waste in one location makes it difficult to understand the potential for new renewable energy in detail [9]. The increase in population, ways of consumption, and lifestyle of urban residents increase waste production and problems in big cities. Problems identified include the amount of waste generation, types of waste, and various waste characteristics [10]. To make waste classification easier, the research intends to detect and categorize different waste types, both organic and non-organic.

II. RELATED WORK

One source of energy that could be produced is organic waste, which the government needs to handle properly [11] [12]. On the other hand, the demand for energy from communities and development organizations is rising [13], particularly for new and renewable sources of energy, which are becoming more and more limited in Indonesia [14]. With information on the different types of waste, landfill locations, transportation routes, and cleaning personnel, the geographic information system has been able to offer waste management services in every sub-district of the city of Makassar [15].

Governments and communities face a problem because they have not fairly and effectively utilised the potential of organic waste, especially in Makassar, Indonesia. To meet the energy needs of residents in a city or region, it can be converted into raw materials for briquettes [16][17]. This project's objective is to establish a prediction system data model for converting organic waste into a fuel that meets societal and industrial goals. An important scientific contribution is the use of detection methods on organic waste objects. Fourteen districts: Ujung Pandang, Bontoala, Makassar, Tamalanrea, Panakukkang, Wajo, Tallo, Mamajang, Manggala, Mariso, Rappocini, Biringkanaya, Ujung Tanah, and Tamalate, already exist inside the city of Makassar. This

*Corresponding Author.

case study is used to develop a system model based on the city's geographic characteristics [18].

III. Material and Method

A. Approach and Type of Research

The research approach uses quantitative methods. This type of research is based on experimental studies (results of literature studies), interviews, and direct observations of city environmental service officers, city government, and communities in the city of Makassar, South Sulawesi province, Indonesia [19].

Object detection is carried out on various sources of organic waste. After obtaining information about the source of the waste, it is then analyzed through digital image detection to determine the classification of the type of waste [20]. Classification is useful for determining raw materials in sorting and grouping for the purposes of effectively and efficiently making biomass briquettes [21][22].

B. Data Sources and Data Collection Techniques

To meet energy needs, it is essential to design a system that can provide data on the market and fuel availability. The amount of energy potential found in organic waste source materials is the anticipated piece of information. The design information in Fig. 1 provides an overview of the anticipated procedures for obtaining data on population numbers and needs [18][19].

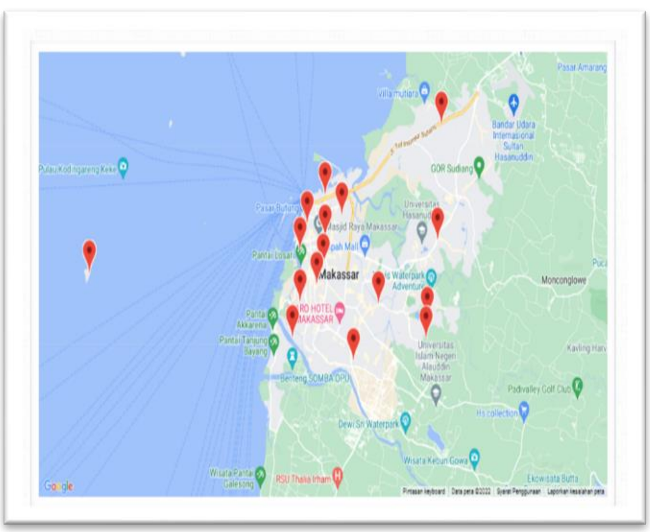
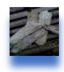


Fig. 1. Model for a waste location mapping system.

Organic waste is used to determine primary data. The Makassar City Environmental Service provided information on the need for secondary data by observing and speaking with staff members and locals on the origin of the organic waste collected.

The primary study data are the raw materials and specifications of organic waste utilized to make biomass briquettes, as compared to 5 (five) different types of organic waste sources. Organic waste can consist of coconut shells [23], sawdust [24], corncob [25], rice husks [26], and plant leaves [27]. The collected garbage data is made from a collection of digital image data in Table I. The predetermined image parameters are color, size (average), texture shape, reference mass, and manual mass (in the photo).

TABLE I. Dataset Organic Waste

No	Type	Image	Color	Size (average)	Shape and Texture	Mass Reference (Average)	Manual Mass (100%)
1	coconut shells		chocolate green	width: 3mm diameter: 95mm	circle variation	140g /unit	75g / half
2	sawdust		white yellow chocolate	/variation	/variation	/variation	40gr (8 oz)
3	corncob		yellow chocolate white gray	width: 21cm diameter: 47mm	tube beam	260g/unit (with corn)	260g/unit (with corn)
4	rice husks		yellow chocolate black	long: 9mm diameter 2.4mm	oval	/variation	50gr (8 oz)
5	plant leaves		green yellow chocolate	/ variation	leaf	/variation	40gr (16 oz) (vegetable leaves)

C. Research Mechanism

The object and model detection mechanism is based on the Machine Learning method approach by conducting a classification consisting of fully connected output with a Convolutional Neural Network (CNN) architecture [28][29].

D. Naive Bayes Classifier

One of the supervised learning algorithms in Fig. 2 that is used in machine learning for binary and multiclass classification processes is the Naive Bayes Classifier Algorithm in Fig. 3 [30][31].

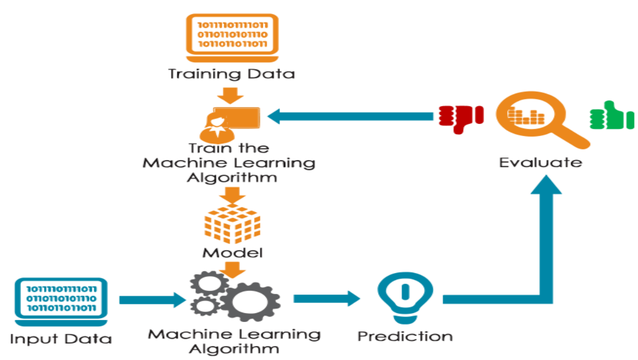


Fig. 2. How machine learning works.

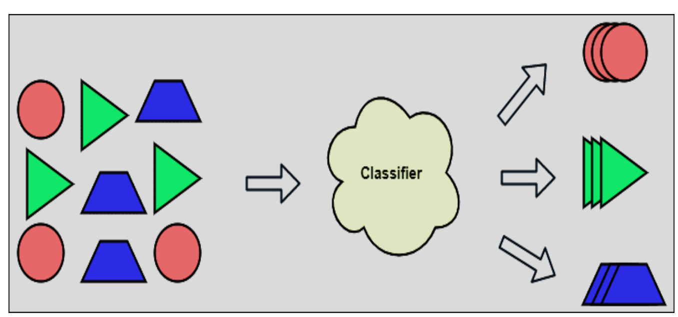


Fig. 3. Naive Bayes classifier method.

E. Formulation

Based on the Bayes principle, the Naive Bayes Classifier is a classification technique as shown in Fig. 4. It is generally agreed that the Naive Bayes Classifier outperforms a variety of other classification techniques. First, a very strong (naive) assumption of independence from each condition or event is the key feature of Naive Bayes. Second, it provides a straightforward, straightforward paradigm. Finally, large data sets can be used with the model [31].

$$P_{ro}(C_l|X_a) = \frac{P_{ro}(C_l)P_{ro}(X_a|C_l)}{P_{ro}(X_a)} \tag{1}$$

Where:

X_a : attributes

C_s : class

$P_{ro}(C_s|X_a)$: probability of even C_s given X_a has occurred

$P_{ro}(X_a|C_s)$: probability of even X_a given C_s has occurred

$P_{ro}(C_s)$: probability of event C_s

$P_{ro}(X_a)$: probability of event X_a

X_a can be written as follow:

$$X_a = X_1, X_2, X_3, \dots, X_n \tag{2}$$

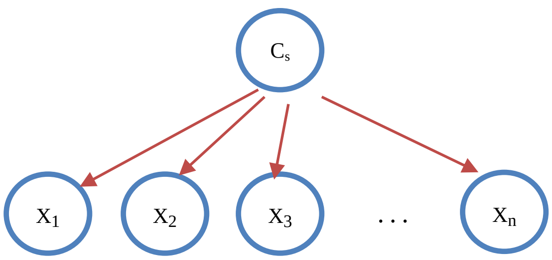


Fig. 4. Naïve Bayes.

F. Data Collection Techniques

The five types of organic waste were taken on a bright and plain background so that the various waste objects could still be seen [32]. Image data creation is carried out in detail by taking pictures of each type of waste [33]. Taking pictures of several combinations of one object with another object [34]. Images are photographed manually using smartphones and digital cameras specifically to get the best image and resolution.

G. Hardware Requirement

Specifications for some of the equipment used in the study include laptop Intel® CoreTM i5-5200U CPU @ 2.20GHz, Windows 10, Memory 8 GB, and AMD RadeonTM Graphics R5 M330. With the OPPO A5S smartphone, which features dual cameras with a configuration of 13 MP (wide), f/2.2, and 2 MP (depth), as well as an AF feature, LED flash, panoramic, HDR, and video 1080p@30fps, you may take images of five different forms of organic waste [35][36].

H. Preprocessing Data

Preprocessing data is a step that includes data collecting, data labeling, and data augmentation operations.

1) Data collection: Three thousand seventy-four photos totaled the information that was gathered and created. Organic waste can consist of coconut shells (cs) [23], sawdust (sd) [24], corncob (cc) [25], rice husk (rh) [26] and plant leaves (pl) [15]. The amount of information contained on the types of organic waste is shown in Table II.

TABLE II. DATASET ORGANIC WASTE

No	Waste Type	Digital Image
1	Coconut shells	686
2	Sawdust	717
3	Corncob	449
4	Rice husk	513
5	Plant leaves	709
Total		3.074

After data collection then proceed with the data preprocessing process. This process is carried out by dividing the pixel image into sizes with low, medium, and high criteria. Digital images will be used as training data to make them more effective in identifying types of organic waste [37].

Images of the five types of organic waste were taken against a bright and plain background to ensure these various types of waste objects could still be seen. Image data is collected by taking pictures of each kind of waste with a certain combination model as shown in Fig. 5 [38].

(a) (b)

Fig. 5. Preprocessing data and type of waste (a) One type of waste (b) More than one type of waste.

2) Labeling: The data labeling process aims in Fig. 6 to give the discarded image data that was taken a name or label so that it can be quickly identified. A train folder and a test folder are the components of creating a folder. At the same time, the test folder is used for running tests and validating data in the training process, and the train folder stores data that is processed throughout the learning process. It is separated into five different categories of organic waste for data labeling.

3) Augmented data: The technical stage in data augmentation is useful for augmenting existing training data using the TensorFlow library. This process is carried out by naming the image data taken to be neat, structured, and orderly.

The data augmentation process seeks to modify image data using the Adobe Photoshop application. Modifications are made based on the type of organic waste by combining many image data into one image data. Efforts were made by combining ten organic waste image data into one digital image data. For optimization purposes, resize the organic waste image data from the original size of 5184 x 3456 pixels to 224 x 224 pixels.

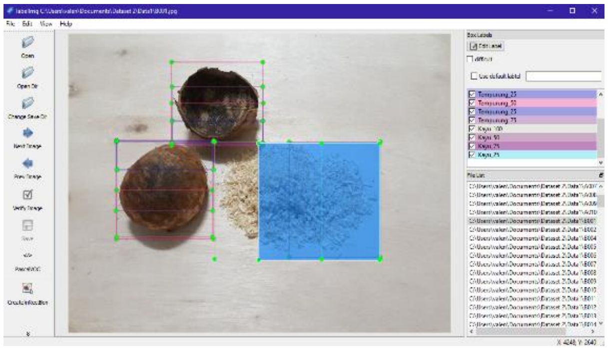


Fig. 6. Object size and mass predictive labeling.

I. *Data Classification*

There are 2473 training data and 293 digital photo test data as shown in Table III for five types of organic waste.

The combination of waste images in Table IV collected in combination A for five types in one image, combination B for three types in one image, and combination C for two types of waste are all in a folder. The other folders provide classification information for each of the five different forms of waste. The categorization that follows is based on the folder that was made.

TABLE III. ORGANIC WASTE

No	Waste Type	Train	Test
1	coconut shells (cs)	548	76
2	sawdust (sd)	589	55
3	corncob (cc)	364	45
4	rice husk (rh)	414	47
5	plant leaves (pl)	558	70
Total		2.473	293

TABLE IV. DATA COMBINATION

No	Combination of Organic Waste	Number of Combinations
1	cs, sd, cc, rh, pl (A)	5 pcs
2	cs, sd, rh (B)	3 pcs
3	cs, sd (C)	2 pcs
4	cs, rh (C)	2 pcs
5	cs, pl (C)	2 pcs
6	sd, pl (C)	2 pcs
7	rh, pl (C)	2 pcs
8	rh, cc (C)	2 pcs
9	rh, sd (C)	2 pcs
10	cs (D)	1 pcs
11	sd (D)	1 pcs
12	cc (D)	1 pcs
13	rh (D)	1 pcs
14	pl (D)	1 pcs
Total		23 pcs

Undoubtedly, a wide range of related factors will affect where and how organic waste is obtained. Table V lists the influential elements that must be calculated and considered.

TABLE V. INFLUENCE FACTORS

No	Factors	Influence
1	Photo Capture Distance	size
2	Object Location (x, y on photo)	accuracy
3	Weather/Temperature	texture
4	Lighting	coloring
5	Place/Environment	area/background

J. *Data Modeling*

The model is created using a number of procedures with the waste type classification model serving as a source of learning data. Five categories are utilized to organize the image data. A data model can be created by doing model design using training data. An illustration of the proposed data modeling flowchart is shown in Fig. 7.

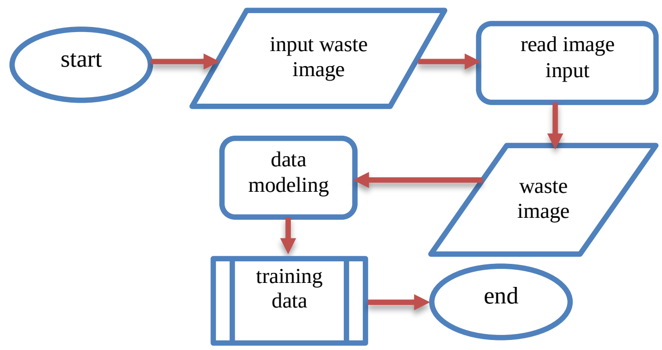


Fig. 7. Modeling flowchart.

K. *Evaluation Method*

A confusion Matrix is an evaluation method that can be used to calculate the classification process's performance or level of correctness. Create a table containing four unique combinations of the expected and actual values. In the Confusion Matrix, the classification process outcomes are denoted by four terms: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The equation that follows is created.

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \times 100\% \quad (3)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

$$\text{F1} = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (6)$$

IV. RESULTS AND DISCUSSION

To produce a good model requires the support of methods, algorithms and organic waste datasets that are relevant and sufficient in number.

A. Modeling CNN

They use two CNN models from scratch and CNN with ResNet transfer learning. The design of the CNN model is carried out with training to produce a model (classifier rules) that classifies waste sources as raw materials for making biomass briquettes. The proposed CNN model is in the form of parameters connected to a vector (flatten) to enter the fully connected layer. After that, enter the dense layer, which reduces the size to 1024 outputs and then reduces them to 256 outputs.

The subsequent stage moves into the last layer of classification, which employs the softmax function to generate the number of classes corresponding to the category in the data. It then moves on to the stage of the image prediction process. The waste detection procedure is as follows.

```
data = np.ndarray(shape=1, 224, 224, 3), dtype=np.float32)
def entry(input_name_img, input_id):
image = Image.open(r"c:\potential\image/"+input_name_img)
size = (224, 224)
…
labels = ['coconut shell', 'sawdust', 'corn cobs', 'rice husk', 'plant leaves']
prediction = model.predict(data)
# print prediction
detection = str(labels[np.argmax(prediction)])
sql = "UPDATE image SET desc = %s WHERE id_image = %s"
val = (detektion, input_id)
cursor.execute(sql, val)
conn.commit()
input_nama_img = str(query_dict['img'])[2:-2]
input_id = str(query_dict['id_c'])[2:-2]
print(content-type: text/html\n\n")
entry(input name img, input id)
```

B. UML Interface Design

There are use cases that are useful for knowing the activity of the relationship between the user and the system in Fig. 8.

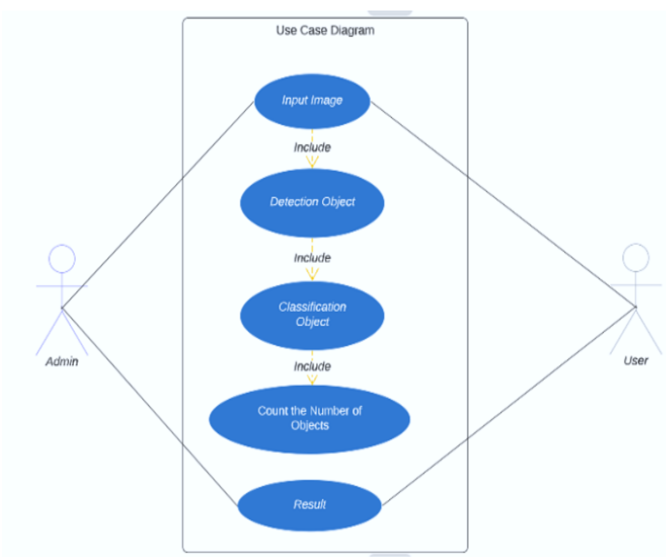


Fig. 8. Use case diagram.

Class diagram Fig. 9 illustrates the structure of class formation in the design of organic waste detection applications.

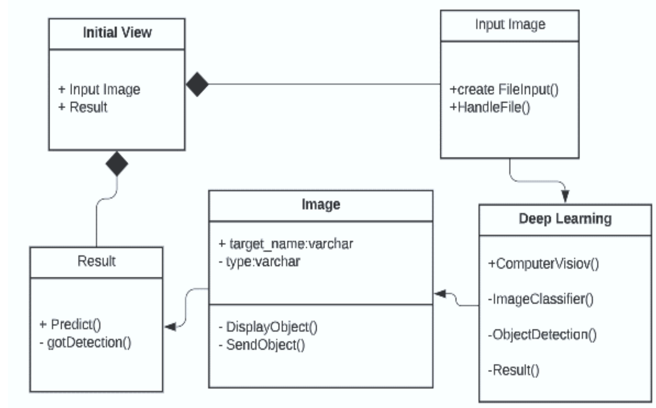


Fig. 9. Data training class diagrams.

Fig. 10 training data according to predefined batch values for all trained data. The results of the weight values are in the form of a JSON file that is used to help classify organic waste.

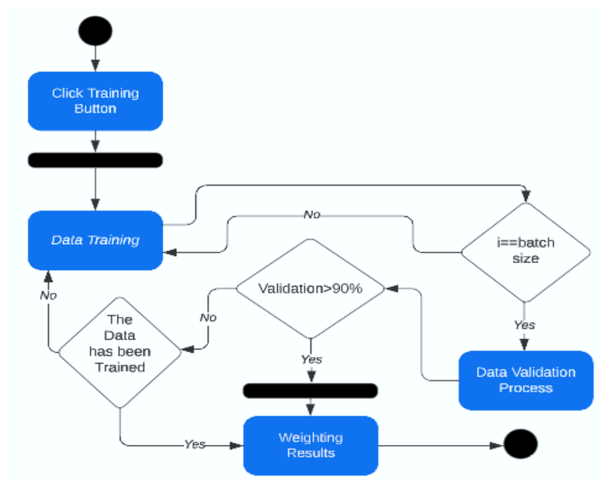


Fig. 10. Data training activity diagrams.

C. Application Interface Design

Input objects are needed by taking pictures in the system to carry out the process of predicting waste images. The data will be executed according to the program that can be detected. Fig. 11 displays the image that will be displayed after pressing the submit button in Fig. 12.

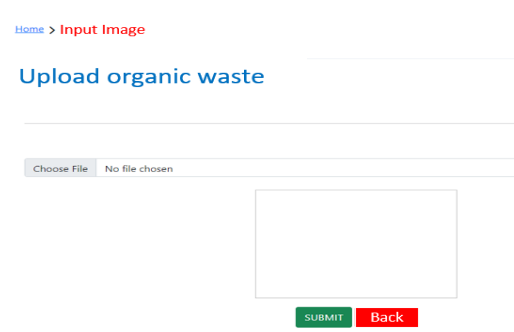


Fig. 11. Image input display on the application.

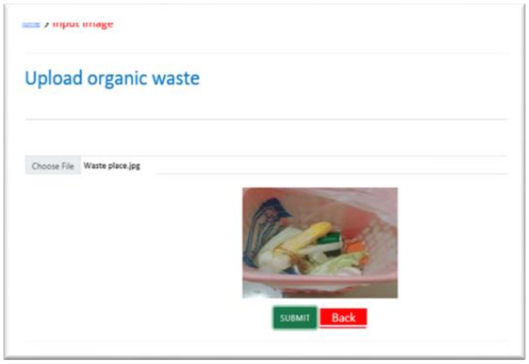


Fig. 12. Image upload view.

D. Training

The stage begins with collecting data used as training data. The image dataset for training purposes consists of 800 coconut shell waste, 750 sawdust, 750 corn cobs, 700 rice husks, and 700 plant leaves. The modeling phase divides the initial dataset into training and test data. The following are the stages of data modeling carried out in the study.

Modeling Script 1: Test data and validation make up each of the two sections of the test data with

```
test_size=0.20, random_state=300)
test_size=0.5, random_state=100)
```

Modeling Script 2: Merging data into each data frame.

```
train size 3359
val size 420
test size 420
```

Modeling Script 3: Organizing test, train, and validation data using the shut-in module.

```
datasource_path = "waste/"
dataset_path = "dataset2/"
```

Modeling Script 4: The process determines how many epochs to use.

```
#Define Input Parameters
Dim = (224, 224)
# dim = (456, 456)
```

Modeling Script 5: The data transformation process used in the image is transformed into image augmentation.

```
rescale=1. / 255, shear_range=0,2, zoom_range=0,2, horizontal_flip=True)
val_datagen
test_datagen
```

Modeling Script 6: Defines the origin directory by source files for the training phase.

```
train_generator = from_directory('dataset1/train/' …,)
val_generator = from_directory('dataset1/validation/' …,)
test_generator = test_datagen.flow_from_directory('dataset1/test/',
num_class = tes_generator.num_classes
labels = train_generator.class_indices.key()
```

Modeling Script 7: Create tf.data to provide high compatibility for TensorFlow.

```
train_data = tf_data_generator(train_generator, input_shape)
test_data = tf_data_generator(test_generator, input_shape)
val_data = tf_data_generator(val_generator, input_shape)
```

Model Script 8: Sequential process for activation.

```
model_Sequential()
model.add(Conv2D(128, (3, 3), padding='same;, input_shape=input_shape))
model.add(Activation('relu'))
model.add(conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
…
model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(num_class))
model.add(Activation('softmax'))
# Compile the model
print('Compiling Model…….')
model.compile(Optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
```

Modeling Script 9: Adding a top layer defined set false to the base model.

```
predictions = layer.Dense(num_class, activation="softmax")(x)
model = Model(inputs=base_model.input, outputs=predictions)
```

Modeling Script 10. Preparing the model to be ready for the training process.

```
# Compile the model
…
metrics=['Accuracy'])
from efficientnet.tfkeras import EfficientNetB1
# get base models
…
```

Modeling Script 11. Creating a machine learning process model in considering class patterns.

```
EPOCH = 2
…
Epoch 1/2
210/210 [=======] – 528s 2s/step – loss: 0.2357 – accuracy: 0,9357 –
val_loss: 0.0439 – val_accuracy: 0.9929
Epoch 2/2
210/210 [=======] – 466s 2s/step – loss: 0.1083 – accuracy: 0,9687 –
val_loss: 0.0244 – val_accuracy: 0.9952
```

Modeling Script 12. The training results get a loss of 0.2 and 0.1 and an accuracy of 0.9.

```
history.history['loss']
[0.2356509417295456, 0,10834924131631851]
history.history['accuracy']
[0.9356759786605835, 0,9687314033508301]
```

model.save (save_model_path, include_optimizer=False) is useful so that TensorFlow does not save the state of the optimizer at the last time it was saved but to save storage media and simplify the deployment process in Fig. 13.

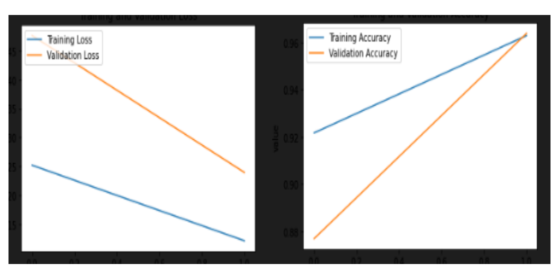


Fig. 13. Training data.

After training is done, then be plotted with extra training. Then the model results will be obtained, which can be saved to detect objects.

```
MODEL_BASE_PATH = “image_model”
PROJECT_NAME = “waste organic”
SAVE_MODEL_NAME = “image_model.h5”
```

E. Testing

After determining the training data, test data is needed which consists of 120 coconut shells, 113 sawdust, 113 corncobs, 105 rice husks, and 105 plant leaves. Before loading the model, it is necessary to define parameters and label the five types of waste. After that, a function is created for pre-processing.

```
model = load_model(‘\medium_project/keras_model.h5’)
data = np.ndarray(shape=1, 224, 224, 3), dtype=np.float32)
…
prediction = model.predict(data)
print(prediction)
```

The script is an image prediction process. Prediction results are displayed in an array based on index 0,1,2,3,4,5. The process of detecting according to five characteristics of waste such as coconut shell, sawdust, corncobs, rice husks, and plant leaves.

```
1/1 [========================] – 0s 415ms/step
[[1.7525636e-02  3.1258736e-03  4.1368250e-03  5.6559354e-04  9.7464603e-01]]
```

Based on the picture in the script for detecting organic waste, which is the result of waste detection, the results of the prediction of waste produce a value of 9.7 or 97% accuracy in detecting the type of waste. Fig. 14 below is the result of testing the image input on object detection.

WASTE DETECTION NAME LIST

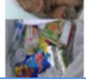
No	Image	Classification	Main Type	Accuracy (0-1)
1		[[0.02571341 0.06457566 0.00188309 0.00711981 0.900708]]	plant leaves	0.90
2		[[7.3195208E-04 5.5418879E-04 6.3202858E-01 3.6427444E-01 2.4108288E-03]]	sawdust	0.63
3		[[0.00912285 0.7043725 0.03887154 0.14210084 0.1055323]]	corncob	0.70
4		[[4.636312RE-03 9.0524495E-01.40854310E-04 3.7500028E-02 5.2210264E-02]]	corncob	0.91
5		[[0.5662812 0.00287437 0.00086904 0.0612988 0.12638068 0.2422959]]	coconut shell	0.77
6		[[3.1776012E-06 1.2340318E-04 3.2447235E-06 6.7795190E-05 1.3054071E-02 9.8674834E-01]]	other objects	0.98

Fig. 14. Waste detection name list.

F. Evaluation

Class 1 coconut shell, Class 2 sawdust, Class 3 corncobs, Class 4 rice husks, and Class 5 plant leaves are among the 735 picture data used for each class. The column shows the actual type class, and the row shows the type being tested. The first column of the first row displays the results that are in Class 1 coconut shell. The coconut shell image tested reads as TP (True Positive) of 661, so the number of images is read exactly according to the type of organic waste class.Likewise for other classes as shown in Fig. 15.

	Class 1	Class 2	Class 3	Class 4	Class 5	Classification overall
Class 1	661	26	18	14	16	735
Class 2	26	661	18	14	16	735
Class 3	18	20	657	22	18	735
Class 4	18	24	25	658	10	735
Class 5	14	16	20	24	661	735

Fig. 15. Confusion matrix.

Testing accuracy, precision, and recall by the confusion matrix using test data that is not sourced from datasets show an accuracy value of up to 73%. This research has produced an application that is able to detect objects properly. Through object detection, it will be known that the image is a potential organic waste which is a raw material for processing biomass briquettes. Even though the results in detecting objects still have a value with a percentage that has not reached a value of 70%, this is a relatively good approach to be used as an alternative model in selecting objects that will be the raw material for making briquettes.

Detection of objects in the form of powder is still relatively difficult to distinguish from similar objects considering that objects consist of small and separate parts. Comparison with large and unified objects will certainly produce a better accuracy value. To overcome this, further research is needed on object detection with the segmentation method.

V. Conclusion

Research on organic waste has produced object detection, namely: the results of identifying the type of organic waste by detecting digital image objects can predict the type of waste contained in the inserted image. The results of testing the organic waste application from digital images have an accuracy rate of 97%.

Acknowledgment

We would want to express our gratitude to the Makassar City Environmental Department as well as to the general public and business owners.

References

[1] A. C. Malina, Suhasman, A. Muchtar, and Sulfahri, “Environmental Assessment of Waste Sorting Sites in Makassar City,” Journal of Innovation and Public Service, vol. 1, no. 1, pp. 14–27, 2017.

[2] S. Asiri and M. Manaf, “The Effect of the Existence of the Tamangapa Landfill on Changes in the Use of the Surrounding Space,” Plano Madani, vol. 8, no. 2, pp. 138–146, 2019.

[3] I. M. Harjanti and P. Anggraini, “Waste Management at the Jatibarang Final Disposal Site, Semarang City,” Jurnal Planologi, vol. 17, no. 2, p. 185, 2020, doi: 10.30659/jpsa.v17i2.9943.

[4] M. Huda and E. B. Santoso, “Development of Regency/City Regional Competitiveness in East Java Province based on Regional Potential,” Journal of Engineering POMITS, vol. 3, no. 2, pp. 81–86, 2014.

[5] S. Cheon, H. Lee, C. O. Kim, and S. H. Lee, “Convolutional Neural Network for Wafer Surface Defect Classification and the Detection of Unknown Defect Class,” IEEE Transactions on Semiconductor Manufacturing, vol. 32, no. 2, pp. 163–170, 2019, doi: 10.1109/TSM.2019.2902657.

[6] F. Elmaz, B. Büyükçakır, Ö. Yücel, and A. Y. Mutlu, "Classification of solid fuels with machine learning," Fuel, vol. 266, no. July 2019, 2020, doi: 10.1016/j.fuel.2020.117066.

[7] V. Wiley and T. Lucas, "Computer Vision and Image Processing: A Paper Review," International Journal of Artificial Intelligence Research, vol. 2, no. 1, p. 22, 2018, doi: 10.29099/ijair.v2i1.42.

[8] H. Kim, J. Kim, and H. Jung, "Convolutional neural network based image processing system," Journal of Information and Communication Convergence Engineering, vol. 16, no. 3, pp. 160–165, 2018, doi: 10.6109/jicce.2018.16.3.160.

[9] Y. Han, T. Jiang, Y. Ma, and C. Xu, "Pretraining Convolutional Neural Networks for Image-Based Vehicle Classification," Advances in Multimedia, vol. 2018, 2018, doi: 10.1155/2018/3138278.

[10] A. Kahfi, "Overview of Waste Management," Jurisprudentie: Department of Law, Faculty of Sharia and Law, vol. 4, no. 1, p. 12, 2017, doi: 10.24252/jurisprudentie.v4i1.3661.

[11] S. Soeprijanto, A. R. Fatullah, S. Agustina, D. F. Amalia, and A. A. Kaisar, "Biogas Production from Vegetables and Fruit Wastes Using Anaerobic Floating Bioreactor," Eksergi, vol. 17, no. 2, p. 99, 2020, doi: 10.31315/e.v17i2.3733.

[12] S. Ma'arif and W. Wardoyo, "Potential of Electric Energy from Waste in Kaliurang Tourism Area, Sleman, Special Region of Yogyakarta," Conserve: Journal of Energy and Environmental Studies, vol. 4, no. 1, pp. 1–8, 2020, [Online]. Available: https://ejournal.up45.ac.id/index.php/cjees/article/view/718.

[13] S. I. Faizah and U. A. Husaeni, "Development of consumption and supplying energy in Indonesia's economy," International Journal of Energy Economics and Policy, vol. 8, no. 6, pp. 313–321, 2018, doi: 10.32479/ijeep.6926.

[14] S. Subagyo, J. P. Moh. Yanuar, P. N. Bambang, and A. Saleh, "Substitution of energy needs with renewable energy sources," IOP Conf Ser Earth Environ Sci, vol. 927, no. 1, p. 012032, 2021, doi: 10.1088/1755-1315/927/1/012032.

[15] N. Saptadi, P. Chyan, and A. C. Pratama, "Geographic Information System for Waste Management for the Development of Smart City Governance Geographic Information System for Waste Management for the Development of Smart City Governance," 2020, doi: 10.1088/1757-899X/854/1/012040.

[16] T. Chen, H. Jia, S. Zhang, X. Sun, Y. Song, and H. Yuan, "Optimization of cold pressing process parameters of chopped corn straws for fuel," Energies (Basel), 2020, [Online]. Available: https://www.mdpi.com/1996-1073/13/3/652.

[17] P. Thomas, N. Soren, N. P. Rumjit, and J. G. James, "Biomass resources and potential of anaerobic digestion in Indian scenario," Renewable and Sustainable Energy Reviews, 2017, doi: 10.1016/j.rser.2017.04.053.

[18] N. T. S. Saptadi, P. Chyan, and A. C. Pratama, "Analysis and Design of Waste Management System Using the Spiral Model Towards Smart Cities," Sisforma, vol. 6, no. 2, p. 41, 2020, doi: 10.24167/sisforma.v6i2.2313.

[19] N. Saptadi, P. Chyan, and A. C. Pratama, "Geographic Information System for Waste Management for the Development of Smart City Governance," IOP Conf Ser Mater Sci Eng, vol. 854, no. 1, 2020, doi: 10.1088/1757-899X/854/1/012040.

[20] A. Chailes, A. Hermawan, and D. Kurnaedi, "Application of the Data Mining Method to Determine Purchasing Patterns Using the Apriori and Fp-Growth Algorithms at Mukara Stores," Journal of Algor, vol. 1, no. 2, pp. 1–8, 2020.

[21] P. M. Dass, I. I. Nkafamiya, B. A. Thliza, and J. I. Joseph, "Analysis of Biomass and Cotton Stalk Charcoal Briquettes Produced from Biu, Nganzai, and Zabarmari in Borno State using a Locally Fabricated Briquetting Machine," International Quarterly Scientific Journal, 2019.

[22] J. Zhang, D. Zheng, K. Wu, and X. Zhang, "The optimum conditions for preparing briquette made from millet bran using Generalized Distance Function," Renewable Energy, 2019.

[23] R. P. Dewi and M. Kholik, "The effect of adhesive concentration variation on the characteristics of briquettes," Journal of Physics: Conference Series, vol. 1517, no. 1, 2020, doi: 10.1088/1742-6596/1517/1/012007.

[24] M. Thabuot, T. Pagketanang, K. Panyacharoen, P. Mongkut, and P. Wongwicha, "Effect of Applied Pressure and Binder Proportion on the Fuel Properties of Holey Bio-Briquettes," Energy Procedia, vol. 79, pp. 890–895, 2015, doi: 10.1016/j.egypro.2015.11.583.

[25] L. Sulistyaningkarti and B. Utami, "Making Charcoal Briquettes from Corncobs Organic Waste Using Variation of Type and Percentage of Adhesives," Journal of Chemistry and Chemistry Education, vol. 2, no. 1, p. 43, 2017, doi: 10.20961/jkpk.v2i1.8518.

[26] P. M. Dass, I. I. Nkafamiya, B. A. Thliza, and J. I. Joseph, "Analysis of Biomass and Cotton Stalk Charcoal Briquettes Produced from Biu, Nganzai, and Zabarmari in Borno State using a Locally Fabricated Briquetting Machine," International Journal of Progressive Sciences and Technologies (IJPSAT), vol. Vol.16, no. 2, p. PP. 83-91, 2019.

[27] S. Zhang, S. Zhang, C. Zhang, X. Wang, and Y. Shi, "Cucumber leaf disease identification with global pooling dilated convolutional neural network," Comput Electron Agric, vol. 162, no. February, pp. 422–430, 2019, doi: 10.1016/j.compag.2019.03.012.

[28] E. N. Arrofiqoh and H. Harintaka, "Implementation of Convolutional Neural Network Method for Plant Classification in High Resolution Image," Geomatika, vol. 24, no. 2, p. 61, 2018, doi: 10.24895/jig.2018.24-2.810.

[29] V. Venkatesh, N. Yallappa, S. U. Hegde, and S. R. Stalin, "Fine-Tuned MobileNet Classifier for Classification of Strawberry and Cherry Fruit Types," Journal of Computer Science, vol. 17, no. 1, pp. 44–54, 2021, doi: 10.3844/jcssp.2021.44.54.

[30] R. Adrian, M. A. J. S. Perdana, A. Asroni, and S. Riyadi, "Applying the Naive Bayes Algorithm to Predict the Student Final Grade," Emerging Information Science and Technology, vol. 1, no. 2, pp. 49–57, 2020, doi: 10.18196/eist.127.

[31] N. Salmi and Z. Rustam, "Naïve Bayes Classifier Models for Predicting the Colon Cancer," IOP Conference Series: Materials Science and Engineering, vol. 546, no. 5, 2019, doi: 10.1088/1757-899X/546/5/052068.

[32] N. Tri, S. Saptadi, A. Suyuti, A. Ahmad, and I. Nurtanio, "Prediction System Data Model In Obtaining Energy Potential of Biomass Briquette Compared to Other," Journal of Southwest Jiaotong University, vol. 57, no. 5, 2022, doi: https://doi.org/10.35741/issn.0258-2724.57.5.38.

[33] P. Hwangdee, C. Jansiri, and S. Sudajan, "Physical characteristics and energy content of biomass charcoal powder," Journal of Renewable Energy and Environment, 2021.

[34] H. C. Law, L. M. Gan, and H. L. Gan, "Experimental study on the mechanical properties of biomass briquettes from different agricultural residues combination," MATEC Web of Conferences, 2018.

[35] N. T. S. Saptadi, P. Chyan, and V. M. Widjaja, "Model Design of Organic Waste Classification into Raw Materials for Biomass Briquettes Using Deep Learning Methods," JIKO (Journal Informatics dan Computer), vol. 6, no. 2, p. 160, 2022, doi: 10.26798/jiko.v6i2.559.

[36] R. Razuan, K. N. Finney, Q. Chen, and V. N. Sharifi, "Pelletised fuel production from palm kernel cake," Fuel Processing Technology, 2011.

[37] W. You, C. Shen, X. Guo, X. Jiang, J. Shi, and Z. Zhu, "A hybrid technique based on convolutional neural network and support vector regression for intelligent diagnosis of rotating machinery," Advances in Mechanical Engineering, vol. 9, no. 6, pp. 1–17, 2017, doi: 10.1177/1687814017704146.

[38] A. M. Torkashvand, A. Ahmadi, and N. L. Nikravesh, "Prediction of kiwifruit firmness using fruit mineral nutrient concentration by artificial neural network (ANN) and multiple linear regressions (MLR)," J Integr Agric, vol. 16, no. 7, pp. 1634–1644, 2017, doi: 10.1016/S2095-3119(16)61546-0.

AUTHORS' PROFILE

Norbertus Tri Suswanto Saptadi was born on June 07 1975 in Cirebon, West Java, Indonesia. He is currently a doctoral student in Electrical Engineering (Informatics), Hasanuddin University, Indonesia. He accomplished Bachelor Degree of Informatics, University of Digital Technology Indonesia in 1998. Master of Management, Hasanuddin University in 2004. Master of Information Technology, Gadjah Mada University in 2007. Engineer Professional Education, Hasanuddin University in 2020. His research interests include artificial intelligence, data science, software engineering, and IT governance. He is member of the Indonesian National Resilience Institute (Lemhannas RI).

Ansar Suyuti was born on December 31 1967 in Sidrap, South Sulawesi, Indonesia. He received a bachelor's degree in 1991, a master's degree in 2002, and a doctorate in 2013 from Universitas Hasanuddin in Makassar, Indonesia. His primary topic of study is Electrical Power Engineering. He is a professor at Universitas Hasanuddin's Department of Electrical Engineering. He is the current head of the Power System Distribution Laboratory. His research interests include distributed generation planning, sensor networks, and environmental engineering, and he has produced numerous articles in electrical power engineering. Prof. Ir. Ansar Suyuti is a member of the Technical Committee for IPU.ASEAN. Eng is also a member of the Association of Electrical Power Engineering Experts and is an assessor for the National Accreditation Bureau for Higher Education. He is the Rector of Institut Teknologi BJ Habibie, Indonesia.

Amil Ahmad Ilham was born on October 10 1973 in Bulu, South Sulawesi, Indonesia. He accomplished his Bachelor Degree of Electrical Engineering, Hasanuddin University, Indonesia in 1997, Master of Information Technology, The University of Newcastle, Australia in 2003 and Doctor of Informatics from Kyushu University in 2011. He is currently a lecturer at Hasanuddin University, Department of Informatics, since 1998. His research interests are Information Systems and Data Analytics. He is the Vice Dean for Academic and Student Affairs of Faculty of Engineering, Hasanuddin University, Indonesia.

Ingrid Nurtanio was born on August 13 1961 in Makassar, South Sulawesi, Indonesia. Her accomplished Bachelor Degree of Electrical Engineering, Hasanuddin University in 1986, Master of Electrical Engineering, Hasanuddin University in 2002, Doctor from Institut Teknologi Sepuluh Nopember in 2013. Her is currently a lecturer at the Hasanuddin University of Informatics, Indonesia since 1988. Her research interests are Artificial Intelligence.