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Household Waste Image Classification Using Deep Learning Model

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Abstract

Household waste management poses a significant challenge in maintaining environmental cleanliness, particularly in the classification process, which is still largely carried out manually. This research aims to develop an automatic classification system for inorganic household waste using a Deep Learning model based on Convolutional Neural Networks (CNN). The waste types classified include glass, plastic, metal, and paper. The system development process involves several stages, dataset collection, image preprocessing, CNN model design using the MobileNetV2 architecture, model training and evaluation, and integration into a web-based application using Flask. Testing results show that the developed system is capable of classifying waste images with an accuracy exceeding 80%. The system offers advantages in classification speed, ease of use, and an intuitive user interface featuring image uploads and real-time classification via the device camera. However, limitations such as dataset diversity and image capture quality still affect prediction accuracy. This research demonstrates that the application of CNN in waste management provides a significant contribution to the efficiency and effectiveness of waste classification systems.

***Keywords**: Image Classification; Deep Learning; CNN; Household Waste; MobileNetV2; Flask*

1. Introduction

Waste is the residue of materials that are no longer used and discarded after a certain process [1]. Household waste is generated from daily activities in the community [2]. Based on the source, waste is classified into household waste, commercial waste, and industrial waste [3]. Waste is also divided into two categories, organic and non-organic [4]. Organic waste comes from living organisms and can decompose naturally by microorganisms [5]. Inorganic waste, on the other hand, consists of plastic, metal, paper, and glass, which take longer to decompose and require special processing.

One of the common problems in waste management is the low awareness of the community in separating waste by type [6]. In addition, errors in classification may decrease the quality of recycling results and increase the workload at landfills. The lack of labor and high operational costs also become obstacles in implementing a more effective waste management system [7].

To overcome these problems, Deep Learning technology using the Convolutional Neural Network (CNN) algorithm can be applied to develop a household waste image classification system. CNN has excellent capabilities in recognizing patterns and features in images, enabling automatic classification of waste types based on captured images. With a CNN-based system, classification can be carried out more quickly, accurately, and efficiently.

2. Literature Review

2.1. Household Waste

Household waste is waste generated from human daily activities in domestic environments [8]. This type of waste is one of the main sources of urban waste and includes food scraps, plastic packaging, bottles, paper, cans, and other used items. The volume of household waste tends to increase in line with population growth and changes in consumption patterns. Poorly managed household waste may lead to soil, water, and air pollution.

Proper waste management is the key to maintaining environmental cleanliness and minimizing negative impacts on public health [9]. One important step in this process is waste separation at the source (households), which helps facilitate recycling, composting, or further processing. Waste is usually divided into two main categories: organic and inorganic. Organic waste such as food scraps and leaves can decompose naturally, while inorganic waste such as plastic, metal, and glass requires special treatment.

A major challenge in waste management is the low awareness of society regarding the importance of separating waste [10]. This often reduces the efficiency of waste management and increases the burden at landfills. Along with technological advancements, waste management has begun to adopt technology-based approaches, such as optical sensors that detect material types in recycling facilities [11].

2.2. Image Classification in Waste Management

In waste management, image classification plays an important role in identifying and separating waste based on visual characteristics. For instance, plastic tends to have a glossy and transparent surface, metal has a distinctive shiny texture and cylindrical forms such as cans, while paper has a dull surface with fiber textures. These image features can be used as input for machine learning-based classification systems to determine the detected waste type. The goal is to support recycling and waste processing with higher efficiency and accuracy.

Fig. 1: Beverage Bottle Waste

Fig. 2: Non-organic Waste

2.3. Deep Learning

Deep Learning is a branch of machine learning that employs artificial neural networks with multiple layers to solve complex data processing problems [12]. This technology mimics how the human brain processes information, recognizes patterns, and makes decisions based on learned experiences.

Deep Learning works similarly to how humans learn to recognize faces or objects, using layered networks of neurons that gradually process information. Each layer extracts increasingly abstract features, allowing the system to perform tasks such as image recognition with high accuracy.

2.4. Convolutional Neural Network (CNN)

CNN is a neural network designed specifically for processing images, videos, and audio data [13]. It uses convolutional layers to extract features and pooling layers to reduce data dimensions while preserving essential features. The main components of CNN include Convolutional Layers, Pooling Layers, Fully Connected Layers, and activation functions such as ReLU (Rectified Linear Unit). ReLU introduces non-linearity into the model, significantly improving efficiency compared to traditional activation functions like sigmoid or tanh [14].

2.5. MobileNetv2

MobileNetV2 is a convolutional neural network architecture developed by Google to provide efficient image classification, particularly on devices with limited resources such as smartphones and IoT devices. It is an improvement over MobileNetV1, utilizing depthwise separable convolutions and inverted residual blocks with linear bottlenecks. Compared to conventional CNN architectures such as VGGNet or ResNet, MobileNetV2 offers competitive accuracy with far greater computational efficiency.

3. Research Method

This research method is designed to systematically describe the stages in the development of the proposed system. The development process is carried out through a series of structured steps, starting from dataset collection, image preprocessing, CNN model design using the MobileNetV2 architecture, model training and evaluation, to the integration of training results into a web-based application using Flask.CNN Model Architecture. The research stages are shown in Figure 1 below.

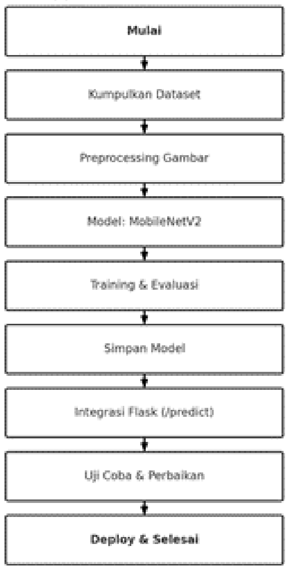

Fig. 3: Research Stage

3.1. Dataset Collection

The dataset was obtained from the TrashNet dataset available on Kaggle https://www.kaggle.com/datasets/feyzazkefe/trashnet as well as additional manually collected images. The dataset was divided into four categories include, glass, paper, metal, and plastic.

3.2. Image Processing

The preprocessing steps were carried out to improve image quality and model accuracy, consisting of:

a. Resize : resizing images to 128×128 pixels.
b. Normalization : normalizing pixel values to the range [0–1].
c. Augmentation : applying techniques such as rotation, flipping, and zooming to increase dataset diversity.

3.3. MobileNetV2

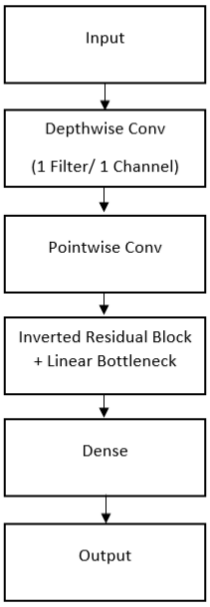

Fig. 4: MobileNetv2 Base Structure

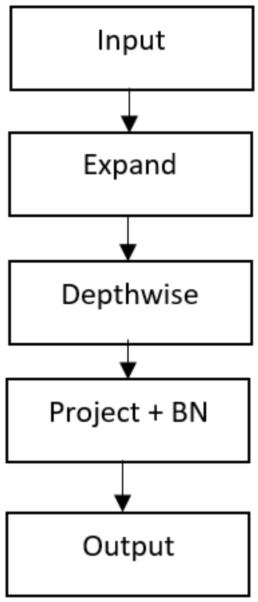

Fig. 5: Inverted Residual Block

The model design was based on MobileNetV2, with the following components:

1. Input Layer : receives the input image.
2. Depthwise Convolution : applies convolution to each channel separately.
3. Pointwise Layer : combines results across channels using 1×1 convolution.
4. Inverted Residual Block :
    a. Expand : The channel is first expanded with 1x1 conv + ReLU6.
    b. Depthwise : After being expanded, each channel will be filtered separately.
    c. Project + BN : Channels are reduced to a smaller dimension (bottleneck) with 1x1 conv. Batch Normalization is used to stabilize data distribution and accelerate training.
    d. Skip Connection : This occurs if the input and output are the same.
5. Linear Bottlenecks : At the end of the inverted residual block, MobileNetV2 does not use ReLU after channel compression (projection). This preserves the information even though the dimensions are small.
6. Dense Layer and Softmax Output : produces class probabilities for glass, plastic, metal, and paper.

3.4. Flow of System Usage

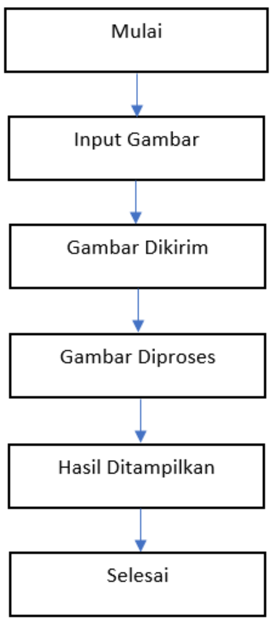

Fig. 6: Flow of System Usage

The usage process of the system is as follows:

1. Start
   The initial step of the system begins when the user accesses the waste classification web application. The system is ready to receive input from the user.
2. Input
   At this stage, users are given the option to upload images from their gallery or camera.
   a. Uploading via the gallery opens the gallery to upload images to the system.
   b. Uploading via the camera opens the webcam to capture images in real time.
3. Image Sent
   After the image is received by the backend, it will go through the processing stage:
   a. Resize the image to 128x128 pixels
   b. Normalize pixels to the range [0 - 1]
   c. The image format will be converted to a tensor so that it can be accepted by the model
4. Image Processed
   The model processes the image input through several layers:
   a. The convolution layer extracts features such as shape, texture, edges, and color
   b. The pooling layer reduces the dimensions and retains important features
   c. Global Average pooling and fully connected layers process the final output
   d. The softmax layer generates probabilities for each class
5. Result
   The frontend will receive the classification results and display them to the user in the form of a website
6. Finished
   The system will display the results to the user and be ready to wait for the next input.

4. Result and Discussion

The following are the results from the model :

4.1 Model Training Results

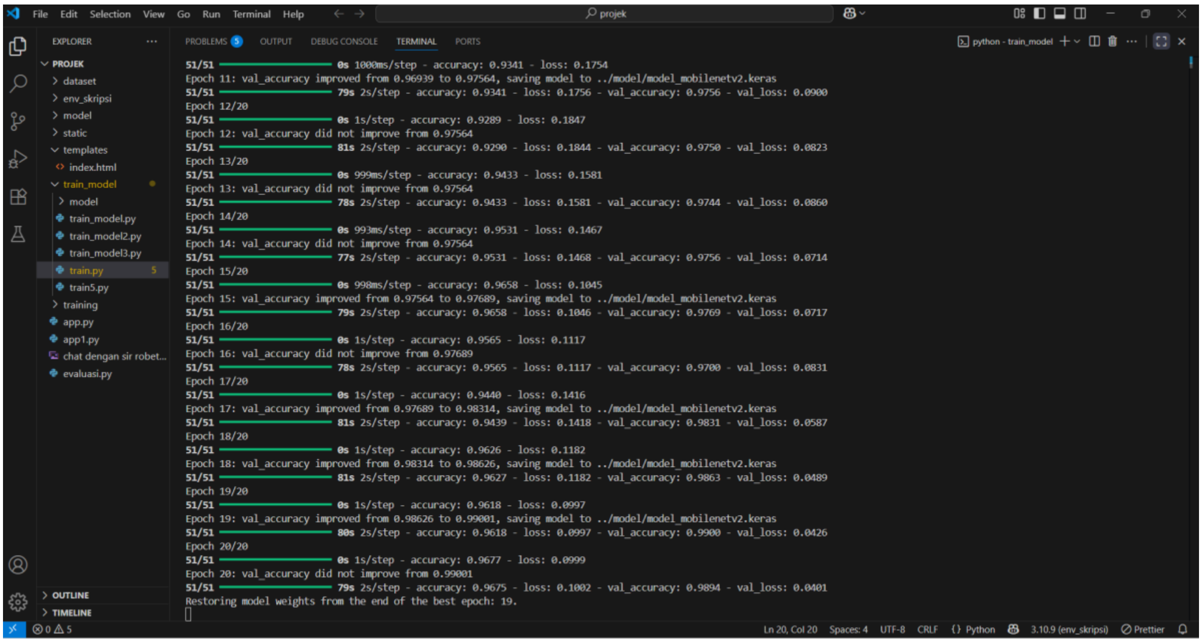

Fig. 7: Training Result

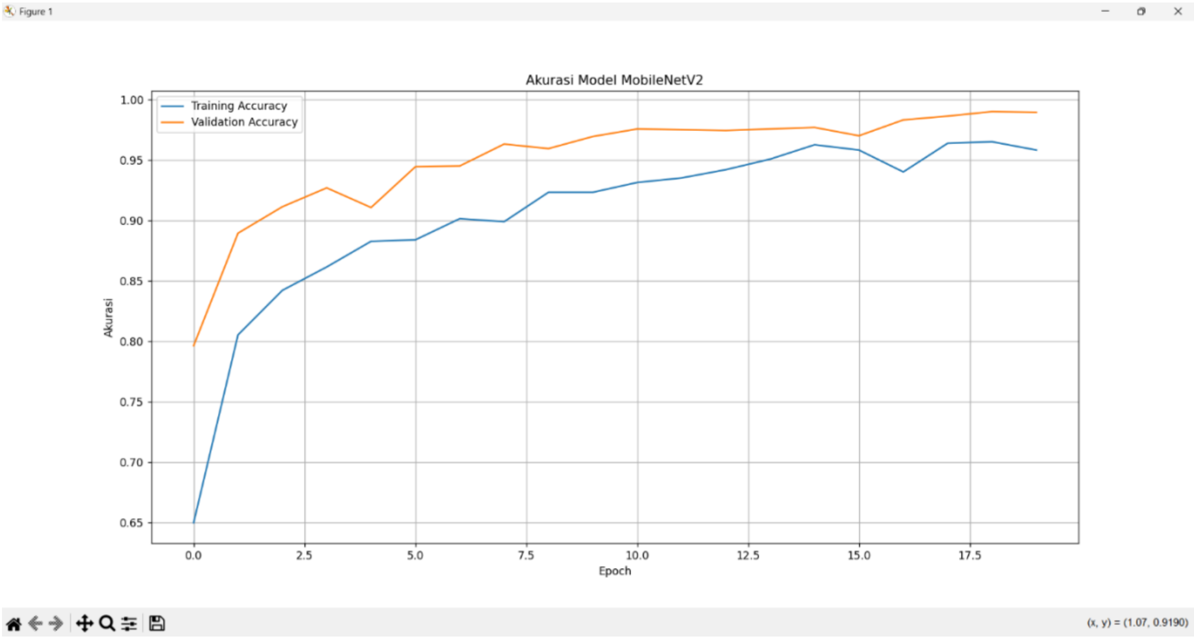

Fig. 8: Training Accuracy Result

```
=== Classification Report ===
              precision    recall  f1-score   support

        kaca       0.98      0.99      0.99       400
      kertas       1.00      1.00      1.00       400
       logam       0.99      0.99      0.99       401
     plastik       0.99      0.98      0.99       400

    accuracy                           0.99      1601
   macro avg       0.99      0.99      0.99      1601
weighted avg       0.99      0.99      0.99      1601

       logam       0.99      0.99      0.99       401
     plastik       0.99      0.98      0.99       400
       logam       0.99      0.99      0.99       401
       logam       0.99      0.99      0.99       401
     plastik       0.99      0.98      0.99       400

    accuracy                           0.99      1601
   macro avg       0.99      0.99      0.99      1601
weighted avg       0.99      0.99      0.99      1601

=== Confusion Matrix ===
[[395   0   3   2]
 [  0 399   0   1]
 [  2   1 397   1]
 [  5   1   0 394]]
(env_skripsi) PS C:\Users\Asus\Documents\Skripsi\projek>
```

Fig. 9: Evaluation Result

4.2 Web Application

1. Initial Display
   This screen displays image preview features, upload buttons, classification buttons, and previews of the results.

Fig. 10: Initial Display

2. Camera Display
   Enables users to capture waste images in real time.

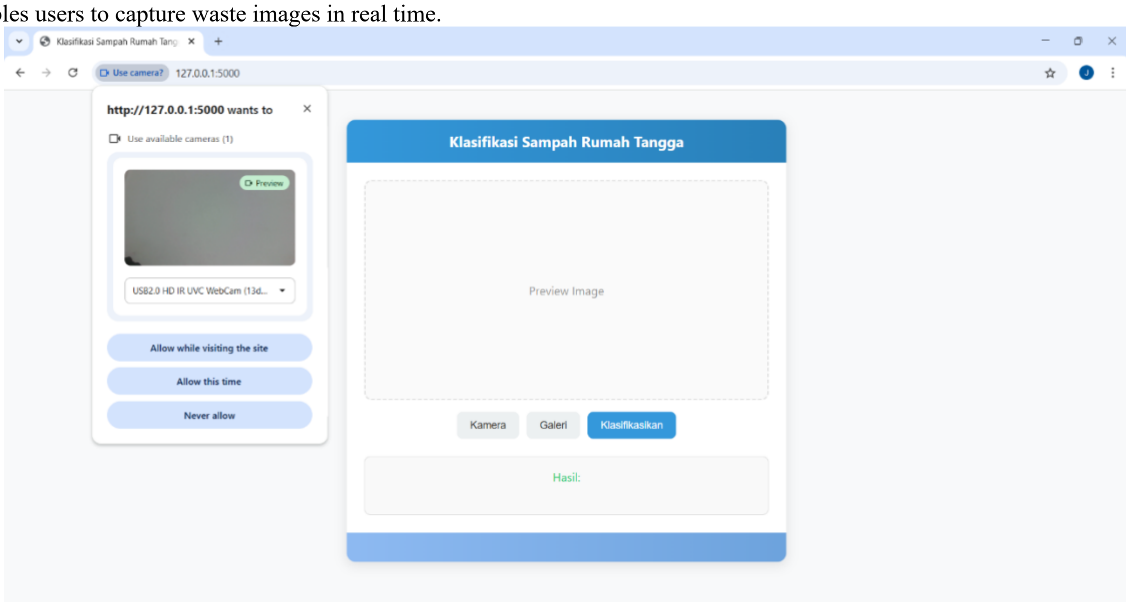

Fig. 11: Camera Notification Display

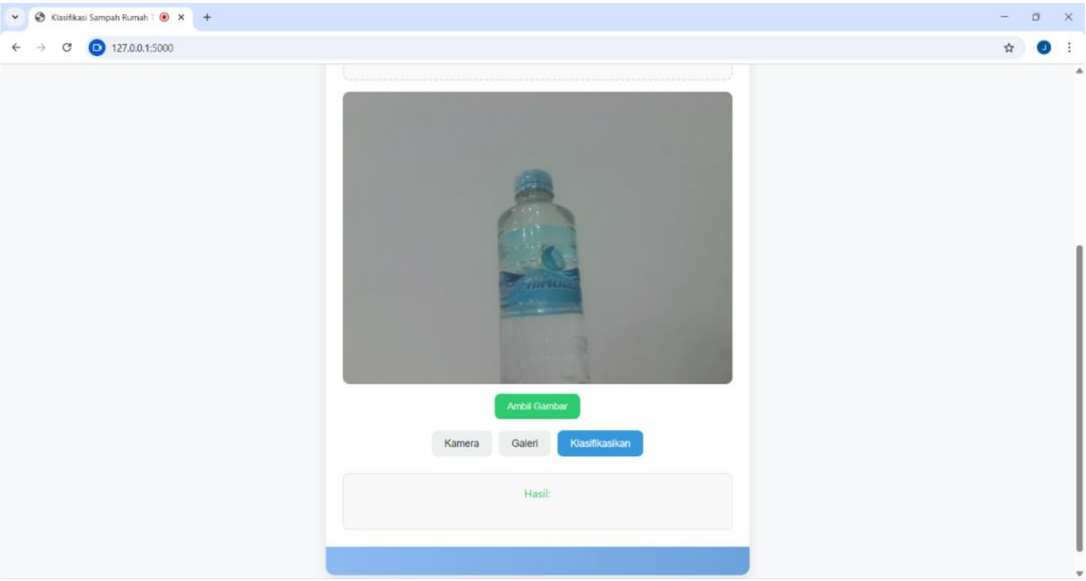

Fig. 12: Capture Display

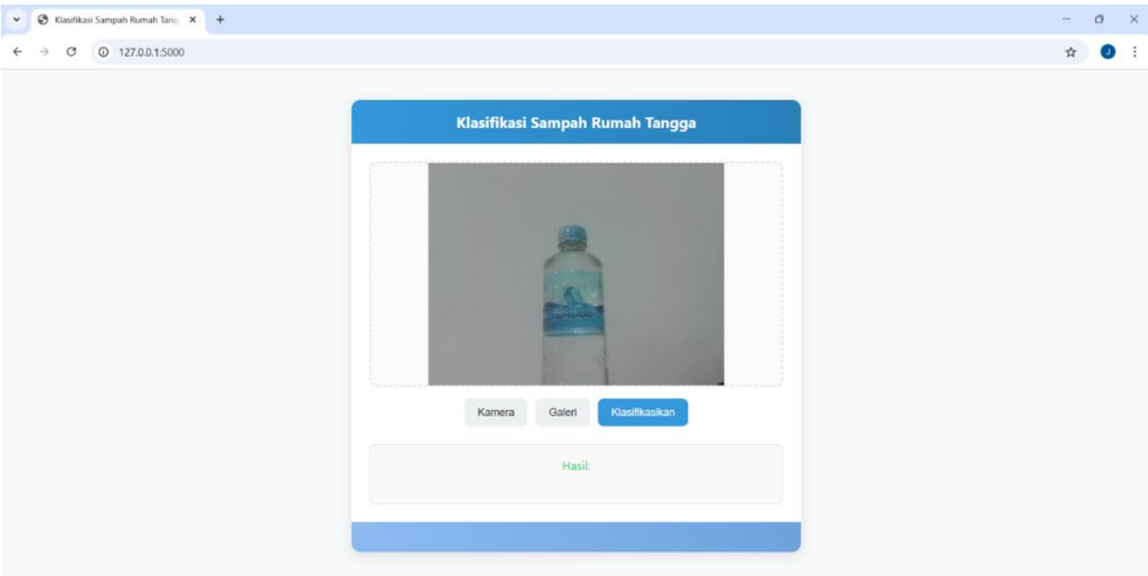

Fig. 13: Preview Display

3. Galery Display
   Allows users to upload waste images from the file explorer.

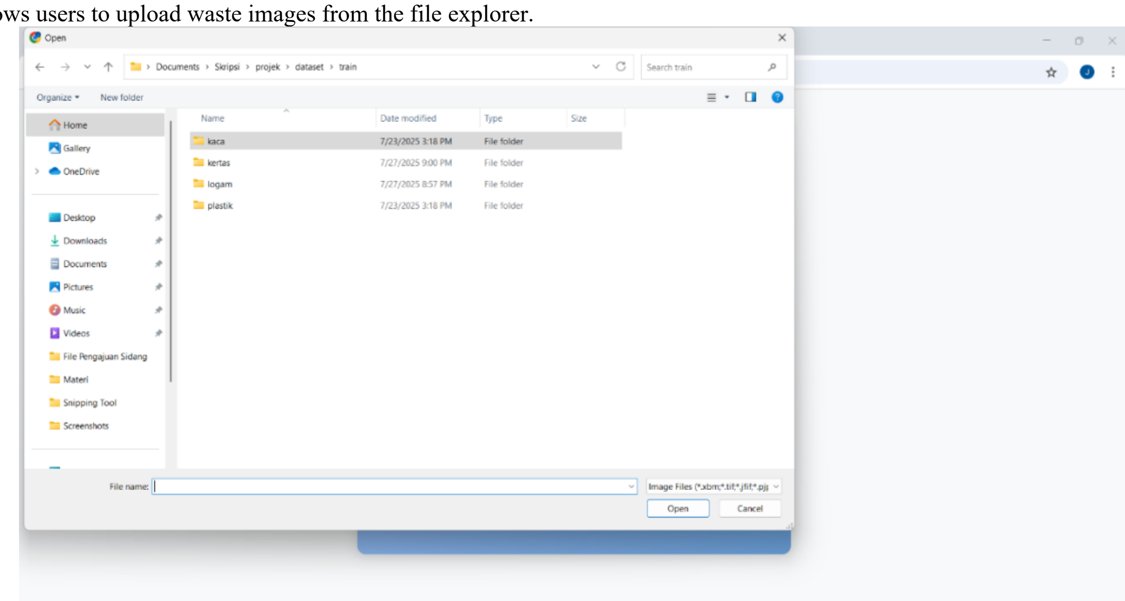

Fig. 14: File Explorer Display

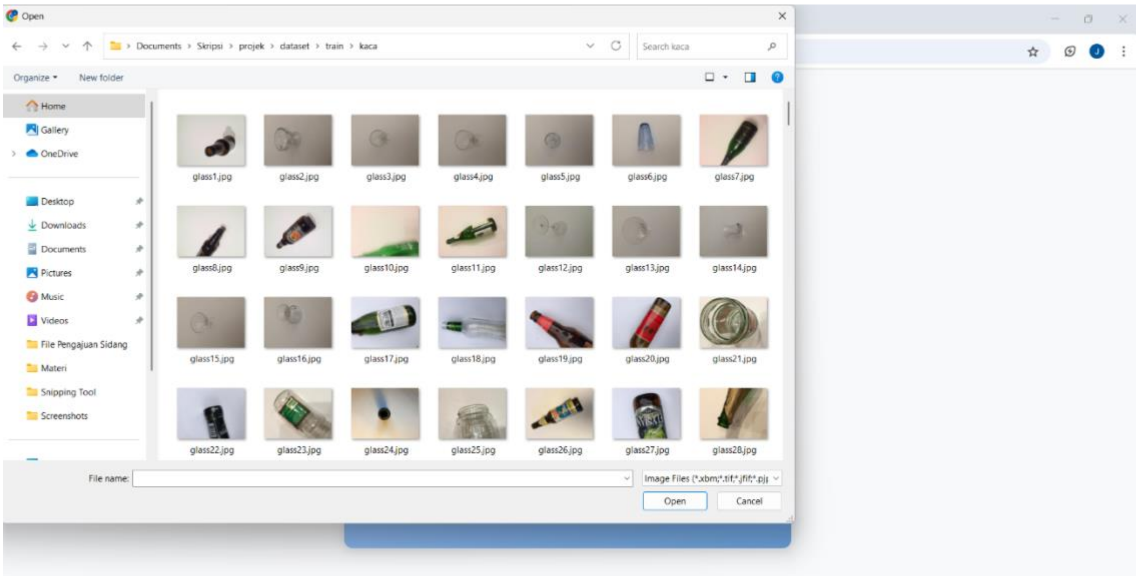

Fig. 15: Upload File Display

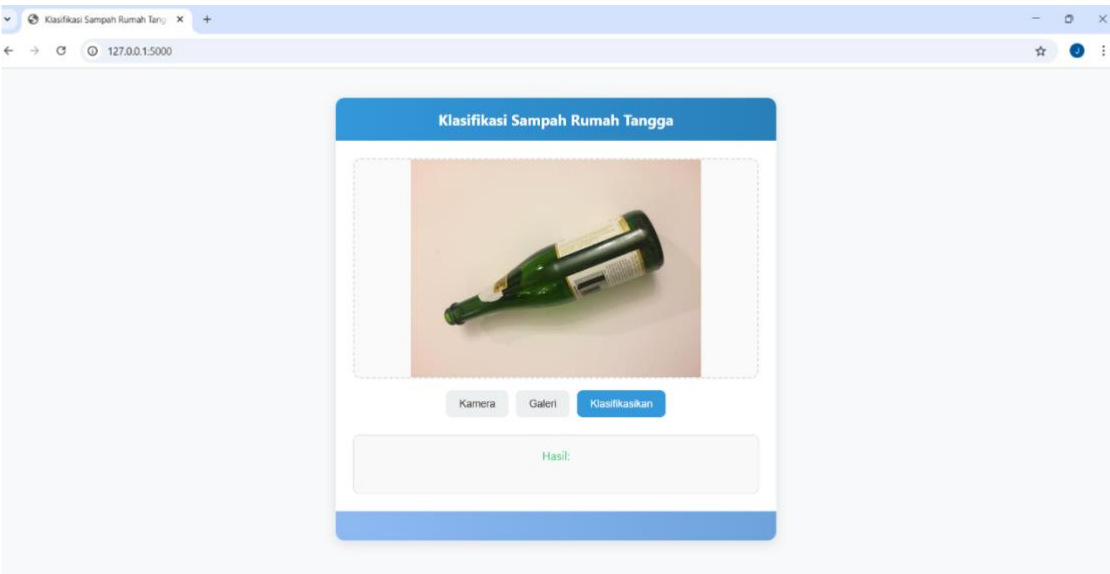

Fig. 16: Preview Display

4. Result Display
   Shows the waste category (glass, plastic, metal, paper) predicted by the model.

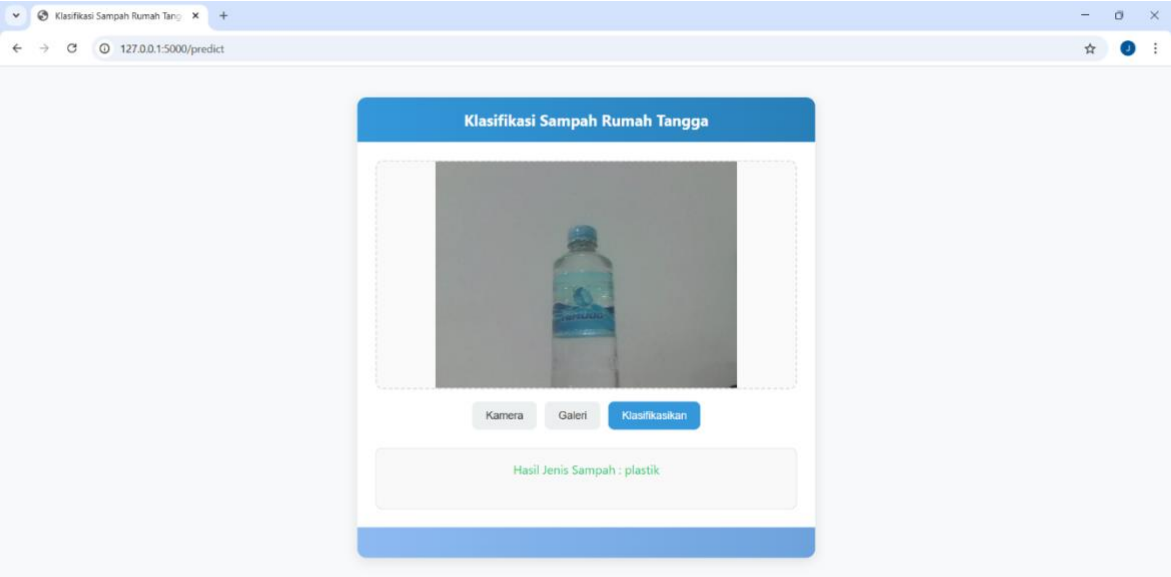

Fig. 17: Camera Classification Display

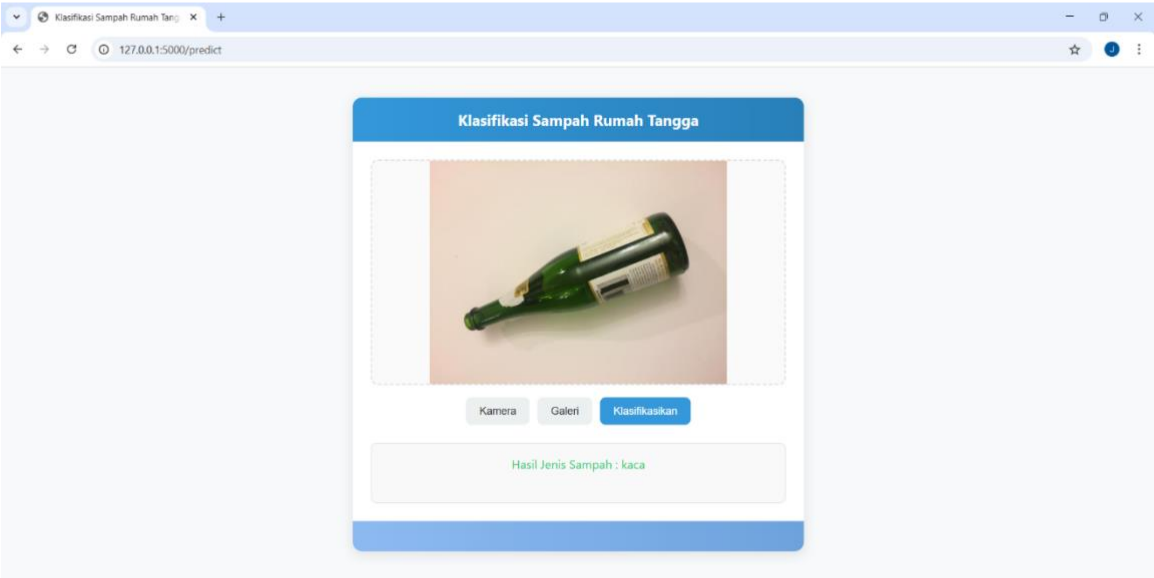

Fig. 18: Image Classification Display

4.3 Discussion
Based on the implementation of a household waste image classification system using the deep learning method, the classification system uses a Convolutional Neural Network architecture with MobileNetV2, providing prediction results with a satisfactory accuracy rate of over 80% in the validation dataset test.

5. Conclusion and Suggestions

Based on the system design and implementation, the following conclusions were obtained:This is a text of acknowledgements. Do not forget people who have assisted you on your work. Do not exaggerate with thanks. If your work has been paid by a Grant, mention the Grant name and number here.

1. Using a CNN model, the system can classify waste images with high accuracy and speed, reducing reliance on manual classification
2. The research results indicate that applying deep learning technology to household waste management improves efficiency and reduces workload in waste classification
3. The system achieved accuracy exceeding 80%, making it reliable for real-world applications

The following are some suggestions that can be provided for further system development:

1. The grouping of dataset types is still categorized into 4 types. Further research is recommended to develop variations and the number of datasets from various lighting and background conditions to improve the model's generalization capabilities.
2. The model is still implemented into a web-based application. Further system development is recommended to be implemented into a mobile-based application by utilizing Tensorflow Lite to make it easier for the wider community to use.

References

[1] Fathoni Dwiatmoko, D. Utami, and Nuari Anisa Sivi, "Klasifikasi Citra Sampah Organik dan Non Organik Menggunakan Algoritma CNN (Convolutional Neural Network)," *Explore*, vol. 14, no. 1, pp. 1–5, 2024, doi: 10.35200/ex.v14i1.103.

[2] R. Hasibuan, "Analisis Dampak Limbah/Sampah Rumah Tangg," *J. Ilm. Advokasi*, vol. 04, no. ANALISIS DAMPAK LIMBAH/SAMPAH RUMAH TANGGA TERHADAP PENCEMARAN LINGKUNGAN HIDUP, pp. 42–52, 2016.

[3] R. W. Aji, "Strategi Pengelolaan Sampah Rumah Tangga di Kabupaten Cilacap Jawa Tengah," *J. Manaj. dan Ekon.*, vol. 2, no. 2, pp. 118–134, 2019.

[4] D. U. No and P. Sampah, "Pengertian Sampah," vol. 2, no. 18, pp. 1–14, 2008.

[5] S. Wahyuningsih, B. Widiati, T. Melinda, and T. Abdullah, "Sosialisasi Pemilahan Sampah Organik dan Non-Organik Serta Pengadaan Tempat Sampah Organik dan Non-Organik," *Dedik. SAINTEK J. Pengabdi. Masy.*, vol. 2, no. 1, pp. 7–15, 2023, doi: 10.58545/djpm.v2i1.103.

[6] F. Nurmaisyah and S. Susilawati, "Pengetahuan Masyarakat dalam Pengelolaan Sampah Rumah Tangga di Kecamatan Percut Sei Tuan," *PubHealth J. Kesehat. Masy.*, vol. 1, no. 1, pp. 91–96, 2022, doi: 10.56211/pubhealth.v1i1.47.

[7] N. P. Fadillah and I. Suryani, "Peranan Dinas Lingkungan Hidup Dalam Pelaksanaan Peraturan Daerah Kabupaten Dharmasraya Nomor 9 Tahun 2015 Tentang Pengelolaan Sampah Dalam Perspektif Fiqih Siyasah Dusturiyah," *JISRAH J. Integr. Ilmu Syariah*, vol. 1, no. 1, p. 13, 2021, doi: 10.31958/jisrah.v1i1.2700.

[8] "UU 18 Tahun 2008," no. 1, 2008.

[9] I. Sriagustini and Nurazijah, "Edukasi Pengolahan Sampah Rumah Tangga Sebagai Upaya Peningkatan Kesadaran Masyarakat Untuk Menjaga Lingkungan," *J. Pengabdi. Masy. Kesehat.*, vol. 1, no. 1, pp. 35–46, 2022, [Online]. Available: http://www.jurnal.stikescirebon.ac.id/index.php/jirah/article/view/286

[10] S. Wahyuni, M. N. Ayu, and S. Ansori, "Peningkatan Kesadaran Masyarakat Melalui Pengelolaan Sampah Dan Budidaya Maggot Bsf Desa Cimekar," *J. Abdimas Sang Buana*, vol. 5, no. 1, pp. 1–9, 2024, doi: 10.32897/abdimasusb.v5i1.2985.

[11] H. Wilts, B. R. Garcia, R. G. Garlito, L. S. Gómez, and E. G. Prieto, "Artificial intelligence in the sorting of municipalwaste as an enabler of the circular economy," *Resources*, vol. 10, no. 4, pp. 1–9, 2021, doi: 10.3390/resources10040028.

[12] R. Adelia, N. Khairunisa, and R. Zulfiqri, "Implementasi Convolutional Neural Network (Cnn) Dalam Mendeteksi Sampah Organik, Plastik, Dan Kertas," *JUTIM (Jurnal Tek. Inform. Musirawas)*, vol. 9, no. 1, pp. 29–37, 2024, doi: 10.32767/jutim.v9i1.2233.

[13] A. Ibnul Rasidi, Y. A. H. Pasaribu, A. Ziqri, and F. D. Adhinata, "Klasifikasi Sampah Organik dan Non-Organik Menggunakan Convolutional Neural Network," *J. Tek. Inform. dan Sist. Inf.*, vol. 8, no. 1, pp. 142–149, 2022, doi: 10.28932/jutisi.v8i1.4314.

[14] K. Azmi and S. Defit, "Implementasi Convolutional Neural Network (CNN) Untuk Klasifikasi Batik Tanah Liat Sumatera Barat," vol. 16, no. 1, pp. 2580–2582, 2023.