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Garbage classification using depthwise separable convolution with data augmentation

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Topics

Data analysis, Convolutional neural network, Deep learning, Telecommunications engineering, Pollution prevention, Ecology, Industry

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Garbage classification using Depthwise Separable Convolution with data augmentation

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Abstract. Good waste management can help maintain the cleanliness and beauty of the surrounding environment, minimize negative impacts on the ecosystem, and ensure the sustainability of the surrounding area. This research aims to differentiate types of non-organic waste. The case study was carried out in the tourism area because the area coverage is not too comprehensive, and the waste managed is not as much as household waste. Additionally, waste management creates opportunities for the recycling industry. By separating, collecting, and processing recyclable waste, such as paper, plastic, metal, and glass, this industry can produce products that can be sold. For this reason, tools are needed to facilitate visual waste sorting in tourism areas. It can be done one of the ways with the help of deep learning. Deep learning research on each type of waste that often appears in the area can help direct visitors to place the trash in its place so that it can be sent directly to the collector. The contribution to the proposed deep learning Convolutional neural network is using a combination of Depthwise Separable Convolution architectural concepts, hoping that computing will be lighter, still maintain accuracy, and remain stable. The relatively small model makes it suitable for mobile devices with limited computing power and storage. The dataset consists of six classes: Cardboard, glass, metal, paper, plastic, and trash. Due to data limitations, augmentation techniques were used. The test results show an average model accuracy of 98.29% with a training computing time to obtain the model of 45 minutes. MSE 0.0343, RMSE 0.1852, and MAE 0.0229. Testing with new experimental data takes an average of 1-2 seconds.

I. INTRODUCTION

Visitors who come to tourist locations want a pleasant and neat experience. Trash that is not well organized can disrupt tourist attractions and disrupt visitor services. With good waste management techniques, tourist attractions can maintain attractiveness and economic benefits. A clean and organized environment usually attracts more tourists. This positive perception can increase self-esteem, visitor enjoyment, and economic impact. It is essential to inform tourists and other stakeholders about the importance of distinguishing between organic and inorganic waste. One way to turn organic waste into fertilizer is to make it into compost, while inorganic waste is sent to waste collectors (1).

Environmental, climatic, technical, and socioeconomic factors are all crucial factors in the complicated waste management process. It categorizes garbage and improves conventional techniques. Complex challenges are required. Effective alternative computational ways to tackle the difficulties of solid waste have been made possible by advancements in artificial intelligence (AI) and image processing. Even though this topic has been the subject of much research, only a few studies have employed deep learning techniques to address various solid waste challenges. This paper proposes a convolutional neural network-based intelligent trash classification model. It has been applied to classification tasks using AlexNet, DenseNet121, and SqueezeNet. The outcomes demonstrate that the classification method was highly successful. With an accuracy score of 94.15%, DenseNet121 showed the best performance (2).

The buildup of garbage is a serious problem that, if improperly managed, may harm the environment and human health. It's crucial to have a comprehensive, intelligent waste management system to handle different types of garbage. Separating waste into its various components is one of the most essential parts of waste management, and it is typically carried out manually by hand-picking the debris. To streamline the procedure, we propose an intelligent waste material classification system that was created using a 50-layer waste mesh pre-train Convolutional Neural Network model (ResNet-50), a machine learning tool and extractor, and a Support Vector Machine (SVM), which was used to categorize waste into various groups/types, including glass, metal, paper, and plastic. It was suggested (3).

The following paper suggests a completely automated waste management system to put waste sorting into practice. The technique combines computer vision and deep learning with an Internet of Things (IoT) system to sort municipal waste into recyclable and organic materials. By minimizing the acquisition and transmission of infectious diseases, eliminating manual sorting from the waste management process lowers the health hazards to city employees. The waste sorting process will be substantially more affordable and faster with automation. This research aimed to develop concepts for an efficient waste management system requiring little human participation (4).

This research examines an image recognition system to identify and categorize used electrical and electronic equipment from images. The primary goal is to make information interchange about rubbish to be collected from people or waste collection locations easier while taking advantage of cell phones' widespread acceptance and use. People will photograph the garbage and upload the photographs to the servers of the waste collection firm, where they will be recognized and categorized automatically. It will improve the planning of waste collection. A server or a mobile application may be used to run the suggested system. A new technique of classifying and identifying objects in images is proposed using neural networks. A deep learning convolutional neural network (CNN) is used to categorize different forms of e-waste, and a quicker. The image's category and size of equipment waste are determined using a region-based convolutional neural network (R-CNN). The selected e-waste categories have recognition and classification accuracy ranging from 90% to 97%. After automatically identifying and classifying the size and kind of garbage from the provided photographs, the e-waste collection business can create a collection plan by allocating an appropriate number of vehicles and load capacity for a specific e-waste project (5). The waste dataset observed in this research is shown in Figure 1.

(a)   (b)   (c)   (d)   e)   (f)

FIGURE 1. Garbage dataset (a) Cardboard, (b) Glass, (c) Metal, (d) Paper, (e) Plastic, and (f) trash

Recycling and landfilling are two processes that help to break down garbage as part of waste management. Real-time data classification and monitoring can be accomplished with the help of deep Learning and the Internet of Things (IoT). This research presents the architecture of a robust IoT and deep learning-based trash management system. With convolutional neural networks (CNN), a well-liked deep learning paradigm, the suggested model offers a clever technique to separate garbage that can be digested from waste that cannot be. With a microprocessor and numerous sensors, this concept also introduces an architectural design for an intelligent garbage can. IoT and Bluetooth connectivity are used in the suggested way to monitor data. IoT allows real-time data control to be exercised from any location, whereas Bluetooth makes it possible for Android applications to monitor nearby data. While Bluetooth helps with short-range data monitoring via Android applications, IoT offers real-time data control from anywhere. The effectiveness of the created model was evaluated by calculating and interpreting the accuracy of waste label classification, sensor data estimate, and system utility-scale (SUS). Based on the CNN model, the proposed architecture has a SUS score of 86% and a classification accuracy of 95.3125 percent. However, real-time waste monitoring can adjust this intelligent system to domestic activities (6).

The literature above shows that a lot of research points to the importance of waste classification. It is necessary because it can help relieve field officers through users or visitors aware of the environment in tourism areas. Technology that can help with visualization includes deep learning because this method is a classification method that can recognize objects well. The gap with previous research is that this research uses Depthwise Separable Convolution, which can ease the computing process. Data augmentation is also used to overcome the limited amount of data. The advantage of previous research is that some research was carried out using machine learning and deep learning with quite good results but still focused on accuracy, so it did not consider the computational processes required. The hope is that in this research, good accuracy will be obtained by considering the time-consuming factor so that it can be used on lighter devices.

II.BACKGROUND AND LITERATURE REVIEW

2.1. Management of organic and inorganic waste

Managing organic and inorganic trash in tourist locations is crucial to preserving cleanliness, protecting the environment, and giving visitors a satisfying experience. A clean tourism area provides a more positive experience for visitors. Scattered rubbish can damage the aesthetics of the environment and make the place look unkempt. The domain will remain clean and attractive to visitors with good waste management (7). Waste that is not managed correctly can pollute the environment. For example, plastic trash can end up in the sea and harm marine animals and their ecosystem. Proper waste management can help protect nature and ecosystems around tourism areas (8). From a public health perspective, if organic waste rots and is not disposed of properly, it can become a nest for bacteria and pests. It can endanger the health of visitors and residents. In terms of legal compliance, many countries have laws that regulate waste management. Non-compliance with these regulations may result in legal sanctions (9).

Regarding saving resources, with good waste management, several types of waste can be recycled or reprocessed. It can save natural resources and reduce the environmental impact of manufacturing new products. Regarding Additional Income, Good waste management can also create economic opportunities. For example, waste collection and processing can be an additional source of income for local communities. It could be an excellent way to improve the economic welfare of societies around tourism areas (10) (11).

2.2. Deep Learning Convolutional Neural Network

Deep learning is a branch of machine learning concerned with using artificial neural networks, which in many cases consist of many layers (deep neural networks) to model and understand data. Convolutional Neural Network (CNN) is a deep learning architecture designed explicitly for tasks related to image and visual processing (12) (13).

- Convolutional Layer: CNN starts its process with a convolutional layer responsible for extracting visual features from the input image. This layer uses convolution operations to apply various filters (kernels) to the entire input image. This filter will scan the photo and identify features such as edges, corners, or complex patterns (14).

$$(f * g)(x, y) = \sum_a \sum_b f(a, b) g(x - a, y - b) \tag{1}$$

  with :*f(x,y) = input function, g(x,y) = kernel function*. m = 2a + 1 is Heigh of kernel, and n = 2b + 1 is width of kernel (15)

- ReLU (Rectified Linear Activation) Layer: After the convolution layer, the CNN usually follows with a ReLU activation layer (16).

$$ReLU\ (x) = f(x) = \begin{cases} x, & jika\ x\ \geq 0 \\ 0, & lainnya \end{cases} \tag{2}$$

  with: $f(x)$ = ReLU Function, x = input

  This layer is responsible for introducing non-linearity into the model. CNNs can understand more complex relationships between features discovered by convolutional layers (17).

- Pooling Layers: Pooling layers, often max-pooling layers, are used to reduce the data’s dimensionality and the number of parameters required in the model. The process is shown in Figure 2 (18).

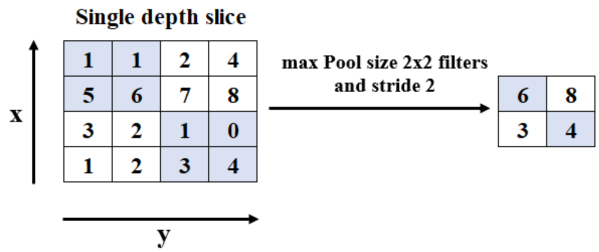


FIGURE 2. Pooling Layer

It is done by taking the maximum value (or average value) of the closest group of pixels in the image. It helps retain the most essential features and reduces overfitting (19).

- Fully Connected Layer: After several convolution and pooling layers, a CNN usually has a fully connected layer (sometimes called a Dense layer) whose job is to carry out classification or regression based on the features that have been extracted. This layer connects each neuron unit with each neuron unit in the previous layer(20).

$$y_{jk}(x) = f\left(\sum_{i=1}^{n_H} w_{jk}x_i + w_{j0}\right) \tag{3}$$

With $y_{jk}(x)$=output fully connected, n_H=number of hidden nodes, w_{jk}=weight, x_i=input, w_{j0}=initial weight (21)

- Output Layer: The output layer depends on the type of task being performed. For example, for an image classification task, the output layer typically has neurons corresponding to the number of possible classes and uses an activation function such as softmax to generate probabilities (22)

$$\begin{bmatrix} 1.3 \\ 5.1 \\ 2.2 \\ 0.7 \\ 1.1 \end{bmatrix} \rightarrow \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \rightarrow \begin{bmatrix} 0.02 \\ 0.90 \\ 0.05 \\ 0.01 \\ 0.02 \end{bmatrix} \tag{4}$$

2.3. Evaluation

Confusion matrix is a tool used in statistics and machine learning to evaluate the performance of classification models, especially in the context of pattern recognition and classification. A table illustrates how well a classification model can predict the correct class or label from test data.

- Accuracy: Accuracy measures the correct accuracy of the model in predicting classes with the formula (TP + TN) / (TP + TN + FP + FN). It is the percentage of all correct predictions.
- Precision: Precision measures the extent to which the optimistic predictions made by the model are correct and is calculated by the formula TP / (TP + FP). It is useful when it is crucial to avoid false positive errors.
- Recall (Sensitivity or True Positive Rate): Recall measures the extent to which the model can identify all proper positive examples, calculated by the formula TP / (TP + FN). It is useful when it is essential to avoid false, harmful errors.
- F1-Score: F1-Score is a composite measure that combines precision and recall with the formula 2 * (Precision * Recall) / (Precision + Recall). It helps find a balance between accuracy and recall.

With TP=True Positive, TN=True Negative, FP=False Positive, FP= False Negative. Besides that, there is Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) measurement.

- Mean Square Error (MSE) merupakan metrik yang mengukur rata-rata kuadrat perbedaan antara nilai sebenarnya (data aktual) dan nilai prediksi yang dihasilkan oleh model.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \ , RMSE = \sqrt{\frac{1}{N_d}\sum_{k=1}^{N_d}(y_k - \hat{y}_k)^2} \quad (5)$$

.

Where n = number of data in a dataset, y_i = actual value, and $\tilde{y}_i$= predicted value. MSE gives greater weight to significant errors because the differences are squared (23) (24).

- MAE is a metric that measures the average absolute difference between actual and model-predicted values. The MAE formula is.

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \quad (6)$$

MAE can be used well in a variety of domains and use cases. It is often used in regression, forecasting, and other modeling where continuous values are predicted (25).

III.RESEARCH METHODS

3.1. Block diagram of research

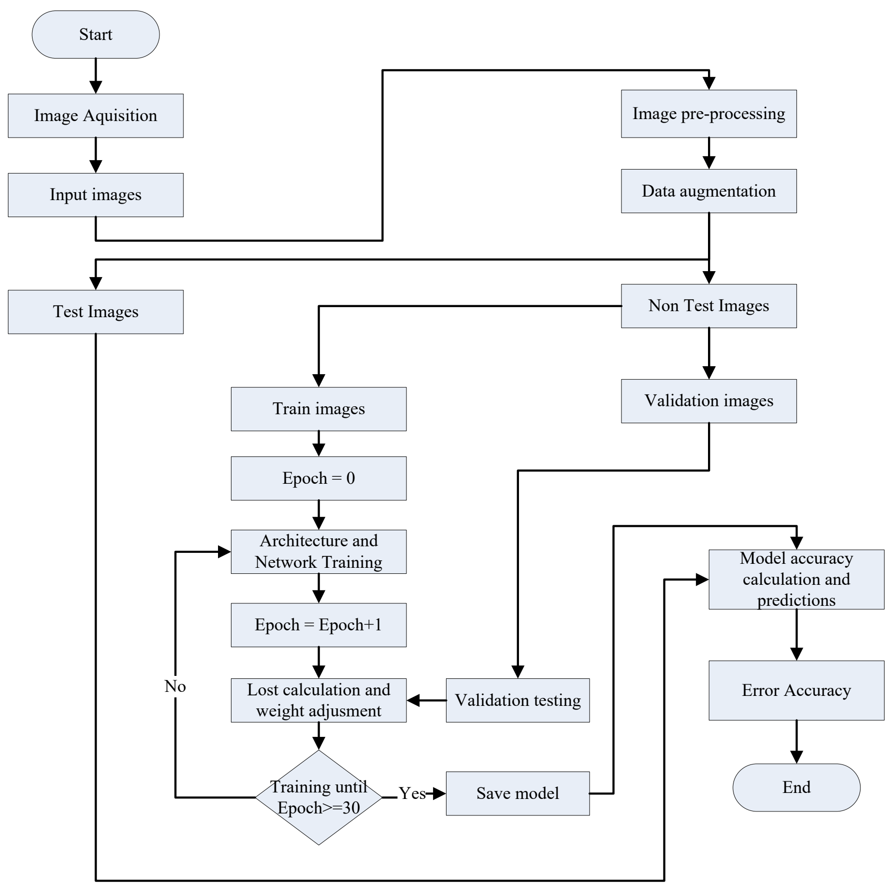


FIGURE 3. Block diagram of Convolutional Neural Network

In the block diagram in Figure 3, the system process generally goes through data acquisition (image acquisition) stages. It is carried out by pre-processing, checking the size and bit depth, and changing it into format [224 224 3]. Scale augmentation, rotation, shears, and reflexion are used to add variation. Non-test image data division is divided into training data and validation data. Next, training is carried out using the selected architecture through a training process. After obtaining a model for accuracy, it can be used as a reference in the prediction process. Predictions compare experimental data or new data that has not participated in training with a reference model successfully prepared during exercise and is proof of confidence accuracy. If the model accuracy is good, then the confidence accuracy results are also good.

3.2. Depth-wise separable convolution

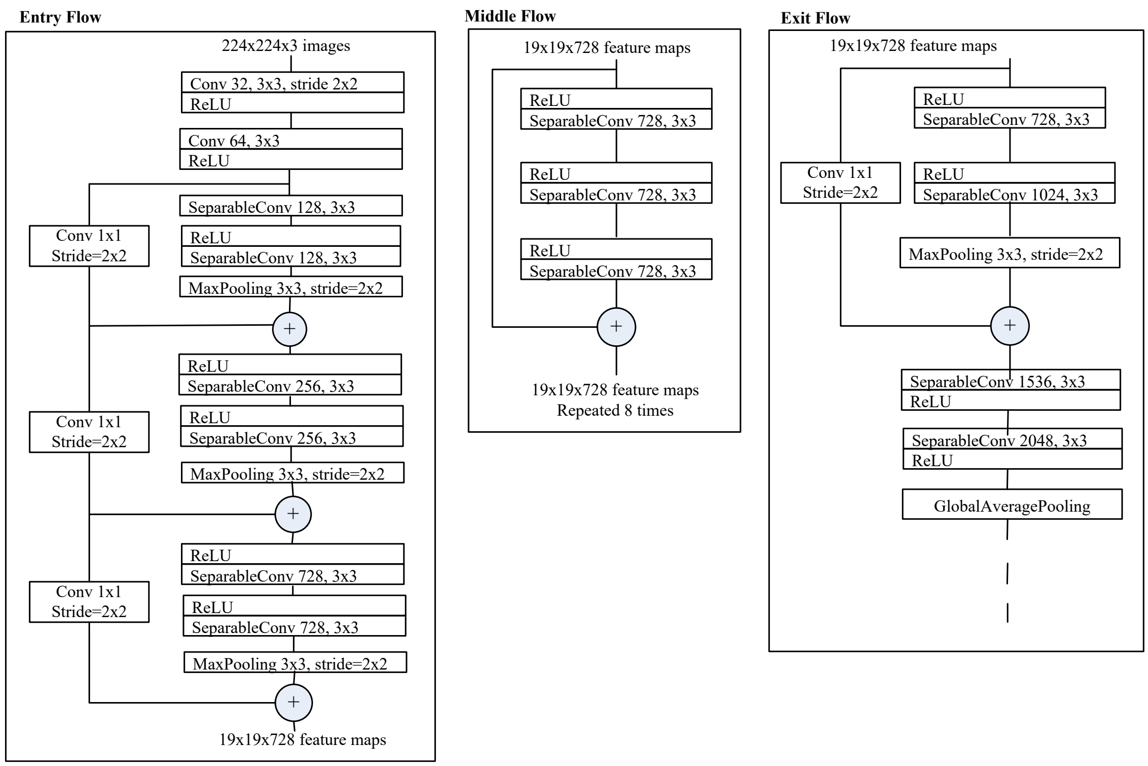


FIGURE 4. Block diagram of Depth-wise separable convolution

The entry, middle, and exit flow shown in Figure 4 is a concept related to artificial neural network architectures that use depthwise separable convolution, as in models such as MobileNet. It refers to how depthwise separable convolution operations are used in different stages of a network. Entry Flow is the initial stage or first layer in the network, where the input image is first processed. At this stage, depthwise separable convolution is used to extract initial features from the image. Depthwise filters will capture basic features such as edges, texture, and color. Its main task is to reduce the spatial dimensions of the input image, thereby allowing the network to focus on higher-order features. Middle Flow is the stages between the entry layer (entry flow) and the network's output layer (exit flow). In these stages, depthwise separable convolution extracts increasingly abstract and complex features from an image. Depthwise filters dig deeper and rely on context to identify more complex image objects and patterns. Exit Flow is the final stage in the network, which produces the final output or prediction. At this stage, depthwise separable convolution is used to summarize the high-level features found in the image and make forecasts or production. The depthwise filter combines and integrates feature information extracted from the previous stage for object recognition or classification. When used in these stages, depthwise separable convolution helps reduce the number of parameters and computations required in the network, making the model more efficient and suitable for devices with limited computing power. In this way, the network can efficiently extract increasingly complex features through several processing stages.

3.3. Dataset used in this research

The data used in this research is secondary data taken from the Kaggle.com website. However, primary data was also collected around the tourism area apart from secondary data. The dataset contains six classes, including cardboard (393), glass (491), metal (400), paper(584), plastic (472) and trash(127). The secondary data address is https://www.kaggle.com/datasets/asdasdasasdas/garbage-classification. Various images were taken from different locations, positions, and shapes. Specifications include a resolution of 1440x1920 with 96 dpi.

3.4. Test Scenario

The scenario included trials with different architectures and training optimizations: adaptive moment, gradient descent, and root mean square prop. Additionally, trials were carried out with changes to the training parameters.

IV.RESULT AND DISCUSSION

4.1. Pre-Processing

The pre-processing technique checks all files in each class folder because each file has a different size and depth. The original image size from the Kaggle repository is 512x384 pixels with a pixel depth of 96 dpi, then change the file size to [224 224 3] shown in Figure 5.

(a) (b)

FIGURE 5. Pre-processing metal (a) before (b) after

Data division is the step after equalizing the resolution size and bit depth. Data distribution is divided into 80% training and 20% test data. Meanwhile, validation data is taken from training data in the 20-80% range.

4.2. Data Augmentation

There are four techniques for manipulating data in data augmentation techniques: scale, rotation, shears, and reflection. It is shown in Figure 6

FIGURE 6. Augmentation (a) Scale and Rotation, (b) Shears and reflexion

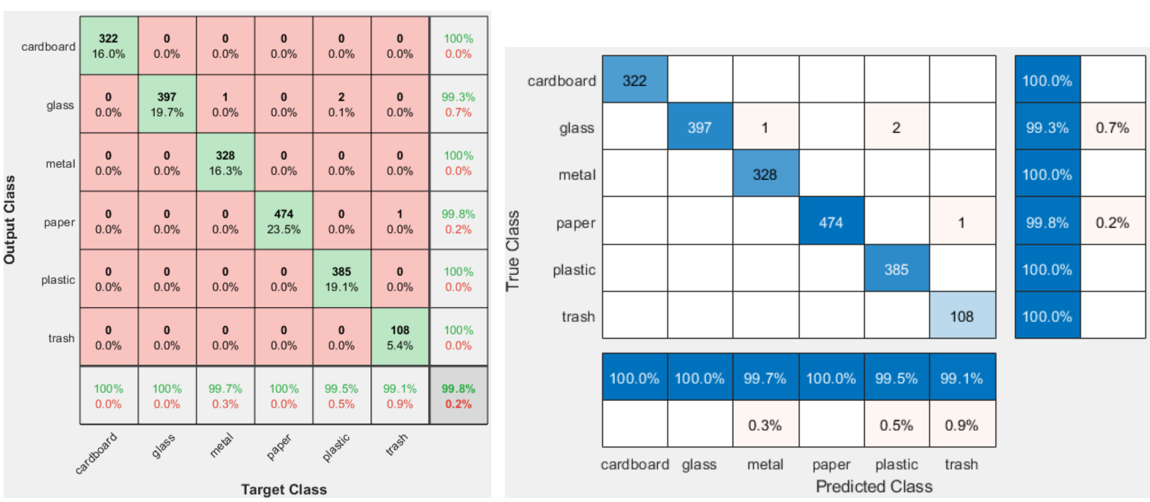
Augmentation helps reduce overfitting, which occurs when a model is too complex and unsuited to the training data, so it performs when tested. With more significant variation in the training data, the model is less likely to overfit.

4.3. Training Process

FIGURE 7. Training Process

The training process results show an accuracy of 98.29 with a training computing time of around 44 minutes, as shown in Figure 7. The graph results show stability between training and validation data and no overfitting. It also shows that the diminishing gradient does not occur during training.

4.4. Confusion Matrix



(a) (b)

FIGURE 8. Confusion matrix (a) Output Class vs Target Class, (b) True Class vs predicted class

The confusion matrix stage is shown in Figure 8 as an error in entering the class when compiling the model, where one glass class image was included in the metal class, two glass class images entered the plastic class, and one paper class image entered the trash class. From the results of one trial, the model accuracy was 99.8%.

4.5. Prediction

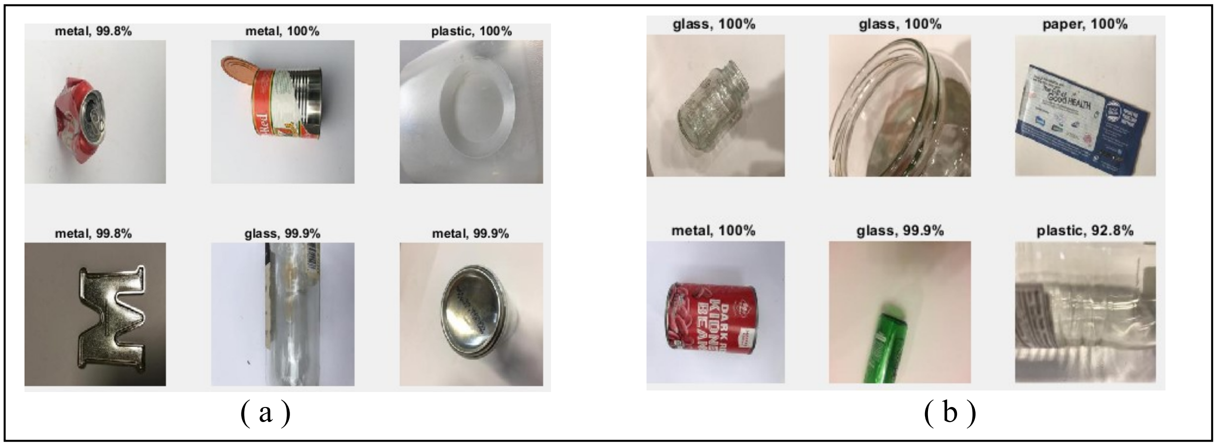


FIGURE 9. Prediction (a) Testing 01, (b) Testing 02

The forecasting results are shown in Figure 9, comparing the new experimental data with the training model that has been prepared. The results show that the system can recognize waste-type objects well. In the first test, predictions had a confidence level of accuracy for metal objects of 99.8% and 99.99%. In the second trial, glass was recognized with a believability accuracy of 99.9% and plastic 92.8%. The higher the model accuracy, the level of accuracy confidence also increases.

4.5. Comparison of Accuracy and Error Classification

Comparison charts are needed to determine the system response using different CNN architectures. It is necessary to know whether or not the training process is repeated to test stability. Deep learning accuracy is the average result of several training processes.

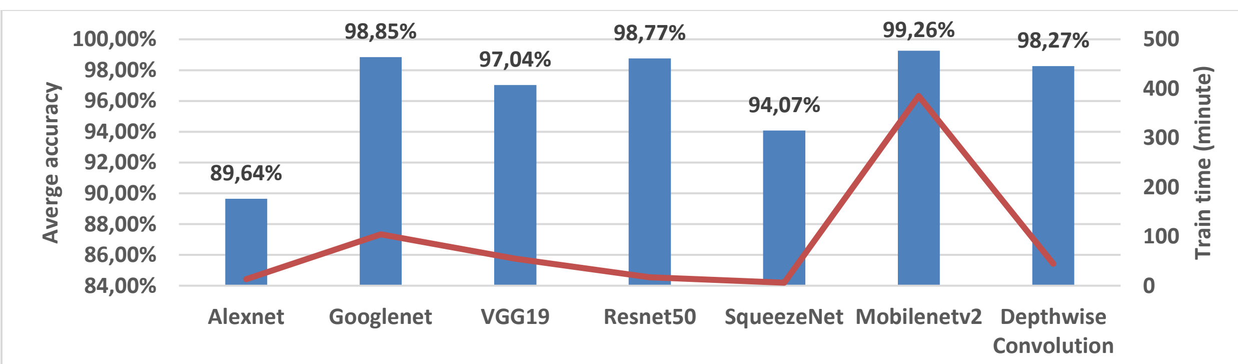


FIGURE 10. Comparison of Accuracy and Error Classification

Several test scenario results are shown in Figure 10. It shows that the system can work well, producing an average accuracy of 98.27% with a computing time of under 50 minutes to develop the model

V.CONCLUSION

The test scenario results show that the system was successfully implemented to recognize six classes of waste objects well. The aim of differentiating types of waste in tourism areas is fulfilled. Initial model selection helps obtain a suitable model. Inception uses small kernels in the convolution process, thereby lightening computation. The six well-identified classes include cardboard (393), glass (491), metal (400), paper (584), plastic (472), and waste (127). Data augmentation helps get the number of files in one class to avoid overfitting. The results obtained by the system can recognize class objects with an average model accuracy of 98.02% with a computing time for the training process to get the model of around 44 minutes. The average MSE value is 0.0343, RMSE 0.1852, and MAE 0.0229. After obtaining the model, predictions are made using experimental data, namely data outside of the training data with a confidence level of 98%-99.8% with a testing time of 1-2 seconds. Future research that can be done is to make recommendations after the classification process has been carried out.

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