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A Novel Intelligent Garbage Classification System Based on Deep Learning and an Embedded Linux System

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ABSTRACT The dramatic increase in the amount of garbage and complex diversity of the materials in the garbage bring serious environmental pollution problems and wastes resources. Recycling reduces waste but manual pipeline waste sorting involves a harsh working environment at high labor intensity with low sorting efficiency. In our paper, a novel intelligent garbage classification system based on deep learning and an embedded Linux system is proposed. The system is divided into three parts. First, a Raspberry Pi 4B is utilized as the master board for the hardware system. The peripherals of the system consist of a touch panel, sensors, a 2-DOF (degree of freedom) servo, and a camera. Second, a new GNet model for garbage classification based on transfer learning and the improved MobileNetV3 model is proposed. Third, a GUI based on Python and QT is employed to build a human-computer interaction system to facilitate system manipulation and observation. A series of garbage classification experiments on the Huawei Garbage Classification Challenge Cup dataset were conducted. The proposed classification system's prediction accuracy was 92.62% at 0.63 s efficiency. The experimental results in this paper demonstrate that the proposed intelligent garbage classification system delivers high performance both in terms of accuracy and efficiency.

INDEX TERMS Deep learning, embedded Linux system, intelligent garbage classification, MobileNetV3, transfer learning.

I. INTRODUCTION

The amount of garbage produced is growing globally, especially in developing countries; and is related to increased population and economic development [1]. This huge amount of garbage has caused severe environmental pollution and resource waste. One fundamental strategy for addressing this garbage problem is related to the "classification" and "recycling" of this solid waste. In recent years, increasingly more nations have started to explore recycling strategies in a new kind of cyclical economy for sustainable development that improves the environmental quality [2]. Manual garbage sorting is the most widely practiced garbage classification method as currently it is the most accurate method. Unfortunately, it is time consuming and requires trained operators, which seriously restricts the classification of garbage. Therefore, an automated garbage classification approach is urgently needed to address this growing challenge and thus has become a research hotspot worldwide.

Nowadays, various automated approaches for garbage classification have been proposed. These approaches can be categorized into the following three groups: mechanical approaches (MAs), Internet of Things approaches (ITAs), and artificial intelligence approaches (AIAs). An MA employs microprocessors, external sensors, and mechanical transmission in an automatic garbage classification system to effectively replace manual garbage sorting. This approach however, does not achieve the desired garbage classification

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effect due to low-accuracy recognition [3]–[5]. To address this problem, a novel ITA approach for automatic garbage classification was proposed. The ITA and a cloud server were used to construct a more automatic and higher accuracy garbage classification system, but it is difficult to install and maintain due to the high costs and complex structure of the system [6]–[9]. The AIAs for garbage classification that utilize artificial intelligence (AI) are highly accurate, adaptive, and robust. A prediction model trained using garbage data can be utilized to execute garbage recognition and classification tasks. However, the existing classification algorithms run on high-performance servers or PCs and do not satisfy the actual demands of garbage classification systems [10]–[13]. Therefore, realizing a highly precise and efficient classification system that satisfies actual real-world demands remains a yet-unsolved challenge.

In this paper, we focus on an embedded system and deep learning to deal with this challenge. First, based on initial work, we observed that the costs and maintainability of an intelligent garbage classification system determine whether the system can be applied in practice. An embedded system is a special purpose computing system applied in application environments or in other computing systems to provide specialized support. An embedded system reduces the complexity of a garbage classification system and simplifies installation and maintenance tasks, thus reducing the costs. Second, the existing image classification algorithms for garbage classification have high computational complexity and usually need a large-scale labeled dataset. Unfortunately, since public garbage datasets do not currently exist, we can only rely on image searches via the Internet and thus limited data are available [14]. Therefore, we apply transfer learning [15] and pre-trained a convolutional neural network (CNN) model [16] on the large-scale ImageNet dataset [17], which helps transfer knowledge from a well annotated dataset to a real-world application without training data. Transfer learning has been widely adopted in various image classification fields [18]–[20]. This strategy can effectively enhance the accuracy and robustness of the system. In addition, a lightweight network is needed to match the computational ability of the embedded Linux system. A series of garbage classification experiments using the Huawei Garbage classification Challenge Cup dataset were conducted, and the results showed that the prediction accuracy of the proposed garbage classification system was 92.62% at an efficiency rate of 0.63 s. The experimental results presented in this paper demonstrate that the novel intelligent garbage classification system achieves state-of-the-art performance.

The contributions of this paper are as follows:

- We analyze and summarize the challenges of the garbage classification system with respect to the prevailing deep learning and garbage classification approaches.
- We present a new model GNet based on transferring the ImageNet model and improving MobileNetV3 [21] for garbage classification. This reduces the data requirements of the model and improves operational efficiency.
- The hardware framework of our system is a Linux embedded system combined with a peripheral device. Moreover, a GUI based on Python and QT is employed to build a human-computer interaction (HCI) [22] system that facilitates the system manipulation and observations.

The remainder of this work is organized as follows. Sec. II briefly describes the implementation of the method, including the hardware and network model design for garbage classification. Sec. III elaborates the experimental results and analysis, including the accuracy and efficiency analysis, the parameter settings, and the system tests. Concluding remarks are presented in Sec. IV.

II. IMPLEMENTATION

The structure for implementing the intelligent garbage classification system is shown in Figure 1. This implementation includes two parts: the garbage classification hardware and network model designs. First, the hardware system consists of a Linux embedded system and a peripheral device. In addition, a GUI based on Python and QT is employed to build a HCI system that enables the manipulation and observation of the system. The expansion board simplifies the connection between the peripherals and the Raspberry Pi 4B. Images of the actual system are on the far right of Figure 1. Second, for the network model design for garbage classification, the core identification part of the system is the GNet model, shown on the far bottom left of Figure 1. GNet reduces the data requirements of the model and improves operating efficiency. The implementation of the system will be discussed in detail in the following sections.

A. HARDWARE DESIGN

A Raspberry Pi 4B is utilized as the master board for the hardware system; and the peripherals consist of a touch panel, sensors, a 2-DOF(degree of freedom) servo, and a camera. The configuration information for the hardware device is illustrated in Table 1. The entire hardware system can be divided into four modules: the master control module, the garbage delivery module, the detection module, and the GUI human-computer interaction module. The detailed functional information is as follows:

1) MASTER CONTROL MODULE

The Raspberry Pi 4B is used as the master board for the hardware system. The Raspberry Pi 4B can capture garbage image information from the camera and transfer the captured image information into the prediction model for recognition. In addition, it can also control and coordinate the operation of other modules.

2) GARBAGE DELIVERY MODULE

This module, which primarily includes the 2-DOF servo and acrylic pallet, is responsible for delivering garbage to the classification barrels. The servo is located in the center of the physical system frame, the pallet is secured to the servo and the Raspberry Pi controls the rotation of the servo through

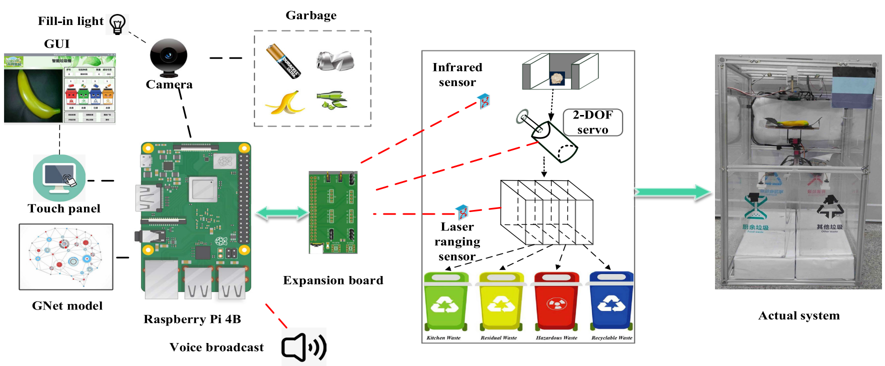


FIGURE 1. The overall design of intelligent garbage classification system.

TABLE 1. Configuration of hardware devices.

Hardware devices	Configuration	Hardware devices	Configuration
Power supply	**Model:** Lithium batteries **Capacity:** 18,000 mAh **Output:** 5.0V	Camera	**Model:** Camera v2 **Physical pixels:** 8 megapixels
Infrared sensors	**Model:** TCRT5000 **Size:** 32mm x 14mm **Rated voltage:** 3~5V **Detection distance:**1mm~25mm	Servo	**DOF:** 2 **Model:** MG996 **Rated voltage:** 4.8~6.8V
Laser ranging sensor	**Model:**TOF10120 **Rated voltage:** 3~5V **Detection distance:** 100~1800mm	System framework and composition materials	**Materials :** Aluminum alloys and acrylic sheets

the universal GPIO port. The servo consists of two parts: the upper servo and the lower servo. The upper servo controls the tray to rotate it vertically up and down and the lower servo controls the tray to rotate it horizontally from side to side. Based on the recognition results, the garbage will be delivered and dumped into the corresponding classification barrels by the servos.

3) DETECTION MODULE

This module is used for system detection and is divided into two parts: garbage drops detection and full load detection. The implementation of the garbage drop detection part is based on an infrared sensor. After the user puts garbage on the acrylic pallet, the infrared sensor will capture this information and immediately send a signal to the Raspberry Pi 4B main control board. The Raspberry Pi 4B will switch from the detection to the recognition state for garbage recognition and classification. The laser ranging sensors are the basic equipment to implement full load detection and are distributed in each of the four classification barrels. The laser ranging sensors are located on one side of the barrel wall of the classification barrel and communicate with the Raspberry Pi through four serial ports. After the laser ranging sensors are started, they can continuously capture the distance. If sensors detect a change in the status and the distance is less than the width of the barrel, they will immediately send a signal to the Raspberry Pi 4B indicating that the garbage barrel is fully loaded, and the Raspberry Pi will provide a full-load warning based on the signal.

4) GUI HUMAN-COMPUTER INTERACTION MODULE

Displaying various kinds of system information is the main responsibility of the GUI human-computer interaction module. The system information can be categorized into the following three groups: collection information, recognition information, and advertisement information. The system displays the garbage images collected by the camera and the full load information detected by the laser ranging sensor. Recognition information, such as the order of delivery, the garbage recognition results, the amount of garbage, and the completion of the task, can be displayed. Advertisement information related to garbage classification and recycling will be played on a loop to strengthen the human environmental awareness of garbage classification and recycling.

B. NETWORK MODEL DESIGN

In order to reduce the data requirements of the model and improve the operating efficiency, we propose a novel

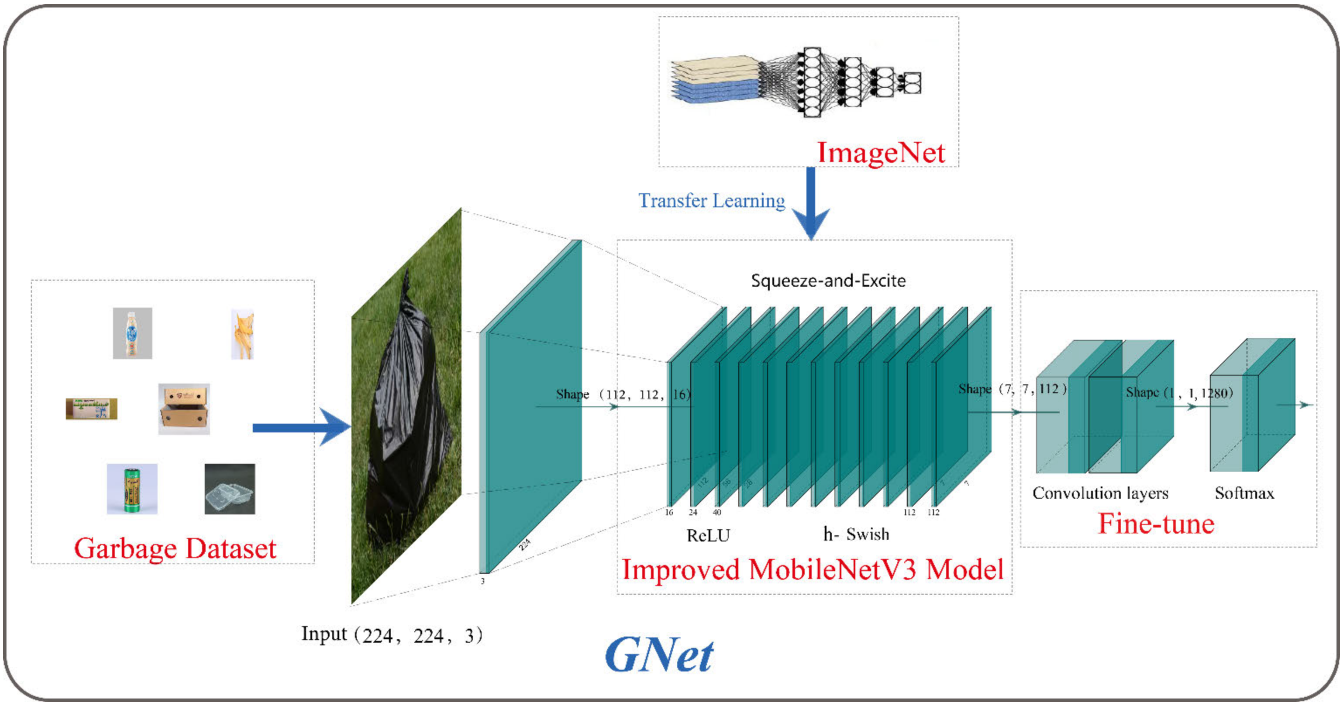


FIGURE 2. **The structural diagram of the GNet model.**

model GNet utilizing transfer learning and an improved MobileNetV3 model. The structure of GNet is shown in Figure 2, and it includes two parts: a pre-trained ImageNet model and an improved MobileNetV3 model. In this section, we will demonstrate the implementation of GNet in detail.

1) PRE-TRAINED IMAGENET MODEL

Transfer Learning (TL) [15] is a method that uses an artificial neural network (ANN) pre-trained on a large annotated image database to complete various tasks. TL focuses on storing the knowledge gained by solving a problem and applying it to different but related problems. The transfer learning process is demonstrated in Figure 3. It essentially uses additional data so that the ANN can decode garbage items using the features of past experiences and develops an improved generalization ability [23].

Transfer learning was employed in this paper to address the problem of the lack of garbage data samples. Using TL technology, we selected the ImageNet model as the source model to extract features from the input layer and bottleneck layer. The ImageNet model has 20 layers is composed of many convolutional layers and pooling layers. The transfer model processes are as follows.

First, in order to utilize the image features more flexibly, we discarded the $1 \times 1 \times 576$ and $1 \times 1 \times 1024$ convolutional layers at the end of the ImageNet model. Second, for the model feature extraction part, the final $7 \times 7 \times 160$ convolution layer and pooling layer are removed, and only the input layer and the bottleneck layer are retained. The parameters of all removed layers were trained on the Huawei Garbage

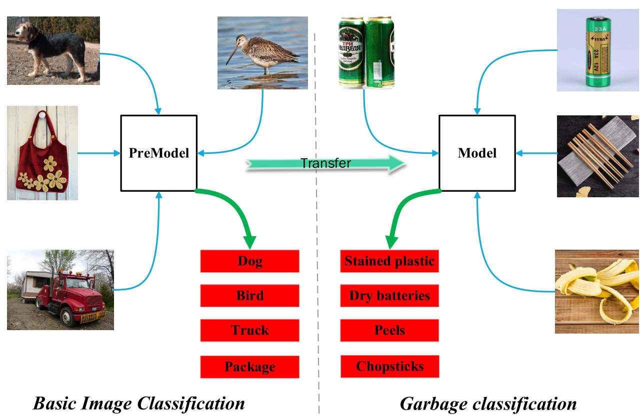


FIGURE 3. **Transfer learning diagram.**

Classification Challenge Cup dataset. The outcome of this design is that not only were the garbage sample requirements reduced but also the generalization ability of the model was improved. Third, we transferred the layers to be reused in the garbage classification domain and use the output of these layers as the input to train the model with fewer parameters and a smaller scale dataset. The garbage classification domain model only needs to understand the internal relationships of specific problems and learns the image characteristics contained in the data through the ImageNet model. This transfer technique retained the feature extraction ability of the pretrained model so that the recognition accuracy and generalization ability were improved while solving the problem of a lack of samples.

TABLE 2. Experimental system environment.

Server	Detail	Embedded system	Detail
Model	Dell PowerEdge R730	Model	Raspberry Pi 4B
CPU	Intel(R) Xeon(R) 2.20GHz	CPU	ARMv7 1.5GHz
GPU	GEFORCE RTX 2080 Ti	*	*
Operation System	CentOS Linux 7	Operating System	GNU/Linux 10
Memory	64GB	Memory	8GB
TensorFlow	Version 2.4.1	TensorFlow	Version 2.1.0
Python	Version 3.6.8	Python	Version 3.7.3

2) IMPROVED MOBILENETV3 MODEL

MobileNetV3, as a new generation lightweight network, combines the deep, detachable convolution, deficit residual structure with linear bottlenecks and a lightweight attention model based on the Squeeze-and-Excite (SE) structure [24]. The developer of MobileNetV3, based on the previous generation MobileNetV2 [25], moved the average pooling layer forward, removed the last convolutional layer in the last step, and introduced the h-swish activation function instead of ReLU [26]. MobileNetV3 provides an embedded system with a lightweight network model that is fast with high efficiency and accuracy [27].

Analyzing the architecture of the MobileNetV3 model revealed that unnecessary computational overhead was caused by redundant bottlenecks since there are only dozens of garbage categories in the common garbage classification scenario. Thus, we modified the architecture to reduce the latency while maintaining the accuracy. There were three modifications: a reduction of the numbers of bottleneck layers and channels, the addition of the SE module, and fine-tuning of the model.

The first modification decreased the numbers of bottleneck layers and channels in order to further increase the efficiency. We removed the $112 \times 112 \times 16$, $56 \times 56 \times 24$, and $28 \times 28 \times 24$ bottleneck layers of the network to reduce the latency of the model while maintaining the accuracy. Thus, the depth of the model is reduced to 12 layers. In addition, according to the adjusted network structure, we also reduced the number of channels of the inverse residual structure in the later bottleneck layers. The outcome of this design is that the computational costs and latency of the feature extraction was further reduced. The second modification adds an SE module to all bottleneck layers. We find that this increased the accuracy with a modest increase in the number of parameters, and no discernible latency costs. We also added two convolution layers to serve the output of the whole feature extraction layer and adopted the SoftMax classifier to convert the result into a probability distribution. With these modifications, we ended up with an improved MobileNetV3 model with 18 layers. The improved MobileNetV3 model has high recognition accuracy with a smaller model size and less calculation time.

III. EXPERIMENT

A. EXPERIMENTAL ENVIRONMENT

The GNet model is trained on a server while the actual operations are performed on the embedded system. Therefore, the experimental environment in our paper is divided into two parts (see Table 2): the server and the embedded system. For the server, we selected the Dell PowerEdge R730 based on the CentOS Linux 7 operating system. The hardware environment of the server is an Intel(R) Xeon(R) CPU E5-2650 v4 @ 2.20 GHz CPU, a GEFORCE RTX 2080 Ti GPU, and 64 GB of memory; and the software environment is based on TensorFlow version 2.4.1 and Python version 3.6.8. For the embedded system, a Raspberry Pi 4B, which is based on the Raspbian GNU/Linux 10 operating system, is employed as the master board. The hardware environment includes an ARMv7 Processor rev 3 (v7l) 1.5 GHz CPU and 8 GB memory, and the software environment is based on TensorFlow version 2.1.0 and Python version 3.7.3.

B. EXPERIMENTAL DATASET

In order to test the effectiveness of the proposed model, the Huawei Garbage Classification Challenge Cup dataset[1] was used, and the detailed information of this dataset is as follows.

This dataset consists of 40 categories garbage (see Figure 4). Residual waste includes the following categories: fast food boxes, stained plastic, cigarettes, toothpicks, pots and bowls, and bamboo chopsticks. Kitchen waste includes the following categories: leftovers, bones, peels, rotten pulp, tea leaves, cauliflower leaves, eggshells, and fishbones. Recyclable waste includes the following categories: portable batteries, packages, cosmetic bottles, plastic toys, plastic bowls, plastic hangers, express paper bags, plugs, used clothes, cans, pillows, plush toys, shampoo bottles, broken glass, leather shoes, chopping blocks, cartons, seasoning bottles, wine bottles, metal food cans, pots, edible oil bottles, and beverage bottles. Hazardous waste includes the following: dry batteries, ointment, and expired drugs. Moreover, in order

[1]The original Huawei Garbage Classification Challenge Cup dataset was downloaded from. https://modelarts-competitions.obs.cn-north-1.myhuaweicloud.com/ _classify/dataset/ garbage_classify _v2.zip

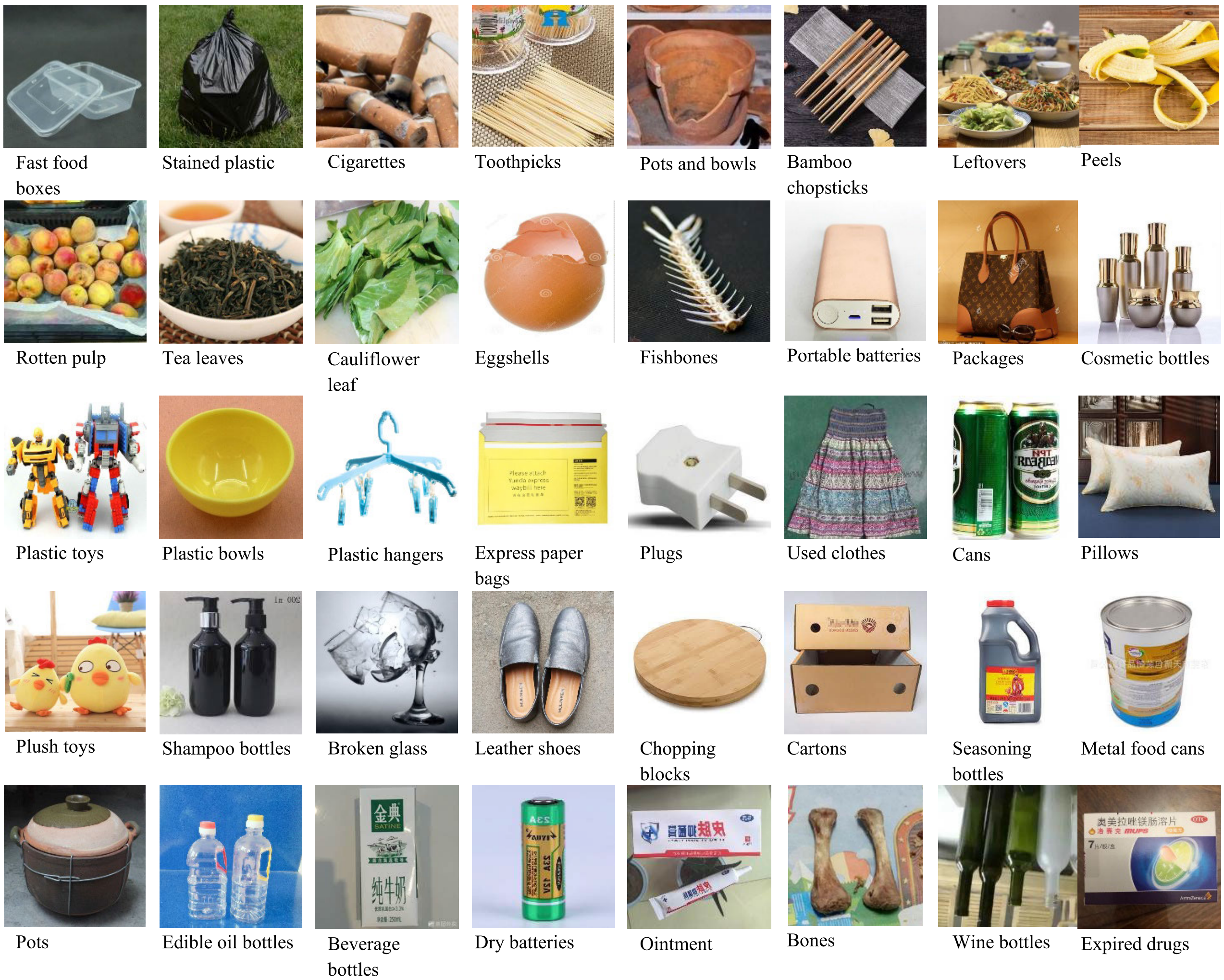


FIGURE 4. The huawei garbage classification challenge cup dataset.

to enhance the generalization ability and robustness of the model, the training samples were expanded and adjusted using techniques including random rotation, random symmetry, random cropping, and others. Each category of the dataset contains 600 images for a total of 24000 images measuring 256×256 pixels, and all images are labeled with garbage categories. The dataset was divided at a ratio of 5:1 in the experiment. We selected 500 images of each category of garbage images as training samples and 100 images as the testing samples.

C. EXPERIMENT AND ANALYSIS

1) EXPERIMENTAL DESIGN

In order to demonstrate the effectiveness of the GNet model, we performed experiments to evaluate the accuracy, efficiency, and parameter settings to determine the effects of various design decisions. The specific experimental designs are described as follows.

a: ACCURACY ANALYSIS

A confusion matrix and the kappa coefficient are utilized to evaluate the accuracy of GNet. A confusion matrix is the most basic and intuitive method to evaluate a classification model. In image classification, the confusion matrix allows the comparison of the classification with the actual measurement values. The ability of the tested methods to correctly identify 40 types of garbage was measured using a confusion matrix.

Precision reflects the proportion of the positive samples that are determined by the classifier to be positive samples. The recall rate reflects the portion of positive cases of correct judgment with respect to the total positive samples. The precision and recall are expressed as in (1) and (2), respectively.

$$precision = \frac{TP}{TP+FP} \tag{1}$$

$$recall = \frac{TP}{TP+FN} \tag{2}$$

where TP (true positives) is the real examples, FN (false negatives) is the false negative examples, FP (false positives) is the false positive examples, TN (true negatives) is the true negative examples, precision indicates the accuracy, and recall indicates the recall rate.

The kappa coefficient is an indicator used to test consistency and measure the classification accuracy and is used to evaluate the overall model classification accuracy. It tests whether the prediction results of the model are consistent with the results of the actual classification. Typically, kappa falls between 0 and 1 and can be divided into five groups representing different levels of consistency: very low consistency (0.0∼0.20), general consistency (0.21∼0.40), moderate consistency (0.41∼0.60), high consistency (0.61∼0.80) and almost perfect consistency (0.81∼1). The calculation formula is shown in equation (3).

$$Kappa = \frac{p_0 - p_e}{1 - p_e} \tag{3}$$

where p_0 is the proportion of cases correctly classified and p_e is the expected proportion of cases correctly classified by chance. If kappa is closer to 1, then the model classification performance for various types of garbage is more accurate.

b: EFFICIENCY ANALYSIS

The trained models are transferred to the embedded system (Raspberry Pi 4B) to evaluate the efficiency. The loading time (LT) and average recognition time (ART) are employed as metrics to evaluate the efficiency. LT is the time required for the Raspberry Pi 4B system to load the model into memory. ART is calculated using the total recognition time (ITT), and the equation is shown in (4).

$$ART = \frac{ITT}{NUM} \tag{4}$$

where NUM represents the total number of test images, ITT represents the total time required for identifying the NUM test images, and ART the indicates average recognition time.

c: PARAMETER SETTINGS

The parameter settings also greatly affect the model accuracy. Therefore, we plotted the loss curve and the accuracy curve at learning rates of 0.01, 0.05, 0.005, 0.002, and 0.001 to discuss the setting of the learning rate and number of iterations in detail.

2) ACCURACY ANALYSIS

The training accuracy and testing accuracy of GNet and other models were recorded, and the confusion matrix and kappa coefficient were utilized to evaluate the accuracy of GNet. We selected five more types of classification models to compare with GNet: ResNet34 [28], VGG16 [29], InceptionV3 [30], DenseNet121 [31], and MobileNetV3. ResNet34 is an improved model proposed by Kang *et al.* [10]. The training accuracy and testing accuracy of each model are shown in Table 3.

TABLE 3. The accuracy and loss of each model.

Algorithm	Training		Testing	
	Accuracy	Loss	Accuracy	Loss
ResNet34	0.9910	0.0312	0.8063	0.7975
VGG16	0.7320	1.0319	0.6344	1.3182
InceptionV3	0.9868	0.0984	0.7712	1.4518
DenseNet121	0.9520	0.1464	0.7047	1.2785
MobileNetV3	0.9984	0.0136	0.8634	0.6186
GNet(ours)	**0.9990**	0.0097	**0.9262**	0.5247

These results show that GNet obtained the highest training accuracy (99.90%) and testing accuracy (92.62%) among the six tested classification models on the Huawei Garbage Classification Challenge Cup dataset. The DenseNet121 network consists of considerably more layers than the GNet model and achieved more accurate performance on many natural image classification benchmarks than other shallow CNN models but did not obtain accurate garbage classification results on the Huawei Garbage Classification Challenge Cup dataset. Furthermore, DenseNet121 was less accurate than ResNet34 and InceptionV3. In addition, the testing accuracy of VGG16 was only 63.44%, which is the lowest accuracy among the tested models.

In order to evaluate the classification performance of the proposed GNet, we created confusion matrices to reflect the classification accuracy of garbage subclasses, as shown in Figure 5. The confusion matrix is divided into two groups: one is the confusion matrix of the forty subcategories of the Huawei Garbage Classification Challenge Cup dataset in the left column (40-CM), and the other is the confusion matrix of four categories of garbage (hazardous waste, kitchen waste, residual waste and recyclable waste) in the right column (4-CM).

When analyzing the confusion matrix (Figure 5) on the Huawei Garbage Classification Challenge Cup dataset, the GNet model gives the most accurate performance, while VGG16 model give the least accurate results. In the 40-CM of GNet (see Figure 5 (k)), there are 25 recognition accuracies above 80% and 13 above 90%. In addition, all of the accuracies in the 4-CM of GNet (see Figure 5 (l)) are above 90%. In addition, the 40-CM of MobileNetV3 (see Figure 5 (i)) also illustrates positive results with accuracy above 80% for 28 categories of garbage and accuracy above 90% for 8 categories of garbage. However, its 4-CM (see Figure 5 (j)) is less accurate than that of GNet, and the classification accuracies of MobileNetV3 for hazardous waste (85%) and residual waste (87%) do not reach 90%. The 40-CM of VGG16 (see Figure 5 (c)) shows that the models' accuracy is approximately 60%, which is the least accurate performance. In addition, its 4-CM (see Figure 5 (d)) also illustrates poor performance. Its accuracy on residual waste is only 64% due to the monotonous network structure and the weak network depth. The kappa coefficient was calculated to verify the overall accuracy of the GNet model.

The kappa coefficients are calculated based on the confusion matrices and are illustrated in Table 4. Conforming to the confusion matrices, the kappa coefficients are also divided

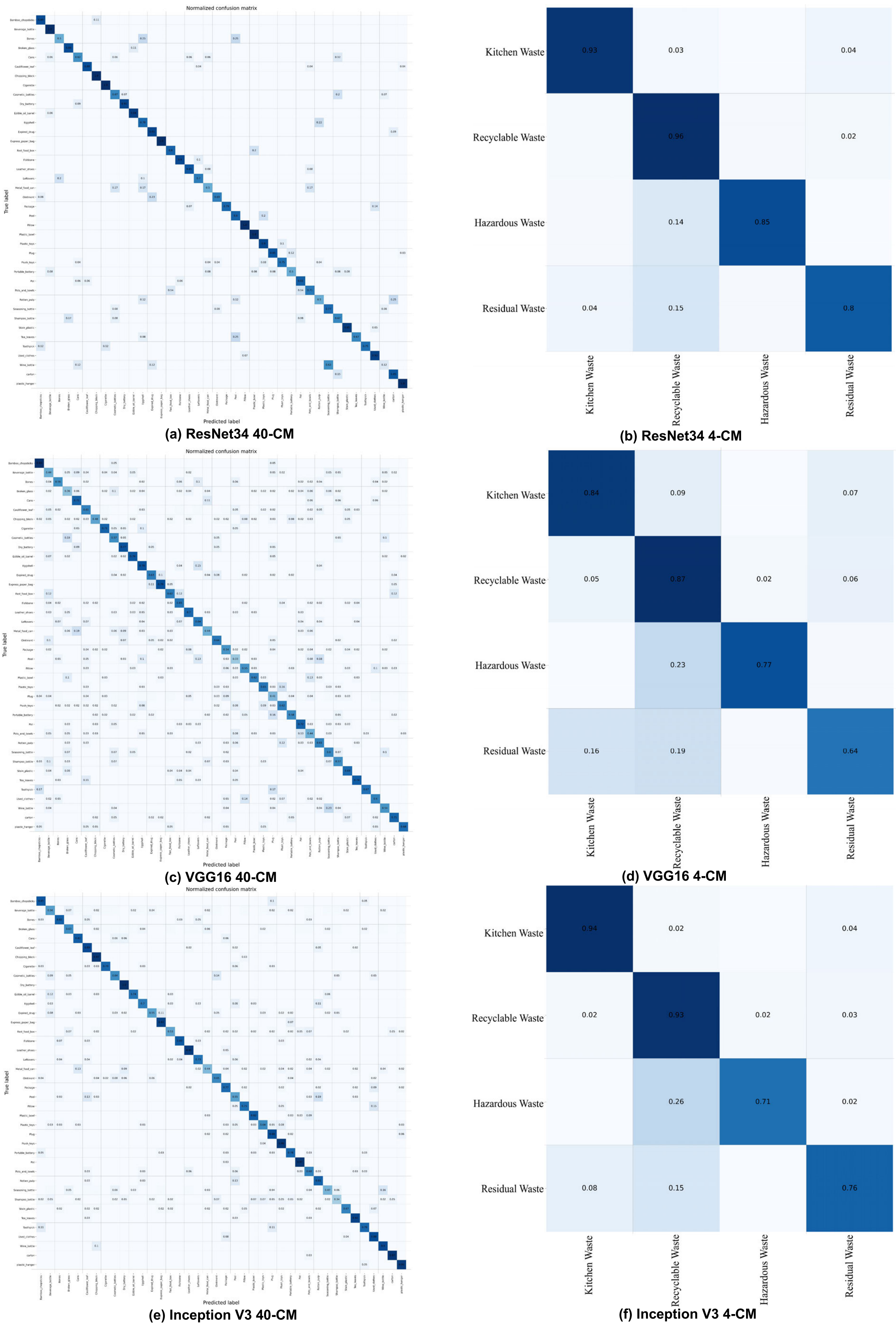
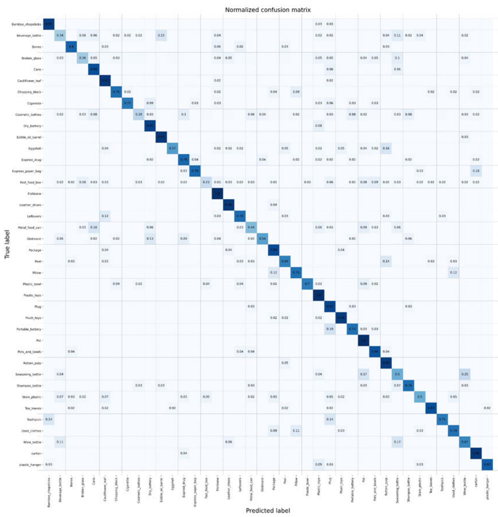
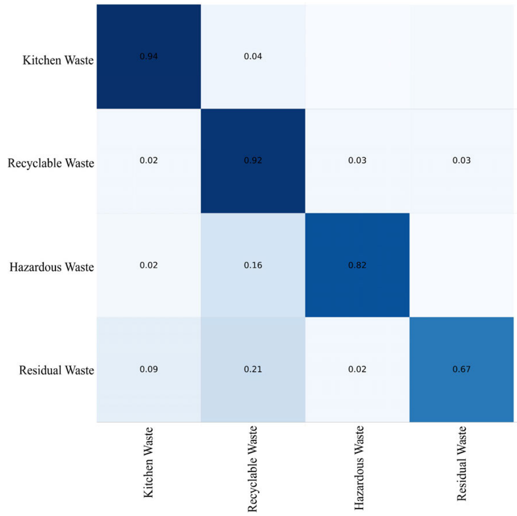


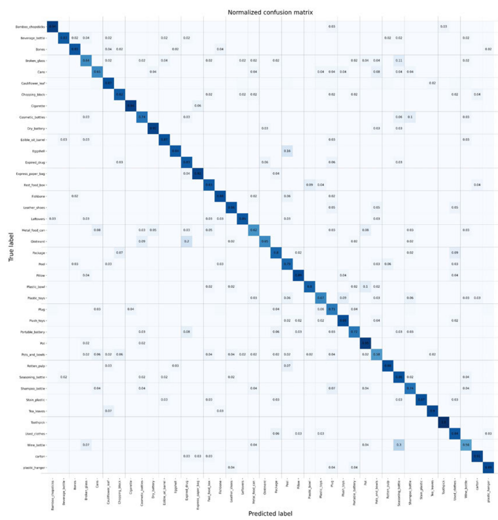
FIGURE 5. Confusion matrix for each neural network. (a) ResNet34 40-class confusion matrix. (b) ResNet34 4-class confusion matrix. (c) VGG16 40-class confusion matrix. (d) VGG16 4-class confusion matrix. (e) InceptionV3 40-class confusion matrix. (f) InceptionV3 4-class confusion matrix. (g) DenseNet121 40-class confusion matrix. (h) DenseNet121 4-class confusion matrix. (i) MobileNetV3 40-class confusion matrix. (j) MobileNetV3 4-class confusion matrix. (k) GNet 40-class confusion matrix. (l) GNet 4-class confusion matrix.



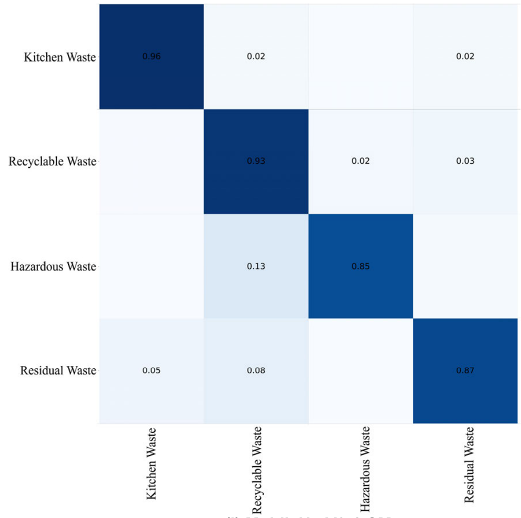
(g) DenseNet121 40-CM



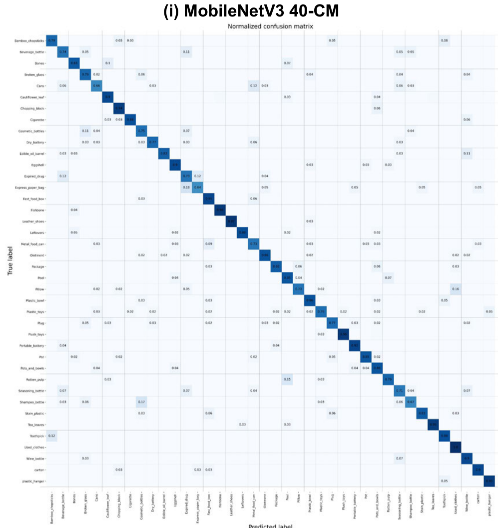
(h) DenseNet121 4-CM



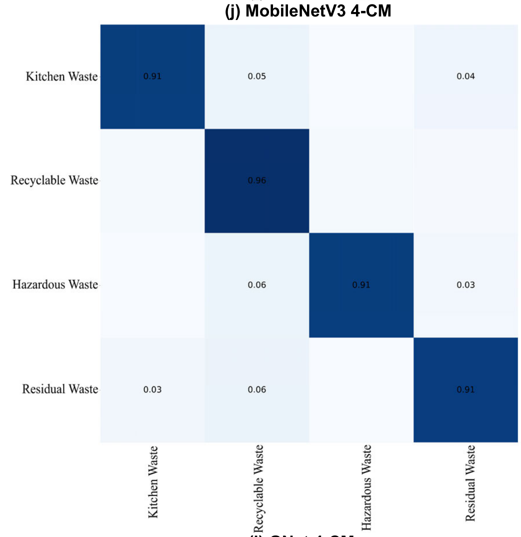
(i) MobileNetV3 40-CM



(j) MobileNetV3 4-CM



(k) GNet 40-CM



(l) GNet 4-CM

FIGURE 5. ***(Contined.)*** **Confusion matrix for each neural network. (a) ResNet34 40-class confusion matrix. (b) ResNet34 4-class confusion matrix. (c) VGG16 40-class confusion matrix. (d) VGG16 4-class confusion matrix. (e) InceptionV3 40-class confusion matrix. (f) InceptionV3 4-class confusion matrix. (g) DenseNet121 40-class confusion matrix. (h) DenseNet121 4-class confusion matrix. (i) MobileNetV3 40-class confusion matrix. (j) MobileNetV3 4-class confusion matrix. (k) GNet 40-class confusion matrix. (l) GNet 4-class confusion matrix.**

TABLE 4. Kappa coefficient for each model.

Algorithm	40-CK	4-CK
ResNet34	0.77	0.81
VGG16	0.63	0.74
InceptionV3	0.74	0.81
DenseNet121	0.63	0.78
MobileNetV3	0.80	0.85
GNet(ours)	**0.85**	**0.90**

TABLE 5. Results of the efficiency evaluation.

Algorithm	Loading time(s)	Average time(s)	Total time(s)
ResNet34	20.30	0.68	273.01
VGG16	**5.01**	1.99	799.19
InceptionV3	35.67	0.81	325.17
DenseNet121	48.52	1.10	438.45
MobileNetV3	18.16	0.40	142.78
GNet(ours)	10.79	**0.23**	109.34

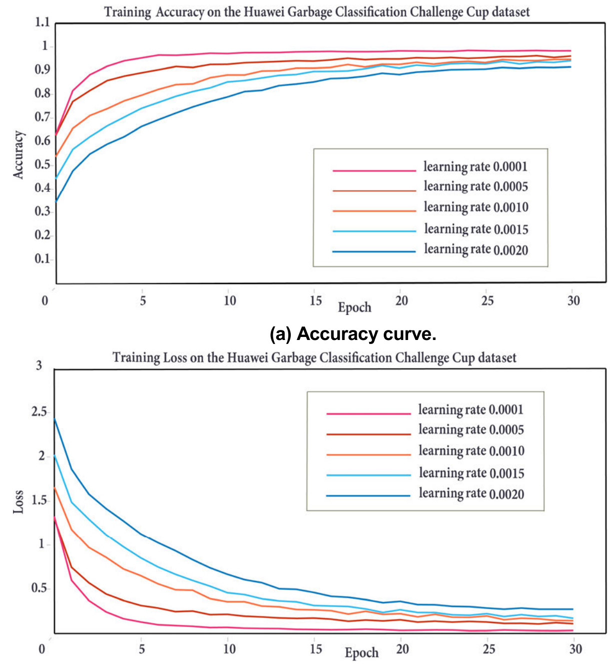
into the kappa coefficient of the forty categories of garbage (40-CK) and the kappa coefficients of the four categories of garbage (4-CK).

The 40-CK and 4-CK of GNet were 0.85 and 0.90, respectively, which fall in the range of 0.8 to 1. These results indicate that GNet obtained an almost perfect consistency result. The other models are inferior to GNet. For example, the 40-CK and 4-CK of VGG16 (see Table 4) are only 0.63 and 0.74, respectively.

However, it was difficult for all models to distinguish garbage with similar characteristics, such as expired drugs, express paper bags, cosmetics bottles, and shampoo bottles. The GNet model is no exception to this and its recognition accuracies for cans and shampoo bottles were only 66% and 67%, respectively. However, the garbage can be distinguished into four categories (hazardous waste, kitchen waste, residual waste and recyclable waste) correctly by GNet, with an accuracy of above 90%. In addition, the 4-CK of GNet is above 90%, which indicates that the performance of GNet in identifying similar garbage conforms to practical needs. Regarding the other models, not only do they have difficulties identifying similar garbage, but also the problem of misclassifying the four categories of garbage exists. The accuracies of InceptionV3 in identifying expired drugs and metal food cans are only 55% and 44%, respectively. In addition, the classification accuracies of hazardous waste and residual waste are only 71% and 76%, respectively. Similarly, VGG16 did not achieve a satisfactory recognition accuracy for similar garbage, such as beverage bottles, broken glass, metal cans, pulp, and plugs, at only approximately 35%. In addition, the classification accuracies of hazardous waste and residual waste are only 77% and 64%, respectively. Based on these results, it can be inferred that GNet has high-precision performance and outperformed the other tested garbage classification models.

3) EFFICIENCY ANALYSIS

Most of the implementation of the intelligent garbage classification system was based on the embedded system. The model needs both high recognition accuracy and high operating efficiency. Therefore, we designed an experiment using the Raspberry Pi 4B board to evaluate the recognition efficiency of models. The loading time (LT) and average recognition time (ART) are employed as efficiency evaluation indexes. We randomly selected 10 images from each category of garbage from the Huawei Garbage Classification Challenge Cup dataset for a total of 400 test images. The 400 test images were entered into the prediction model, and the load times (LTs) and total recognition times (ITTs) of the models were recorded. The results of the experiment are shown in Table 5.



(a) Accuracy curve.

(b) Loss curve.

FIGURE 6. Convergence curve. Learning rate 0.0001 (lr-0.0001), learning rate 0.0005 (lr-0.0005), learning rate 0.001 (lr-0.001), learning rate 0.0015 (lr-0.0015) and learning rate 0.002 (lr-0.002).

GNet achieved the lowest ART and the second lowest LT, which is the most efficient performance. The GNet load model took only 10.79 seconds, and the ART took only 0.23 seconds. In addition, VGG16 achieved the shortest LT due to its concise network depth and small number of parameters. However, this also leads to low efficiency and recognition accuracy. The ART of VGG16 is 1.99 seconds, and it is the least efficient. GNet outperformed the other models in terms of both LT and ART, but the overall efficiency of MobileNetV3 is second only to GNet. The overall efficiencies

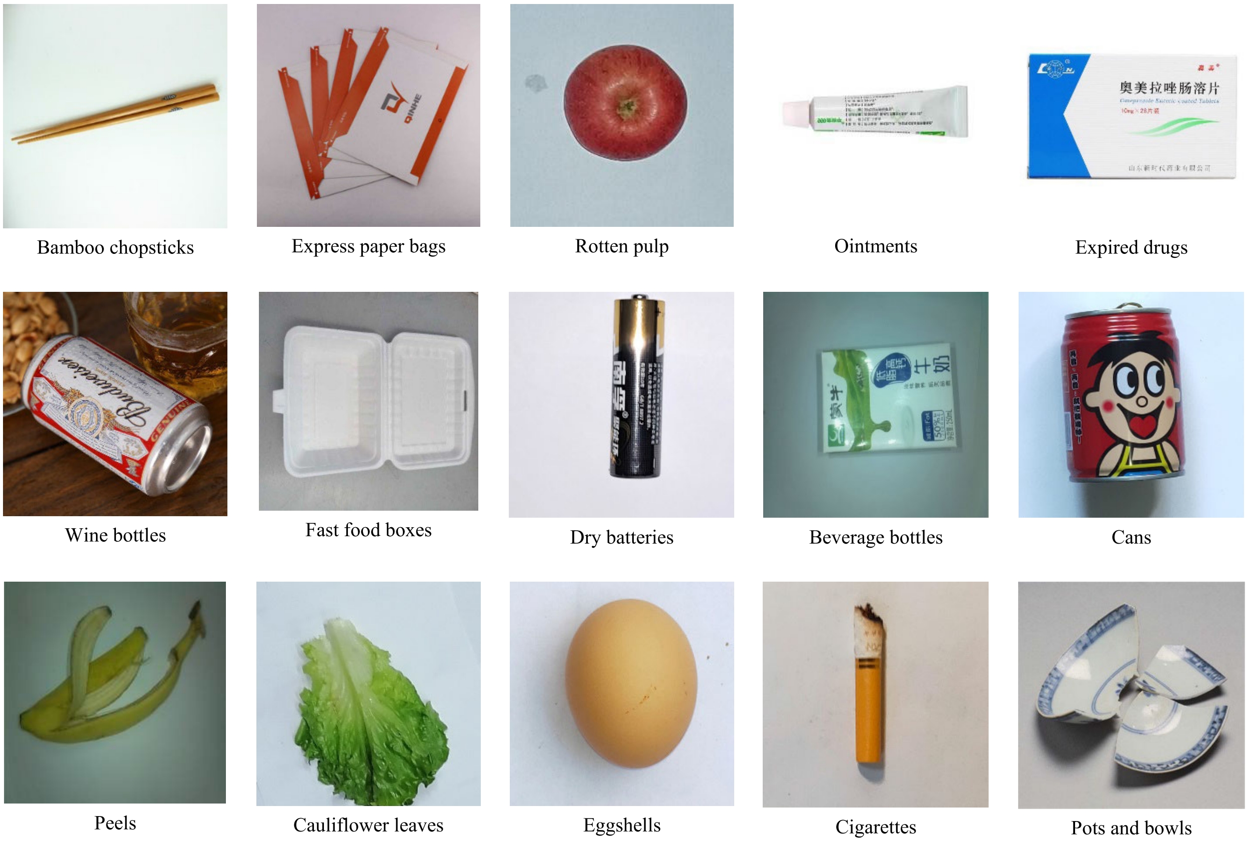


FIGURE 7. Actual garbage test set.

of ResNet34, InceptionV3, and DenseNet121 were in third, fourth, and fifth places, respectively. Therefore, it is clear that although the proposed GNet obtains the second LT, its overall efficiency is the most compelling compared with those of the other tested models. The experimental results indicate that the GNet proposed in this paper is the most efficient model in terms of operational efficiency in an embedded environment.

4) PARAMETER SETTINGS

In this section, we analyze the training parameters in detail and discuss the setting of the learning rate and the number of iterations. As is known, the parameter settings also greatly affect the model accuracy. Therefore, the loss curves and the accuracy curves are plotted at learning rates of 0.01, 0.05, 0.005, 0.002, and 0.001, as shown in Figure 6.

As Figure 6 shows, when accuracy and loss are close to the convergence point, lr-0.002 was the least accurate, and lr-0.0001 had the most accurate performance. All the accuracy and loss curves of GNet tend to be gentle in the later training period and only fluctuate across a small range. Because we used the transfer learning approach, the accuracy and loss curves of GNet converge successfully after only about 20 rounds of training. In the lr-0.0001scenario, GNet successfully converged after only 10 rounds of training with the highest accuracy (99.98%) and the lowest loss (0.014). However, the learning rate of 0.02 is too high and leads to the slowest convergence speed of the curve and the lowest

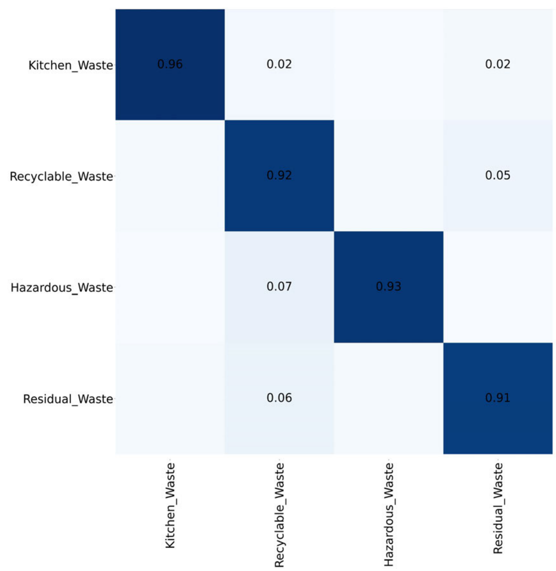


FIGURE 8. The overall test confusion matrix (4-CM).

accuracy. Based on these results, the learning rate was set to 0.0001 and the number of iterations set to 15.

5) SYSTEM TESTING

We evaluated the overall performance of the intelligent garbage classification system proposed in this paper through field tests using real garbage. We collected 150 images of garbage and uniformly labeled them into 15 categories, shown in Figure 7. These included bamboo chopsticks, plush toys, leftovers, cartons, packages, plugs, pillows, dry batteries, alcohol bottles, cans, rotten pulp, cauliflower leaves, eggshells, cigarettes, and pots and bowls.

The 15 categories of garbage were delivered to the garbage classification system, and their respective average period, 4-CM, and kappa coefficient were recorded and calculated. The average processing period is the time from when the garbage is put into the system to when the garbage is automatically delivered to the classification bucket. The performance results for the entire intelligent garbage classification system test results are given in Figure 8.

Figure 8 shows that the actual garbage recognition accuracy of the intelligent garbage classification system in field tests was consistent with the experimental results. All of the accuracy results in the 4-CM confusion matrix were above 90%. In addition, we also found that the average processing period of the intelligent classification system is only 0.63 seconds and the 4-CK was as high as 0.90, which indicates that the garbage classification system has high efficiency and high accuracy. These test results indicate that the intelligent garbage classification system based on deep learning and embedded system presented in this paper not only can accurately identify garbage but also operate efficiently and steadily.

IV. CONCLUSION

Currently, garbage classification can promote environmental conservation, develop a circular economy and relieve the pressure of resource consumption. In this paper, we proposed a novel intelligent garbage classification system based on deep learning and an embedded Linux system. This system provides a new solution for automatic garbage classification. A series of garbage classification experiments were conducted on the Huawei Garbage Classification Challenge Cup dataset. The experimental results in this paper demonstrate that the intelligent garbage classification system accurately and efficiently identified specific garbage categories on a limited number of training samples. Moreover, field tests of the garbage classification system show that the average processing period was only 0.63 seconds and the 4-CK is as high as 0.90, which indicates that the system can not only accurately identify garbage but can also operate efficiently and steadily. In the future, the object detection system will be utilized to recognize multiple types of garbage simultaneously, which benefits the automation of the garbage classification system.

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(Bowen Fu, Su Li, Jiangdong Wei, Qiran Li, Qingnan Wang, and Jihui Tu contributed equally to this work.)

AUTHOR CONTRIBUTIONS

Bowen Fu conceived and initialized the research, conceived the algorithms, and designed the experiments; Su Li, Jiangdong Wei, and Qiran Li conducted the comparative experiments; Jihui Tu reviewed the article; and Qingnan Wang checked the spelling and provided advice.

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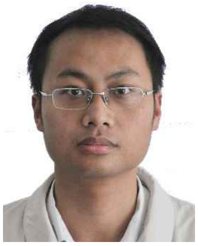

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