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Intelligent dustbin based on convolution neural network, spectroscopy and internet of things

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Abstract. Aiming at the problems of low level of intelligent automation of garbage classification, low flexibility, low efficiency, high cost and difficulty in large-scale production, this paper proposes a multimodal data fusion intelligent garbage bin system based on neural network, spectral technology and ultrasonic technology, which can effectively classify and recover different types of garbage. This paper mainly includes the following aspects: (1) The accuracy of MobileNetV2 was improved to 76.3% by using an experimental research method; (2) The near-infrared spectrum was studied by literature study and simulation method, and the characteristic wavelength reflectance ratio was used to establish the model; (3) The literature research method and quantitative analysis method were used to judge the types of solid and liquid waste according to the cavitation effect; (4) Integrate the above three technologies and design the corresponding intelligent trash can model, so that the system can perform multimodal data fusion according to the items put by users, jointly determine their categories and assign them to the corresponding categories of trash cans.

Keywords: garbage classification, improved MobileNetV2, near-infrared spectroscopy, cavitation effect, attention mechanism.

1. Introduction

In traditional garbage classification methods, manual classification is inefficient, costly and prone to errors. An intelligent garbage system is a device that uses artificial intelligence technology to achieve automatic garbage classification [1]. It can improve the efficiency and accuracy of garbage classification, thereby promoting environmental protection and resource recovery [2]. Therefore, an automated and intelligent garbage bin using MobileNetV2 neural network, near-infrared spectral identification and ultrasonic cavitation technology is proposed in this paper. The main drop-in scenario of the dustbin is the residential area, which not only provides the efficiency and accuracy of classification but also improves the public's awareness and attention to the classification of garbage.

The second part of this paper introduces the composition and function of the smart dustbin. The whole is divided into five parts: garbage collection, garbage identification, plastic spectral subdivision, ultrasound-assisted classification and garbage disposal. The third part is the application of neural networks, near-infrared spectroscopy and ultrasonic sensor in the smart garbage bin. Firstly, the optimized MobileNetV2 algorithm is used to classify garbage, then near-infrared spectroscopy is used to identify and classify plastic garbage, and finally, ultrasonic sensor cavitation is used to analyse and identify solid and liquid garbage data. The fourth part introduces the overall framework design of the smart garbage bin and describes the classification process in detail. The fifth part summarizes the conclusions of this paper and the future direction of smart dustbins based on neural networks, near-infrared spectroscopy and ultrasound technology. The significance of this study is to make up for the shortcomings of traditional image recognition technology in the recognition of complex garbage situations and broaden the design thinking of garbage recognition systems.

2. Composition and function of intelligent waste sorting bin

The intelligent waste classification box can be divided into three categories: waste input, identification, and storage. The relationship is shown in the following figure:

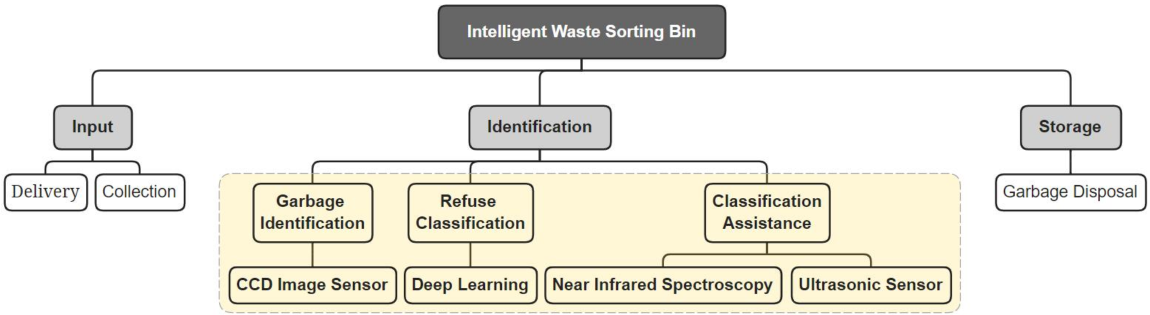

Figure 1. Composition of intelligent sorting bin.

As shown in Figure 1, garbage input is divided into resident input and collection. The identification part is divided into garbage identification based on CCD, garbage classification using neural networks, and assisted classification using near-infrared spectroscopy and ultrasonic sensors. The storage part includes garbage input.

2.1. Input

In order to be convenient and efficient, community residents need to put garbage into the garbage sorting box in batches, without the need for manual garbage classification or individual garbage discharge. Garbage will enter the garbage collection area after being dumped in piles. In this section, garbage passes through a Z-shaped channel and a horizontal conveyor belt. The speed difference between garbage passing through the Z-shaped channel is utilized to achieve a single garbage separation in the garbage heap. The waste is then transported through a horizontal conveyor belt to the waste identification area.

2.2. Identification

In this section, a garbage classification model is designed based on garbage image recognition, supplemented by near-infrared spectroscopy and ultrasonic cavitation effects.

After entering the identification area, garbage passes through a conveyor belt and is detected by sensors. The micro-camera will then take photos of the garbage. After that array detector and ultrasonic sensors will identify the garbage and process relevant data.

The garbage image obtained from the identification area will enter the classification area through data transmission. In order to achieve efficient and accurate garbage image classification, this article uses an improved MobileNetV2 garbage image classification model.

Firstly, the optimization of the model mainly involves introducing channel and spatial attention mechanisms into its convolutional layer [3]. These two attention mechanisms complement each other and can improve the model's ability to capture details and differences in spam images. In addition, due to the habit of classifying and placing garbage on community streets, garbage has the characteristics of pre and post-correlation. This article adds a prediction correction mechanism to the model. When the prediction accuracy of MobileNetV2 is low, using this correlation, a mathematical model is established to obtain weight ratios of similar types, and then weighted to obtain the final weight vector.

However, as the main means of garbage classification, image recognition is difficult to accurately identify special garbage such as transparent plastic. Therefore, to further improve garbage classification efficiency, this paper proposes two auxiliary classification models. The first is to use near-infrared spectroscopy to identify and detect unknown plastic waste.

In addition, the combination of image recognition and spectral technology cannot completely distinguish all garbage, and further classification research on mixed garbage is lacking. Therefore, ultrasonic technology has been introduced to detect solid-liquid mixed waste, mainly for detecting residual liquid layers in empty bottles. It complements spectral technology and plays a further role in refining and classifying garbage.

The combination of image recognition, spectral technology, and ultrasonic technology can improve the accuracy and efficiency of garbage classification.

2.3. Storage

After algorithmic analysis of the data, the category of garbage will be given, and in this process, multiple conveyor belts and flipping devices will be used to place the garbage into the corresponding trash can according to the given garbage category.

3. Garbage identification

3.1. Garbage image classification model based on improved MobileNetV2

This section is improved from the following three points: First, the pre-trained image data is processed in batch format conversion and the cutout algorithm is used for data enhancement. Second, in view of the disadvantage that the depthwise separable convolutional block may lose too much feature information, we added a channel attention mechanism and a spatial attention mechanism hybrid module in the middle of the MobileNetV2 structure. Third, based on the specific place where this article is applicable, we built a forecast correction mechanism, recorded three historical forecast results, and designed an algorithm to correct low-accuracy samples.

Firstly, the data enhancement.

Since there are some ideal pictures in the data set, the data augmentation methods used in this paper are random geometric transformation and cutout. The cutout method is based on the use of occlusion to allow the neural network to better utilize the global information of the image, rather than relying on a small part of the specific visual features in the image [4].

Secondly, the improved structure of MobileNetV2 is constructed as follows.

MobileNetV2 is a lightweight convolutional neural network model with a special Linear Bottleneck structure [5]. It consists of a 1x1 convolutional layer, a 3x3 depthwise separable convolutional layer, and a 1x1 convolutional layer with Batch Normalization between them.

Convolutional block attention module (CBAMBlock) is a simple and effective feed-forward convolutional neural network attention module [6]. Its structure of it consists of a channel attention mechanism and a spatial attention mechanism to pay more attention to both of these features.

This paper adds CBAMBlock based on MobileNetV2, aiming to improve the accuracy of the network without changing the lightweight. Experiments have proved that the addition of this module is effective, and the effect of adding the module is the best before the depth c of the output feature matrix of MobileNetV2-121 is 32. Figure 2 shows the improved bottleneck structure under stride 1 and 2.

Thirdly, the forecast correction mechanism has been proposed.

The types of waste before and after are highly correlated. Add a prediction correction mechanism to correct waste types with low network prediction accuracy.

The mechanism will start when the network prediction accuracy rate is lower than 0.9 and the 3 historical categories are different from the current type. According to the historical categories, the type

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with the most occurrences and its similar types are weighted into the weight list of the neural network in a certain proportion to get the final classification type.

Fourthly, test and analysis the improved structure through experiments.

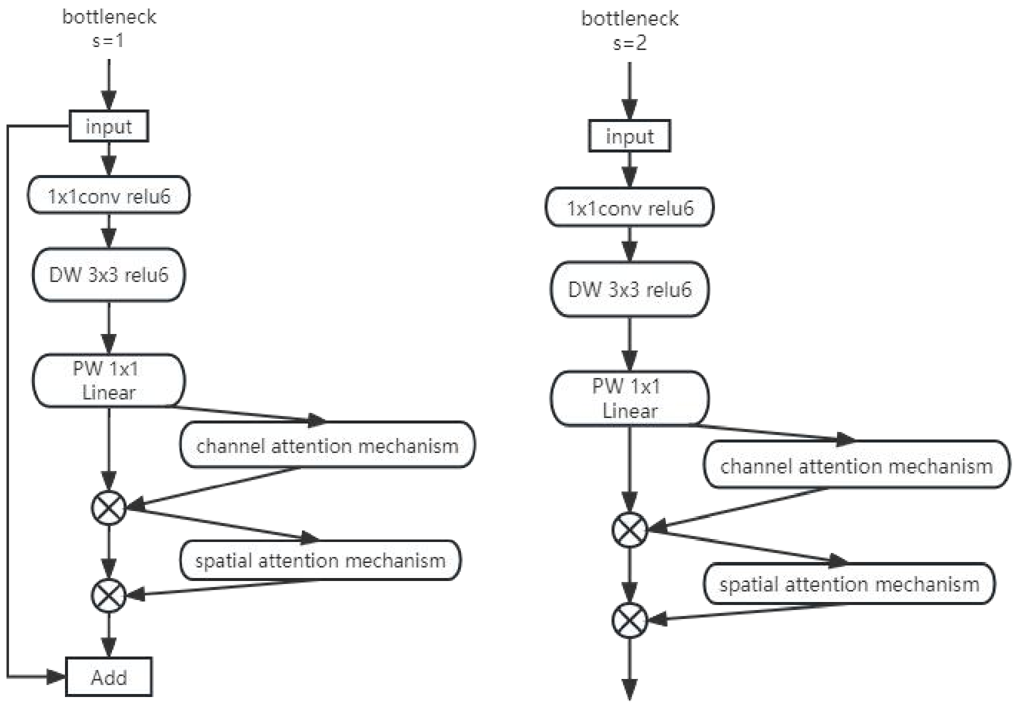

Figure 2. Improved bottleneck structure under two-step sizes.

Table 1 shows the main experimental results to verify the effectiveness of the improved MobileNetV2 and the correction mechanism proposed in this paper.

Table 1. Experimental results.

No.	Description	Top1 Accuracy %
1	Original MobileNetV2	72.0
2	No.1 + data enhancement + Forecast correction mechanism	73.4
3	No.2 + add CBAMBlock before the first layer + ratio=1/16	74.8
4	No.2 + add CBAMBlock before the first layer + ratio=1/4	74.4
5	No.2 + add CBAMBlock before the first layer + ratio=1	74.5
6	No.2 + add CBAMBlock after c=24 layer + ratio=1/16	76.3
7	No.2 + add CBAMBlock after c=24 layer + ratio=1/4	75.6
8	No.2 + add CBAMBlock after c=24 layer + ratio=1	75.9

It can be seen that the MobileNetV2 with data enhancement and prediction correction mechanism has achieved a high recognition rate on this data set, reaching 73.4%. The addition of CBAMBlock can significantly improve the accuracy of the network. The accuracy is higher when CBAMBlock is added after c=24 layers (before 32 layers), and the Reduction ratio of the channel attention mechanism is 1/16.

Figure 3 below shows the normal network prediction result and the result of activating the prediction correction mechanism.

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Figure 3. Garbage Image Recognition Effect. (a) Sample Garbage Image number 08. (b) Classification output result (The accuracy is greater than 90% so no need forecast correction mechanism). (c) Sample Garbage Image number 09. (d) Classification output result: (The original accuracy is 67.6% , lower than 90% so use forecast correction mechanism to correct the final result).

The advantage of this structure is that it can improve the accuracy of the model even without adding the model size. However, if multiple types of waste are identified together, it may affect accuracy.

3.2. Classification model of plastics based on near-infrared spectroscopy

Image recognition is not efficient because most plastics are transparent. Near-infrared light has low reflectivity and absorptivity [7], which is suitable for identifying organic compounds. Depending on the nature of the vibrational transition of light absorbed by a molecule at a specific wavelength, a unique spectrum can be obtained and the component information, structural information and the specific content of certain components can be detected.

The specific process is as follows:

Firstly, array detectors are used to collect near-infrared spectral data, set up datasets and label classifications [8].

Secondly, use MATLAB and toolkit SIMCA to pre-process the data, use a variety of methods and compare the cumulative contribution value after the final principal component analysis, and select the best pre-processing method.

Thirdly, the characteristic wavelengths are extracted from the load map of the principal component analysis, and the reflectivity of the five plastics at each characteristic wavelength is obtained. To ensure accuracy, the reflectivity ratios of two or more different characteristic wavelengths are selected to establish the discrimination model and to be used for validation of unknown dataset identification.

3.3. An auxiliary classification model based on the ultrasonic cavitation effect

This project also uses ultrasonic sensors to test the cavitation effect to analyse whether the waste contains liquid components. The main mode of operation is to use ultrasonic sensors to send out sound waves with the same energy according to the cycle, to promote the energy reaction inside the liquid. Suslick et al. [9] measured that the surface of a solid suspended in a liquid can be rapidly destroyed by a huge instantaneous pressure. Through the cavitation data monitored, the energy signal generated is converted into an electrical signal, and the digital analogue converter is converted into the cavitation sound pressure curve [10], getting the characteristic vectors, so as to realize the difference between whether the garbage contains liquid inside. This is helpful to further eliminate the near-infrared spectrum and image recognition cannot take into account the hidden trouble, and eliminate interference. Obviously, for the cavitation effect, the difference in the degree of cavitation effect of liquid and the energy loss caused by the external environment will also be the drawbacks that hinder the normal operation of sensors.

4. Design of intelligent garbage classification technology

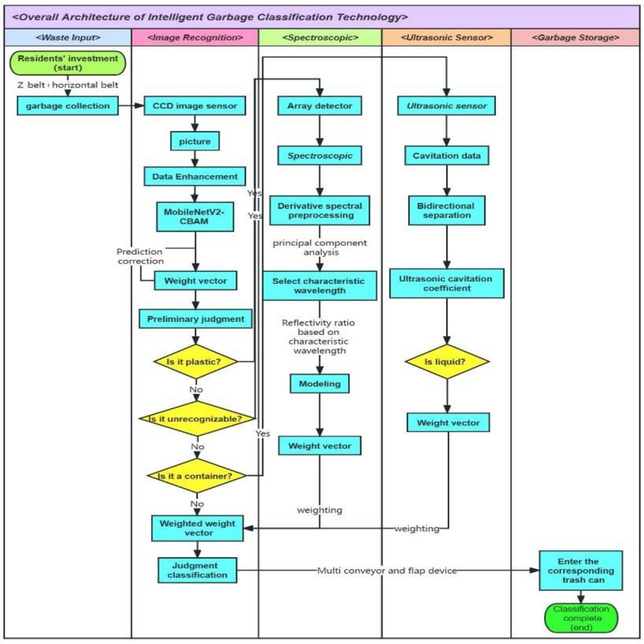

Figure 4. Design of intelligent garbage classification technology.

As shown in Figure 4, garbage will be transported, identified and sorted through such a systematic process. After the garbage is dropped by the residents, it enters the garbage collection device through a conveyor belt and is then detected by sensors in the identified area and transmitted to the classification area. After the image data enters the classification area, in-depth learning is conducted through the optimized MobileNetV2 to obtain the weight vector, and preliminary judgment is made on it. If it is judged as plastic or unrecognizable, the garbage will enter the spectral plastic subdivision classification model to further classify the plastic, obtain the corresponding weight vector and weight it; If garbage is judged as a container, it will enter an ultrasonic-assisted classification model to detect the presence of liquid inside the object, and the resulting weight vector will be weighted. Finally, the algorithm will judge and classify based on the weighted weight vector to obtain the final result and use the Turn-device to enter the corresponding trash can.

5. Conclusion

In summary, the paper selects the lightweight model MobileNetV2 in the neural network recognition stage of the smart garbage bin, uses flip, cutout and other methods to improve the robustness of the model, and adds the convolution block attention module CBAMBlock to improve the accuracy. Finally, a predictive correction mechanism is innovatively proposed, and the accuracy of the model is improved to 76.3% using its relevance and other characteristics. The plastics are then identified using near-infrared spectroscopy, and the recognition model is built using the characteristic wavelength reflectance ratio, which ensures the recognition accuracy and makes the process as efficient as possible. In addition, in order to make up for the deficiency of neural networks and infrared near-infrared spectroscopy in solid and liquid waste identification, an ultrasonic sensor is added as an aid. It can be identified by the difference between the cavitation curves of solid waste and pure solid waste. Considering the characteristics of these three technologies, the three recognition results are weighted to determine the garbage category.

This novel intelligent garbage bin and garbage bin system can divide domestic garbage more carefully, and the identification process is also more efficient and accurate. In the future, we will focus more on improving the entire garbage classification system and exploring more applications of intelligent garbage cans, such as using WSNs technology and capacity sensors to conduct real-time monitoring of garbage cans, improve the efficiency of garbage cans, and also achieve the integration and industrialization of garbage collection, truly realizing the intelligence, sustainability, and industrialization of garbage collection.

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