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A Novel Framework for Trash Classification Using Deep Transfer Learning

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ABSTRACT Nowadays, society is growing and crowded, the construction of automatic smart waste sorter machine utilizing the intelligent sensors is important and necessary. To build this system, trash classification from trash images is an important issue in computer vision to be addressed for integrating into sensors. Therefore, this study proposes a robust model using deep neural networks to classify trash automatically which can be applied in smart waste sorter machines. Firstly, we collect the VN-trash dataset that consists of 5904 images belonging to three different classes including Organic, Inorganic and Medical wastes from Vietnam. Next, this study develops a deep neural network model for trash classification named DNN-TC which is an improvement of ResNext model to improve the predictive performance. Finally, the experiments are conducted to compare the performances of DNN-TC and the state-of-the-art methods for trash classification on VN-trash dataset as well as Trashnet dataset to show the effectiveness of the proposed model. The experimental results indicate that DNN-TC yields 94% and 98% in terms of accuracy for Trashnet and VN-trash datasets respectively and thus it outperforms the state-of-the-art methods for trash classification on both experimental datasets.

INDEX TERMS Trash classification, computer vision, deep neural networks.

I. INTRODUCTION

With the improvement of computer hardware, deep learning has become a solution for many problems including facial analysis [1]–[4], medical diagnosis [5]–[9], smart agriculture [10]–[13], energy consumption prediction [14], [15] and business intelligence [16]–[19]. Allagwail et al. [1] developed an efficient method for face recognition that yields 100% in terms of accuracy for both Olivetti Research Laboratory (ORL) and Yale datasets. Next, Vo et al. [2] proposed a deep convolutional neural network namely RR-VGG which is a fine-tuning model based on VGG for race recognition from facial images. Then, Vo et al. [3] developed a hybrid framework (HF-SD) using deep learning for smile detection from facial images with several class imbalance scenarios. Later, Hu et al. [4] introduced a new local feature descriptor namely center-symmetric local signal magnitude pattern (CS-LSMP). Utilizing this descriptor for extracting texture features from facial images, the author proposed a framework for facial expression recognition on the JAFFE and CK+ facial expression datasets. The above facial analysis models can be used in a lot of industrial applications including security, marketing, and advertising. Moreover, medical diagnosis is also a promising application of deep learning in the health sector. Acharya et al. proposed two models using deep convolutional neural networks for myocardial infarction detection [5] and congestive heart failure diagnosis [6] from electrocardiography (ECG) signals. Utilizing deep convolutional neural networks, Raghavendra et al. [7] proposed a deep model for glaucoma diagnosis from digital fundus images while Hemanth et al. [8] developed a framework for detecting the abnormal brain tumor images. For smart agriculture, An et al. [12] used a deep convolutional neural network model to identify and classify different drought stress levels (optimum moisture, light drought stress, and moderate drought stress) of maize. This model can help the manager early and accurate detect drought stress, which is of great significance for maize precision irrigation,

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water consumption reduction, and to ensure a high and stable yield of maize. Meanwhile, Liu et al. [13] utilized deep convolutional neural networks to propose a robust model to detect apple leaf diseases for controlling the spread of infection as well as ensuring the healthy development of apple fields. From these above studies, we easily found the application of deep learning in all areas of life. Le et al. [15] developed a prediction model utilizing the combination of Convolutional Neural Network and Bi-directional Long Short-Term Memory to predict electric energy consumption. From the above analysis, deep learning has applications in many fields.

Recycling is necessary for a sustainable society as it helps minimize the amount of waste. However, the current recycling process requires recycling facilities to sort garbage manually and use a series of large filters to separate more defined objects. Therefore, trash classification attracted a lot of researchers recently is also a promising application of computer vision in the industry. Utilizing deep learning to classify trash has the potential to make processing plants more efficient. This will not only have positive environmental effects but also beneficial economic effects. Recently, Salimi et al. [20] developed a trash bin robot that can detect and classifies trash to organic and non-organic waste. This robot will travel in public places for scanning and processing trash automatically. This is a promising project in the Internet of Things (IoT) era. Meanwhile, Chu et al. [21] introduced a multilayer hybrid deep-learning system to automatically sort waste disposed of by individuals in the urban public area. This model uses a CNN-based algorithm to extract image features and the multilayer perceptron (MLP) method to consolidate image features and other feature information to classify wastes as recyclable or the others. In 2016, Yang and Thung [22] released Trashnet dataset which is often used to evaluate trash classification models [23]–[25]. However, these models are not effective in cases where the class contains many objects. Therefore, the performance results of these models on this dataset still need to improve. Moreover, these methods also need to be verified on other datasets regarding trash classification. Therefore, this study develops a deep neural network model for trash classification namely DNN-TC to achieve the forecasting capabilities. The main contributions of this study are as follows. (1) This study first collects 5904 images belonging to three different classes including Organic, Inorganic and Medical wastes from Vietnam to create the VN-trash dataset. (2) DNN-TC is developed for efficient trash classification. (3) The experiments were conducted to show the effectiveness of the proposed model compared with the state-of-the-art approaches for trash classification on both datasets including Trashnet and VN-trash datasets. The experimental results indicate that our method is very positive and outperforms the state-of-the-art methods on Trashnet and VN-trash datasets.

The rest of this study is organized as follows. The related works on trash classification utilizing computer vision are surveyed in Section 2. In section 3, this study develops a deep neural network model for trash classification using deep transfer learning technique. The experiments are conducted in Section 4 to show the ability of DNN-TC model for trash classification. Finally, the conclusions of this study and future directions are introduced in Section 5.

II. RELATED WORKS

In 2016, Yang and Thung [22] released Trashnet dataset consisting of six classes: glass, paper, cardboard, plastic, metal, and trash. The images in this dataset were taken by several mobile devices such as Apple iPhone 7 Plus, Apple iPhone 5S, and Apple iPhone SE. The detail descriptions of this dataset will be presented in the next section. Several studies regarding trash classification problem [23]–[25] utilizing Trashnet dataset for evaluating their proposed approaches which are summarized as follows.

Firstly, Aral et al. [23] utilized the transfer learning models originated from several well-known CNN models for image classification including Densenet121, DenseNet169, InceptionResnetV2, MobileNet, and Xception to classify trash on Trashnet dataset. In their experiments, the authors used 70% of Trashnet dataset for training, 13% for validation and 17% for testing. In addition, the batch and the input size were selected as 8 and 224×224 respectively. According to the experimental results, a transfer learning model of DenseNet121 archived the best accuracy which yields at 95%. Therefore, we reimplement and perform this model with the above settings denote by Densenet121_Aral model in our experiment.

Next, Bircanoglu et al. [24] developed a light-weight convolutional neural network model namely RecycleNet for trash classification. Although RecycleNet only achieved 81% in terms of accuracy for Trashnet dataset with 70% of images for training, 13% for validation and 17% for testing, it reduced the time complexity by reducing the number of parameters from seven million to three million. Therefore, RecycleNet is a lightweight model for several systems that restrict hardware devices.

Then, Ruiz et al. [25] evaluated the use of several CNN models including VGG, Inception and ResNet for the automatic trash classification. In this study, the authors used 80% of Trashnet dataset for training, 10% for validation and the remaining 10% for testing. The best performance results were obtained by using a ResNet-based architecture with 88.66% in terms of average accuracy for Trashnet dataset. In our experiments, we reimplement this method which is denoted by ResNet_Ruiz.

Besides the above methods developed for trash classification that the study have just introduced above, several famous CNN models such as ResNext [26], ImageNet [27], VGG [28], ResNet [29], and DenseNet [30] for image classification also can be used to classify trash as a based model. Among the above CNN models, this study found that ResNext is the best model for transfer learning to classify trash. Therefore, this research modifies this model by applied the transfer

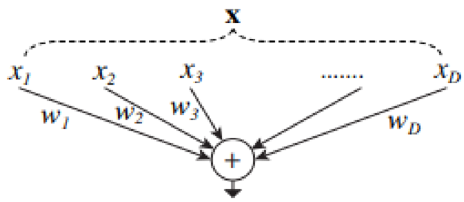

FIGURE 1. A simple neuron performing the inner product [26].

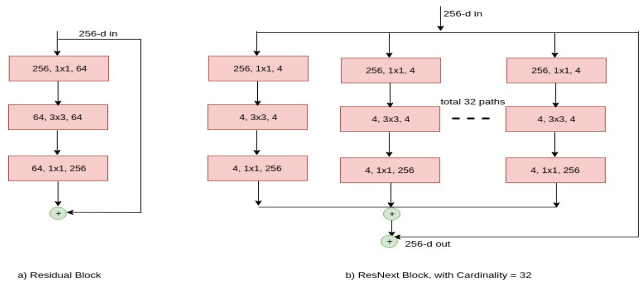

FIGURE 2. The comparison between (a) Residual block and (b) ResNext block.

learning approach to propose a deep neural network model for trash classification.

III. A DEEP NEURAL NETWORK MODEL FOR TRASH CLASSIFICATION

A. RESNEXT MODEL

ResNext was proposed by Xie et al. [26] in 2017, also known as Aggregated Residual Transformations Network for image classification. This model is developed over the split-transform-merge strategy and the standard residual block with exposing a new dimension, which is called cardinality (the number of branches) or the size of the set transformations. In each block, ResNext used the split-transform-merge strategy of the inception module to approach the representational power of large and dense layers. In a simple neural, the inner product can be considered as a combination of splitting, transforming, and aggregating operators as in Figure 1.

The splitting operator is considered as the vector $\mathbf{x}$ which is spliced in a low-dimensional embedding $\mathbf{x} = [x_1, x_2, x_3, \ldots, x_D]$ where D-channel input vector to the neuron, it simply like as a single dimension subspace x_i. Meanwhile, the transformation that is the low dimensional representation is transformed with scale simply $w_i x_i$. Finally, the transformations in all embedding are aggregated as the following equation.

$$\sum_{i=1}^{D} w_i x_i. \tag{1}$$

From this idea above, the elementary transformation ($w_i x_i$) is considered to replace with a more generic function or can be a network. Hence, Equation 1 could be reformulated as follows.

$$F(x) = \sum_{i=1}^{C} T_i(\mathbf{x}), \tag{2}$$

where T_i can be an arbitrary function and C is referred to as cardinality that is normally assigned by 32.

The cardinality C and the internal dimension for each path d are different between Residual block and ResNext block (see Figure 2). This design allows ResNext to become flexible to extend without specialized designs. Besides, all T_i's have the same topology as illustrated in Figure 2b, so that it can be easily isolated as a factor, the aggregated transformation for each ResNext block is formulated as the following equation.

$$y = x + \sum_{i=1}^{C} T_i(\mathbf{x}), \tag{3}$$

where y is the output. Moreover, the ResNext model shows not only considerably simpler design than Inception model, but also outperforms than the other deep neural networks as ResNet-101/152, Inception-v3, and Inception-ResNet-v2. With the above advantages, this study chooses ResNet architecture as a base model for applying transfer learning to propose our model for trash classification.

B. THE PROPOSED FRAMEWORK

In this section, a robust framework utilizing Deep Neural Networks for Trash Classification (DNN-TC) is introduced. Because of the effectiveness of ResNext architecture compared with the others demonstrated in [26], this study uses ResNext as a base model combining with several improvements. In detail, this study modified the original ResNext-101 model by adding two fully connected layers after the global average pooling layer with output 1024 and N_class dimensions respectively to decrease the redundancy as illustrated in Figure 3.

In the data preprocessing phase, the brightness values of input images are normalized to give the values between 0 and 1. Then, the input images will be applied several preprocess techniques such as the horizontal flip and random crop around the image with 224×224 to generate more images in the training and testing phase. In the training phase, the input images which present for each specific waste classes are fed into our proposed architecture. In the last layer, log softmax function is used to compute the confidence for each label as follows.

$$y_j = \frac{e^{x_j}}{\sum_i^{N\_class} e^{x_i}}, \tag{4}$$

where N_class denotes the number of trash labels, y_j is the probability output of each label, while x_i and x_j are the final hidden outputs. Therefore, log softmax function is referred to $\log(y_j)$. However, in empirically, log softmax is rewritten to easy computation as follows.

$$y_j = x_j - log\left(\sum_i^{N_{class}} e^{x_i}\right). \tag{5}$$

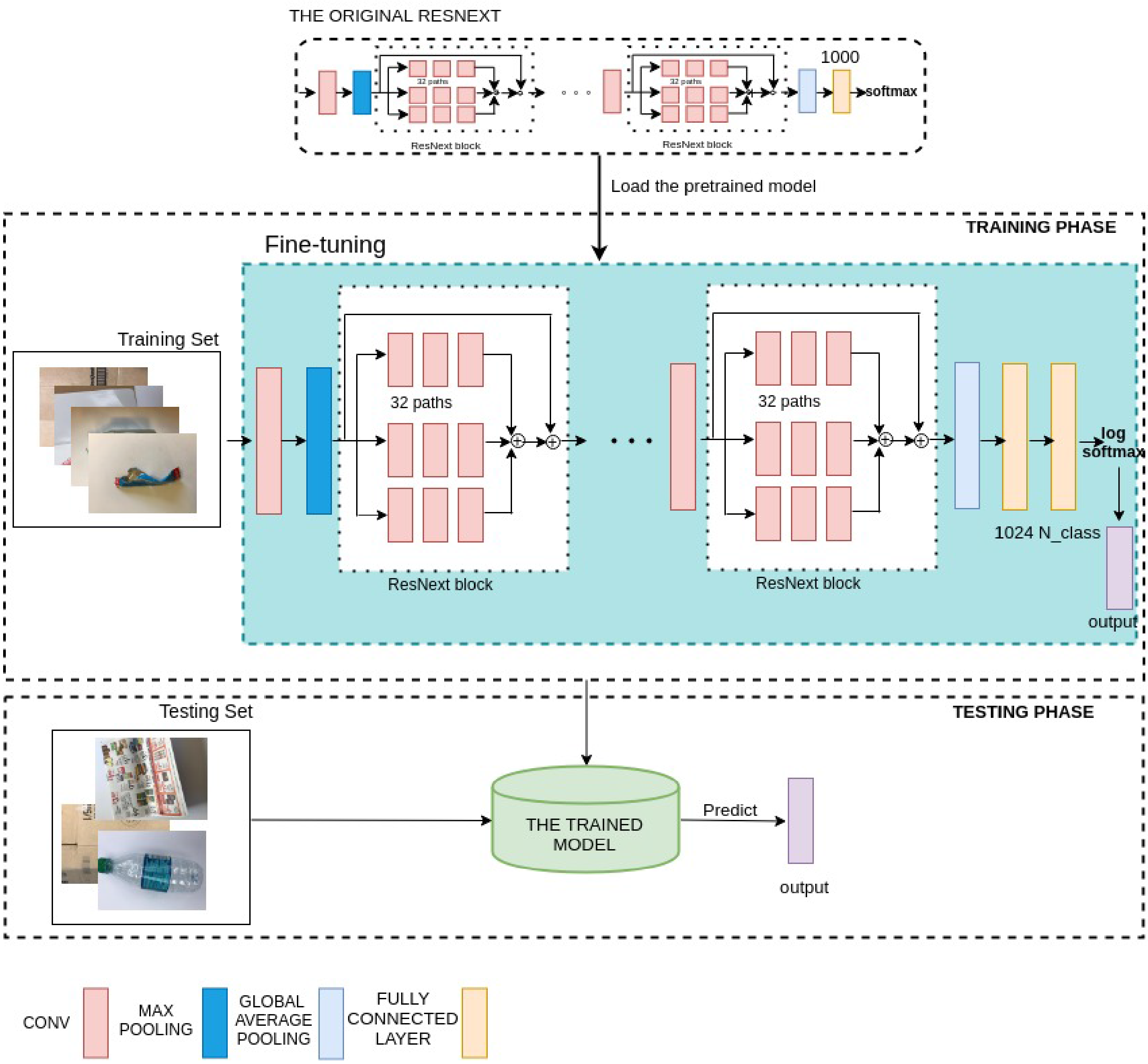

FIGURE 3. Overview of the proposed framework.

The log softmax function could practically help to improve gradient optimization and the effect of heavily penalizing the model when it fails to classify a correct class. Firstly, the proposed model initialized the weight model by loading the pre-trained weight from the original ResNext-101 on the ImageNet dataset. In the next stage, this model performs the fine-tuned process to learn the characteristics of type wastes from the trash dataset and then the model with the best accuracy is selected by an estimate on the validation set. In the testing phase, we evaluate the best model on the testing set to predict the final output for each input image.

IV. EXPERIMENTS

A. EXPERIMENTAL DATASETS

The first dataset namely Trashnet dataset [22] was collected by mobile devices, which contains 2527 images with six classes such as glass, paper, cardboard, plastic, metal, and trash. The object of images was placed on a white background and using sunlight and/or room lighting. The statistic of images for each class was presented in Table 1 while Figure 4 shows several samples in each class of this dataset.

TABLE 1. The statistic of Trashnet dataset.

No	Classes	Number of images
1	Glass	501
2	Paper	594
3	Cardboard	403
4	Plastic	482
5	Metal	410
6	Trash	137

In addition, this study also collects another dataset named VN-trash dataset for the trash classification problem.

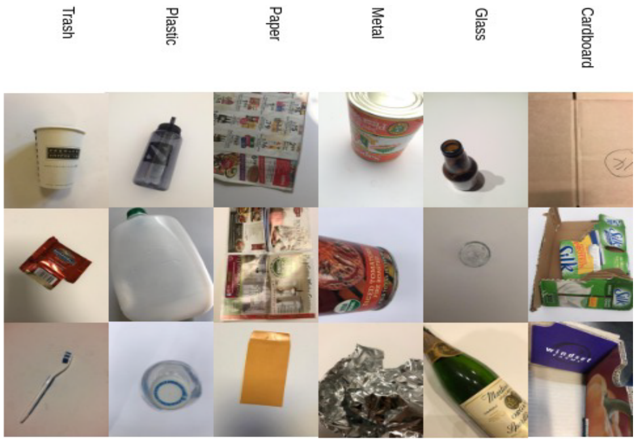

FIGURE 4. Example samples of Trashnet dataset.

TABLE 2. The statistic of VN-trash dataset.

No	Class	Objects	Number of images
1	Organic	Juice peel, cardboard, plants, seeds, paper, etc...	2015
2	Inorganic	Eggshell, plastic, glass, bone, etc...	2003
3	Medical waste	Bandages, gloves, needles, scalpels, swabs, tissue, etc...	1886

TABLE 3. Number of images in training/validation/testing sets on two experimental datasets.

Number of images	Trashnet dataset	VN-trash dataset
Training set	1516	3772
Validation set	506	1061
Testing set	505	1071

This dataset consists of three types of wastes including Organic, Inorganic and Medical wastes. The 5904 images in this dataset were collected by crawling internet resources as well as taking pictures in the natural environment. The description and statistics of VN-trash dataset are shown in Table 2. Moreover, several samples in each class in VN-trash are illustrated in Figure 5.

For conducting the same experimental environment on both datasets, this section splits the experimental datasets including Trashnet and VN-trash datasets into 60%, 20% and 20% for training, validation, and the testing sets respectively. The numbers of images in the training, validation and testing sets of two experimental datasets are shown in Table 3.

B. EXPERIMENTAL SETTING

The experimental methods were implemented in Python 3.7 and performed on Pytorch framework which is a free software deep learning library for the Python programming language. The operating system is Ubuntu 16.04 LTS with an Intel Core i7-4790K (4.0 GHz × 8 cores), 16 GB of RAM and GeForce GTX 1080.

This study utilizes state-of-the-art methods for trash classification including Densenet121_Aral [23], RecycleNet [24] and ResNet_Ruiz [25] as well as a famous deep learning model for image classification namely ResNext-101 [26] to compare with the proposed approach for trash classification. Specifically, three methods including Densenet121_Aral, RecycleNet, and ResNet_Ruiz were implemented based on the same configurations which were described in their works. For ResNext-101 model, we pre-trained and fine-tuned by replacing the final fully connected layers. In these processes, the Stochastic Gradient Descent (SGD) is used as an optimizing algorithm for the ResNext-101 model with a learning rate $\alpha = 0.0001$. For the proposed framework, the hyper-parameters of Adam optimizer are set up with the learning rate $\alpha = 0.001$, two momentum parameters $\beta_1 = 0.9$ and $\beta_1 = 0.999$ were utilized for the first 10 epochs. Then, SGD is used as an optimizing algorithm for the fine-tuning model with a learning rate $\alpha = 0.0001$ for the next 100 epochs. In addition, this research uses mini-batch size $= 8$ with 100 epochs and evaluates the model's performance on the validation set for every epoch in during training processing. In the testing phase, this study performs the comparison between the experimental methods based on the testing set for trash classification.

FIGURE 5. Samples of VN-trash dataset.

TABLE 4. The accuracy of the experimental methods on Trashnet dataset.

No	Methods	Accuracy (%)
1	Densenet121_Aral [23]	91
2	RecycleNet [24]	68
3	ResNet_Ruiz [25]	72
4	ResNext-101 [26]	90
5	DNN-TC	94

C. EXPERIMENTAL RESULTS

This section provides quantitative evaluations of the proposed framework and the state-of-the-art methods on two experimental datasets including Trashnet and VN-trash datasets that were introduced in the previous section. In the first experiment, the accuracy of the proposed framework compared with the other experimental approaches for the Trashnet dataset was presented. The experimental results in terms of accuracy and confusion matrix are shown in Table 4 and Figure 6. Firstly, Table 4 shows that DNN-TC model outperforms other approaches for the Trashnet dataset. Specifically, DNN-TC

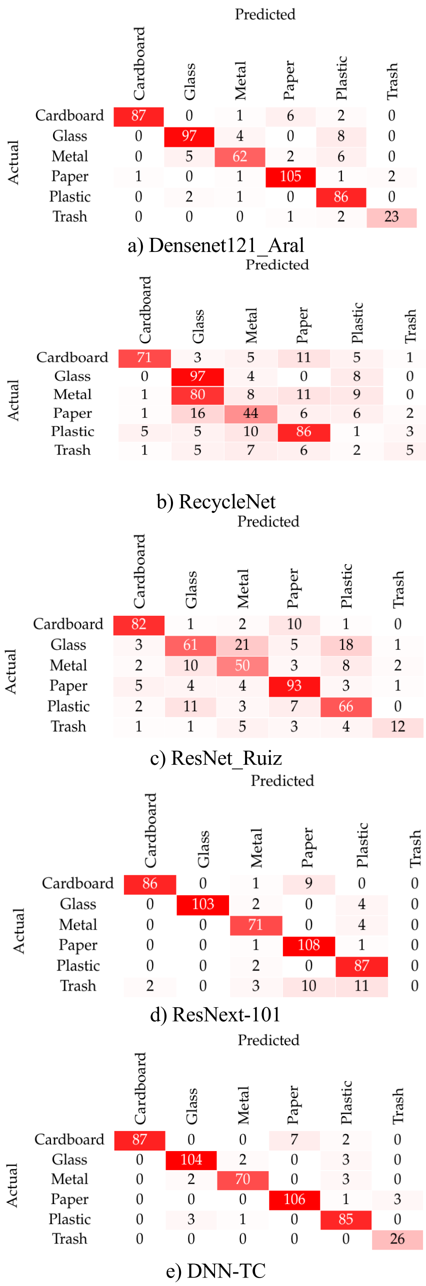

FIGURE 6. **Confusion matrices of the experimental models for Trashnet dataset.**

achieved 94% while Densenet121_Aral, RecycleNet, and ResNet_Ruiz obtained 91%, 68% and 72% in terms of accuracy respectively. Meanwhile, the proposed method is also better than the original ResNext-101 model on Trashnet dataset around 4% when ResNet-101 only got 90% in terms of accuracy.

In addition, Figure 6 presents the confusion matrices of all experimental methods. Most incorrect predictions of all experimental methods for Trashnet dataset are in the trash class which has many types of objects. In detail, ResNext-101, RecycleNet, and ResNet_Ruiz are not good models for

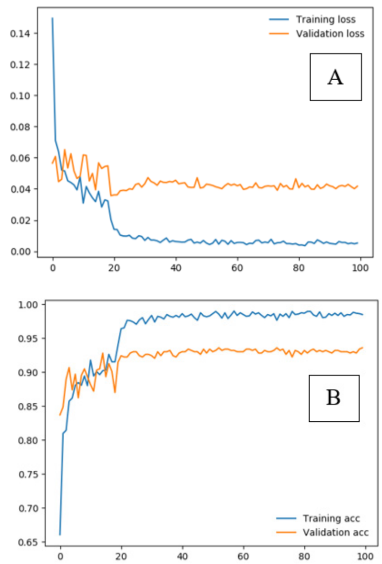

FIGURE 7. **The loss (A) and accuracy (B) in the training and validation processes of DNN-TC for Trashnet dataset.**

this class when they only predict 0, 5 and 12 objects correctly in this class. Meanwhile, Densenet121_Aral model predicts 23 objects correctly in the trash class. However, DNN-TC model has the largest number of correct predictions in the trash class which yields 26 objects. Besides, the DNN-TC method outperforms ResNext-101, Densenet121_Aral, RecycleNet, and ResNet_Ruiz models for classifying the glass and cardboard. Nevertheless, for the metal, paper, and plastic classes, DNTT-TC has a slight decrease compared with ResNext-101 model but is better than Densenet121_Aral, RecycleNet, and ResNet_Ruiz. Generally, DNN-TC method achieved the best performance on Trashnet dataset for all cases.

Figure 7 shows the loss and accuracy variation of training and validation sets over 100 epochs for Trashnet dataset of the proposed approach. This image indicates that DNN-TC model obtains the highest accuracy and the smallest loss value after 50 epochs. This means that the proposed model could quickly achieve the stable and generalization on the Trashnet dataset over 50 epochs.

Next, we continuously perform the experimental methods on the VN-trash dataset which contains many objects in each class to show the effectiveness of the proposed approach. As the experimental results are shown in Table 5, DNN-TC model achieved the best performance compared with all experimental methods for the VN-trash dataset which yields 98% in terms of accuracy. More particularly, Densenet121_Aral archived 90% while RecycleNet and ResNet_Ruiz obtain 80% and 85% respectively in terms of accuracy. Meanwhile, the ResNext-101 achieves 96% which is less than 2% compared with the proposed model.

Besides, Figure 8 shows the confusion matrices of all the experimental models for VN-trash dataset. This figure

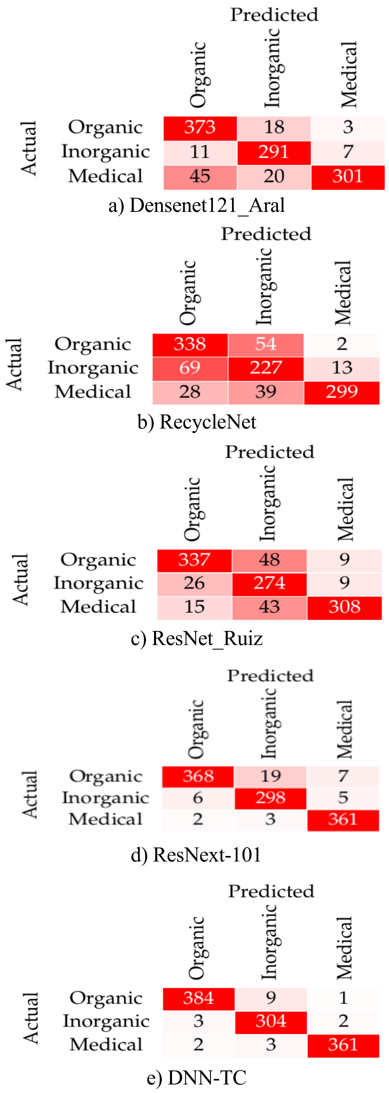

FIGURE 8. **Confusion matrices of the experimental models for VN-trash dataset.**

TABLE 5. **The accuracy of the experimental methods on VN-trash dataset.**

No	Methods	Accuracy (%)
1	Densenet121_Aral [23]	90
2	RecycleNet [24]	80
3	ResNet_Ruiz [25]	85
4	ResNext-101 [26]	96
5	DNN-TC	**98**

indicates that it is difficult to classify the Organic and Inorganic classes because of the similar characteristic of these classes. Even though, DNN-TC demonstrated that it improves the accuracy of the trash classification problem when it reduced the incorrect cases between Organic and Inorganic classes. However, the incorrect cases for medical class did not improve compared with that of the ResNext-101 model.

Moreover, Figure 9 shows the loss and accuracy variation of training and validation sets over 100 epochs for VN-trash dataset. Our proposed model obtains the highest accuracy and

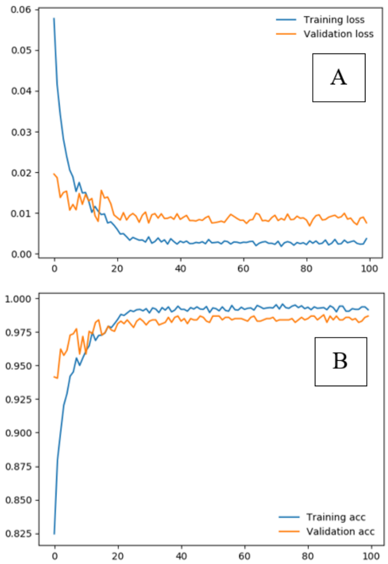

FIGURE 9. **The loss (A) and accuracy (B) in the training and validation processes of DNN-TC for VN-trash dataset.**

the smallest loss value after 30 epochs, which has proven that DNN-TC could quickly achieve the stable and generalization for VN-Trash dataset.

V. CONCLUSION

This paper proposed a deep neural network model for trash classification namely DNN-TC. As the first contribution of this study, we collected the 5904 images in three classes in VN-trash dataset. Secondly, we developed the DNN-TC model which relied on the ResNext architecture attached with several modifications to improve the classification performance. To demonstrate the effectiveness of the proposed framework, this study compared the predictive performance of our approach and the state-of-the-art methods dealing with trash classification problems on both Trashnet and VN-trash datasets. Trashnet dataset is a small dataset in which most images contain a single object while VN-trash dataset contains many objects in each class. The experimental results indicated that DNN-TC outperforms the state-of-the-art methods not only for Trashnet dataset but also for VN-trash dataset. Specifically, DNN-TC achieves 94% and 98% Trashnet and VN-trash datasets respectively.

In future work, we will continuously develop the results of this work to improve the effectiveness of the proposed framework to apply in the real system. Several segmentation techniques will be applied to preprocessing the input images to improve the performance of trash classification. In addition, the number of images in each trash category usually unbalanced, therefore, a deep model for trash classification in imbalance scenarios would be studied.

REFERENCES

[1] S. Allagwail, O. S. Gedik, and J. Rahebi, "Face recognition with symmetrical face training samples based on local binary patterns and the Gabor filter," *Symmetry*, vol. 11, no. 2, p. 157, 2019.

[2] T. Vo, T. Nguyen, and C. T. Le, "Race recognition using deep convolutional neural networks," *Symmetry*, vol. 10, no. 11, p. 564, 2018.
[3] T. Vo, T. Nguyen, and C. T. Le, "A hybrid framework for smile detection in class imbalance scenarios," *Neural Comput. Appl.*, vol. 31, no. 12, pp. 8583–8592, 2019.
[4] M. Hu, C. Yang, Y. Zheng, X. Wang, L. He, and F. Ren, "Facial expression recognition based on fusion features of center-symmetric local signal magnitude pattern," *IEEE Access*, vol. 7, pp. 118435–118445, 2019.
[5] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Application of deep convolutional neural network for automated detection of myocardial infarction using ecg signals," *Inf. Sci.*, vol. 415, pp. 190–198, Nov. 2017.
[6] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, and R. S. Tan, "Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals," *Appl. Intell.*, vol. 49, no. 1, pp. 16–27, 2019.
[7] U. Raghavendra, H. Fujita, S. V. Bhandary, A. Gudigar, J. H. Tan, and U. R. Acharya, "Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images," *Inf. Sci.*, vol. 441, pp. 41–49, May 2018.
[8] D. J. Hemanth, J. Anitha, A. Naaji, O. Geman, D. E. Popescu, and L. H. Son, "A modified deep convolutional neural network for abnormal brain image classification," *IEEE Access*, vol. 7, pp. 4275–4283, 2018.
[9] N. Nasrullah, J. Sang, M. Alam, M. Mateen, B. Cai, and H. Hu, "Automated lung nodule detection and classification using deep learning combined with multiple strategies," *Sensors*, vol. 19, no. 17, p. 3722, 2019.
[10] Y. Y. Zheng, J. L. Kong, X. Jin, X. Y. Wang, T. L. Su, and M. Zuo, "CropDeep: The crop vision dataset for deep-learning-based classification and detection in precision agriculture," *Sensors*, vol. 19, no. 5, p. 1058, 2019.
[11] J. Kim, S. Kim, C. Ju, and H. I. Son, "Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications," *IEEE Access*, vol. 7, pp. 105100–105115, 2019.
[12] J. An, W. Li, M. Li, S. Cui, and H. Yue, "Identification and classification of maize drought stress using deep convolutional neural network," *Symmetry*, vol. 11, no. 2, p. 256, 2019.
[13] B. Liu, Y. Zhang, D. He, and Y. Li, "Identification of apple leaf diseases based on deep convolutional neural networks," *Symmetry*, vol. 10, no. 1, p. 11, 2018.
[14] M. A. Hannan, M. Faisal, P. J. Ker, L. H. Mun, K. Parvin, T. M. T. Mahlia, and F. Blaabjerg, "A review of Internet of energy based building energy management systems: Issues and recommendations," *IEEE Access*, vol. 6, pp. 38997–39014, 2018.
[15] T. Le, M. T. Vo, B. Vo, E. Hwang, S. Rho, and S. W. Baik, "Improving electric energy consumption prediction using CNN and Bi-LSTM," *Appl. Sci.*, vol. 9, no. 20, p. 4237, 2019.
[16] J. Kim, H. J. Kim, and H. Kim, "Fraud detection for job placement using hierarchical clusters-based deep neural networks," *Appl. Intell.*, vol. 49, no. 8, pp. 2842–2861, 2019.
[17] Y. Song, J. W. Lee, and J. Lee, "A study on novel filtering and relationship between input-features and target-vectors in a deep learning model for stock price prediction," *Appl. Intell.*, vol. 49, no. 3, pp. 897–911, 2019.
[18] T. Le, B. Vo, H. Fujita, N. T. Nguyen, and S. W. Baik, "A fast and accurate approach for bankruptcy forecasting using squared logistics loss with GPU-based extreme gradient boosting," *Inf. Sci.*, vol. 494, pp. 294–310, Aug. 2019.
[19] T. Le, M. Y. Lee, J. R. Park, and S. W. Baik, "Oversampling techniques for bankruptcy prediction: Novel features from a transaction dataset," *Symmetry*, vol. 10, no. 4, p. 79, 2018.
[20] I. B. S. Salimi Dewantara and I. K. Wibowo, "Visual-based trash detection and classification system for smart trash bin robot," in *Proc. ES-KCIC*, 2018, pp. 378–383.
[21] Y. Chu, C. Huang, X. Xie, B. Tan, S. Kamal, and X. Xiong, "Multilayer hybrid deep-learning method for waste classification and recycling," *Comput. Intell. Neurosci.*, vol. 2018, Nov. 2018, Art. no. 5060857.
[22] M. Yang and G. Thung, "Classification of trash for recyclability status," Mach. Learn., Stanford, CA, USA, Project Rep. CS229, 2016.
[23] R. A. Aral, S. R. Keskin, M. Kaya, and M. Haciomeroglu, "Classification of trashnet dataset based on deep learning models," in *Proc. BigData*, Dec. 2018, pp. 2058–2062.
[24] C. Bircanoglu, M. Atay, F. Beser, O. Genc, and M. A. Kizrak, "RecycleNet: Intelligent waste sorting using deep neural networks," in *Proc. INISTA*, 2018, pp. 1–7.
[25] V. Ruiz, Á. Sánchez, J. F. Vélez, and B. Raducanu, "Automatic image-based waste classification," in *Proc. IWINAC*, vol. 2, 2019, pp. 422–431.
[26] S. Xie, R. B. Girshick, P. Dollár, Z. Tu, and K. He, "Aggregated Residual Transformations for Deep Neural Networks," in *Proc. CVPR*, 2017, pp. 5987–5995.
[27] A. Krizhevsky, I. Sutskever, and G. S. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, no. 6, pp. 84–90, 2017.
[28] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in 2014, *arXiv:1409.1556*. [Online]. Available: https://arxiv.org/abs/1409.1556
[29] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. CVPR*, 2016, pp. 770–778.
[30] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jul. 2017, pp. 2261–2269.

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