Hybrid Deep Learning Model for Garbage Classification

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Abstract
Trash classification is an effective measure to protect the ecological environment and improve resource utilization. With the advancement of deep learning, it is now possible to classify trash using deep convolutional neural network. . This work suggests a hybrid deep learning model based on deep transfer learning, which incorporates upper and lower streams, to categorize the trash of the Trash Net dataset, which consists of six classes of rubbish photos.. First, the upper stream classifies the input garbage image into either category CGT or category MPP (metal, paper, and plastic class) (cardboard, glass, and trash class). The bottom stream then makes a precise rubbish classification prediction based on the upper stream's findings. In comparison to other state-of-the-art methods, the suggested hybrid deep learning model obtains the best results with a 98.5% accuracy rate. The suggested model may legitimately use the attributes of the image for classification through the verification of CAM (class activation map), which explains why this mode performs better.
Keywords -- Convolutional Neural Network, Garbage Classification, Deep learning.

Introduction –
Trash classification has changed globally as a result of increased attention being paid to environmental protection and resource efficiency. Global garbage production amounts to billions of tonnes per year, which can have a significant negative influence on the environment [1]. Meanwhile, there are a tonnes of recyclable materials in trash. Higher recycling rates, paper and plastic waste fractions, and trash collection rates in 2025 will increase the benefits recyclable materials have for the environment and energy use. [2]. However, it is essentially a difficult and expensive procedure to divide diverse wastes into separate categories, such as metal, glass, plastic, and paper. Some of the current options almost demand human sorting, which is labor-intensive and expensive. Therefore, with the rise of deep learning, it is a feasible direction to use machines instead of manual waste classification.

Deep learning enables computer models with several processing layers to learn data representations at various degrees of abstraction. These methods have greatly enhanced modern speech recognition, object identification, visual object recognition, and many other domains, including drug discovery and genomics. [3]. Waste classification has emerged as a promising deep learning application as a result of the success in these fields. Recently, interest has increased in transfer learning, a unique machine learning paradigm. Transfer learning uses auxiliary source data from other closely related source domains when the training data in a target domain are insufficient to learn prediction models successfully. [4]. The transfer learning model, however, can efficiently extract picture information and drastically cut model parameters.

Mechanical sorting is less effective than manual sorting, which is primarily used in developing nations. [5]. However, handpicking requires handling potentially dangerous materials and can lead to a number of negative issues. As a result, using deep learning to the classification of trash benefits both the environment and the workers' health.. Recently, Salimi et al. [6] developed a visual waste separation system based on Hindawi Journal of Electrical and Computer Engineering Volume 2022, Article ID 7608794, 9 pages https://doi.org/10.1155/2022/7608794 classification with a pretrained neural network. The issue of waste separation using material- and object-based class distinctions is amenable to this strategy. Meanwhile, Ramsurrun et al. [7] introduced a deep learning approach using computer vision to automatically identify the type of waste, which consists of an automated recycling bin. In 2016, Yang and Thung [8] released the TrashNet dataset, which consists of six main classes (glass, paper, metal, plastic, cardboard, and trash), and some subsequent studies are based on this dataset. The distinctive qualities of trash in the TrashNet dataset are, however, barely mentioned in the pertinent studies that are currently available.Different deep neural networks have varying capacities to extract their distinctive features.This paper created a hybrid deep learning model that comprises of two networks, the upper network and the lower network, to fully utilise the image's attributes.The image is divided into two major categories by the upper network, and the lower network then assigns the image to one class based on the upper results.To demonstrate the usefulness of the suggested model, experiments were done on the TrashNet dataset to compare the performance and CAM (class activation map) [9] of our proposed model with the leading garbage classification techniques. The main contributions of this paper are as follows:

(1) We suggested a two-stream hybrid system for garbage separation that offers a distinctive viewpoint and method for trash categorization using deep learning.

(2) This paper fills a vacuum in the literature concerning difficult-to-classify classes in the TrashNet dataset, such as the "garbage" class, which has mostly been ignored.

(3) Experiments revealed that the suggested model performs better than the cutting-edge classification techniques on TrashNet and is very effective.

Proposed Work

2.1. Dataset. The classification of recyclable materials is crucial for civilisation and humanity. Numerous research use the Waste Net dataset, a sample dataset for trash classification, to assess the proposed methods. Therefore, it is crucial to increase this dataset's accuracy in order to properly classify waste. The image on this dataset from the 2 Journal of Electrical and Computer Engineering was created with a white background and lit either by natural light or artificial light. The original dataset is about 3.5 GB in size and each image was reprocessed to 512x384 pixels. Table 1 displays the statistics of photos for each class. But some sample photos from the collection are shown in Figure 1.

2.2. Res Next Model and DNN-TC Model

2.2.1. Model Res NeXt. A straightforward, highly modular network architecture for image categorization called Res Next was described by Xie et al. in 2017 [18].In addition to the dimensions of depth and width, this method of the model revealed a new dimension called "cardinality" (the size of the set of transformations) as a crucial element. ResNeXt followed VGG [21] and ResNet [22] by adopting a highly modularized design. It is made up of a stack of leftover blocks. The topology of these blocks is the same. The split-transform-merge technique was employed by the template module to approach the representational capability of big, dense layers.Figure 2 depicts the constructions between the ResNeXt block and the residual block. One type of aggregating transformation is represented by the inner product of the most basic neurons.As shown in Figure 3, the input to the neuron is a D-channel vector x = [x1, x2, . . . , xD] and wi is a filter's weight for the i-th channel.

$$\sum_{i=1}^{D} w_i x_i \quad \ldots(1)$$

The elementary transformation (wixi) from the analysis of a simple neuron above can be swapped out for a more general function or network. Consequently, the equation may be combined as follows:

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

where C is in a position identical to D in equation (1), which is often assigned by 32, and Ti(x) can be any function. The size of the collection of transformations is measured by cardinal. Additionally, because all Ti have the same topology, it is possible to isolate specific factors and apply to a vast number of transformations.The residual function in equation (2) is the aggregated transformation of each Res NeXt block.

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

where *y* is the output.Model DNN-TC. Vo et al. [17] presented DNN-TC (deep neural networks for garbage categorization) in 2019.Figure 4 shows how the DNN-TC model changed the original ResNeXt model for the TrashNet dataset by adding two fully connected layers after the global average pooling layer with output 1024 and N-class dimensions, respectively, to reduce redundancy.The log soft max function is used by the DNN-TC model to calculate each label's confidence as follows:

$$y_j = x_j + \log\left(\sum_{i}^{N_{class}} e^{x_i}\right), \quad \ldots\ldots(4)$$

where xi xj are the ultimate hidden outputs, yj is the output of each classification label, and Nclass is the total number of labels.Structure of the proposed model. This paper offered a hybrid deep learning model for rubbish classification in this section. We noticed an intriguing behaviour in accordance with the experimental results of the ResNeXt model and DNN-TC model. In more detail, the global average pooling layer and two fully connected layers that produced l024 and Nclass dimensions were added by the DNN-TC model to the original ResNeXt model. However, Table 2's comparison of the ResNeXt model's and DNN-TC model's test set accuracy reveals that DNN-TC performs better for classifying glass, cardboard, and rubbish than ResNeXt-101. When it comes to metal, paper, and plastic, DNN-TC has a little lower performance than the ResNext-101 model. We created a hybrid deep learning model based on deep transfer learning for this attribute. When it comes to metal, paper, and plastic, DNN-TC has a little lower performance than the ResNext-101 model. The model developed in this paper consists of two streams of

CNN. The TrashNet dataset was first divided into two segmentsMetal, paper, and plastic (MPP) was one category, and the category CGT was included in the other (cardboard, glass, and trash). In order to classify the image based on the two categories of MPP and CGT, a primary CNN model architecture was created. Five convolutional layers and three fully linked layers made comprised the model's upper stream. The last layer, which was a two-neurons layer with the softmax function to carry out the classification, was one of the three fully connected layers. The secondary CNN model (lower stream) was created to carry out a classification based on the garbage subcategory from the upper stream's output.The ResNeXt-101 model was utilised in the lower stream to extract the features. After the global average pooling layer, we specifically inserted two classifiers. To make a point even more clearly, the deep transfer learning model used in this paper frozen the parameters.The model only needs to train on a small number of parameters as a result. Figure 5 illustrates a specific model architecture.

Experiments, Results, and Analysis

Experiment Settings. An Intel Core i7 11th CPU with 16 GB of RAM and an Nvidia GeForce RTX 3070 GPU were used to implement the experimental models. This study makes use of the PyTroch framework, a free deep learning toolkit for Python. Data augmentation is used to prevent overfitting during training because the TrashNet dataset is deficient in pictures.ICutting, scaling, and rotation are just a few of the methods used to enhance the training dataset's data samples. The amount of data increases to roughly three times what it was without data augmentation.

Table 1: Dataset information.

Class	Number of each class	Training	Validation	Test
Paper	594	403	83	108
Glass	501	354	65	82
Plastic	482	347	61	74
Metal	410	286	56	68
Cardboard	403	287	46	70
Trash	137	91	17	29
Total	2527	1768	328	431

Figure 1: Sample images of dataset.(a) Cardboard. (b) Cardboard. (c) Metal. (d) Metal. (e) Glass. (f) Glass. (g) Plastic. (h) Plastic. (i) Paper. (j) Paper. (k) Trash. (l) Trash.

We replicate modern trash classification models such RecycleNet [7], ResNet-50 [11], DNN-TC [17], RexNeXt-101 [18], and M-b Xception [19] to compare with the proposed modelTo be more specific, we used the ResNet-50 model and the RecycleNet model with the same configurations from their research.It's crucial to remember that the DNN-TC model only acts as a partial reference for determining the learning rate for our model..In this research, we compare the training effects of the SGD and Adam algorithms, and we experimentally show that the Adam approach outperforms the SGD approach in our model. With a learning rate of 0.0001 and two momentum parameters of 0.9 and 0.999 for the first 10 epochs, respectively, the Adam optimizer's hyperparameters are set up.After that, the learning rate decreases by 10% per ten epochs. The experiment in this study also employs a 12-minibatch size with 50 epochs.We chose epoch = 50 because, given the length of training and overfitting of the model, we found that the change in accuracy and loss of our model is comparatively minimal after 50 epochs..For more information, see how we use the parameters and the ImageNet-based pretrained model before keeping the fully connected layers. For more information, see how we use the parameters and the ImageNet-based pretrained model before keeping the fully connected layers.In the interim, we set dropout for the fully linked layer to be 0.2. The upper and lower streams of the model are then trained independently. The higher model converts the two TrashNet dataset categories into straightforward binary categories.Because the bottom stream comprises two classifiers designed for subclassification, the two classifiers must be trained separately.

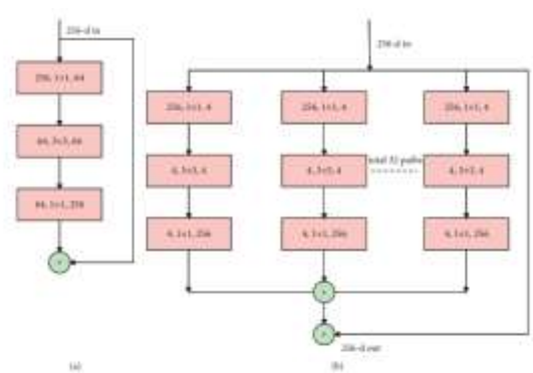

Figure 2: The constructions between the residual block and ResNeXt block [18]. (a) A block of ResNet. (b) A block of ResNeXt with carnality = 32.

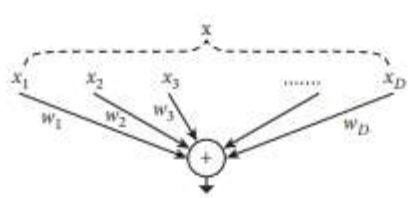

Figure 3: A simple neuron that performs inner product [18].

2.3. Experiment Results. The suggested model was evaluated using the TrashNet dataset, and its results were used to compare it to the state-of-the-art techniques described in Section 4.1.In Table 3, the experiment's accuracy is displayed.For the TrashNet dataset, the suggested model performed better than alternative methods. The hybrid deep learning model obtained 90.5%, 91.7%, 92.1%, 94.3%, and 71%, respectively, while ResNet-50, ResNeXt101, DNN-TC, M-b Xception, and RecycleNet obtained 99.2%, 99.2%, and 98.5% in the overall class. The loss and accuracy variation of the training and test sets over 50 epochs for the hybrid deep learning model on the TrashNet dataset is shown in Figure 6. The model simply needs to train a small number of parameters.Consequently, the hybrid deep learning model's training period is brief. 4.2.This graphic shows that after 50 epochs, the hybrid deep learning model had a greater accuracy and a reduced loss value. On the TrashNet dataset, the model was able to quickly reach a stable and generalised state.

2.4. Experiment Analysis. This study's trial revealed that practically all cutting-edge models did poorly in the rubbish class. The number of objects properly predicted by each model in the rubbish class is shown in Table 2.Unfortunately, none of the earlier studies described above provided an explanation.We maintain that this phenomenon has two main outcomes. First off, the data is unbalanced because there are less photographs in the rubbish category than in other categories.Another is that the model as it is is unable to extract accurate features for this category. The significance of each place for the class is represented by the CAM (class activation map). In order to comprehend which aspect of the image gives the model the ability to make the final judgement, the CAM illustrates the significance of each position to the class. In the garbage class and paper class images of Figure 7, the CAM of the DNN-TC model and the model of this paper are displayed.The model's focal point is shown by the portion of the figure that is highlighted. Orange among them denotes the highest level of focus, while blue denotes the lowest level of attention.

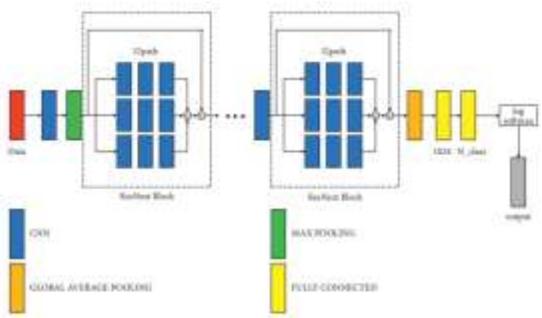

Figure 4: Structure of the DNN-TC model.

Table 2: The test set accuracy of ResNeXt model and DNN-TC model

Class	Classification accuracy of the ResNeXt-101 model	Classification accuracy of the DNN-TC model (%)
Metal	88.7%	87.5%
Pape	85.2%	83.4%
Plastic	81.3%	79.4%
Cardboard	97.6%	100%
Glass	94.4%	95.4%
Trash	0	88.6%
Total	91.7%	92.1%

According to the experimental findings, our model gives more attention to the crucial components in the image of the rubbish class.Both the hybrid deep learning model and the DNN-TC model perform similarly for the paper class.This article discovered that the majority of models concentrate on the backdrop through CAM analysis of prediction error samples of the rubbish class. The author's future study will centre on how to get the model to pay attention to the parts that are more crucial. Although our model performed well on the TrashNet dataset, it is still important to take into account its classification of medical waste because COVID19 continues to have an impact on the globe.However, since there isn't a dataset for medical waste, we are unable to quantitatively assess how well our model categorises medical rubbish. We consequently decide to explore the Kumar et al. [20] case in qualitative detail.In line with our model's proposed categorization scheme, waste in the upper stream can be separated into domestic and medical waste.Medical trash comprises the polyethylene terephthalate (PET) category stated by Kumar et al. while domestic waste covers the metal, paper, and glass categories.Then, based on the upper stream's classification outcomes, the lower stream of our model performs an accurate subclassification. Additionally, our methodology has the benefit of allowing us to categorise garbage into domestic and medical categories without having to segregate it into subcategories by using only the upper stream. In conclusion, we think that our approach can be used to classify medical waste to some extent. Undoubtedly, this will be a focus of our further research.

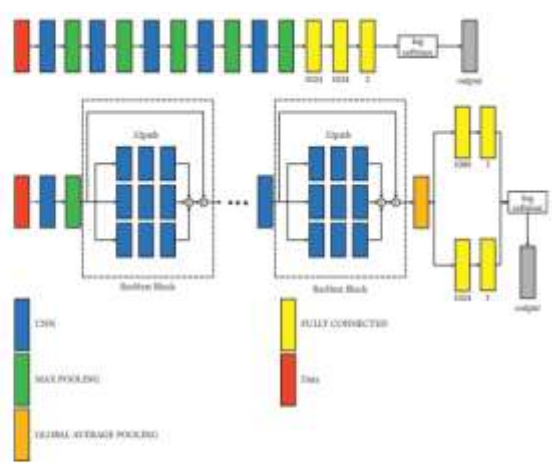

Figure 5: The proposed mode

Table 3: The accuracy of the experimental models

No	Methods	Accuracy in %
1	ResNet-50	90.5
2	ResNeXt-101	91.7
3	RecycleNet	71
4	DNN-TC	92.1
5	M-b Xception	94.5
6	Hybrid model-MPF	97.9
7	Hybrid model-CGT	98.2
8	Hybrid model-total	98.5

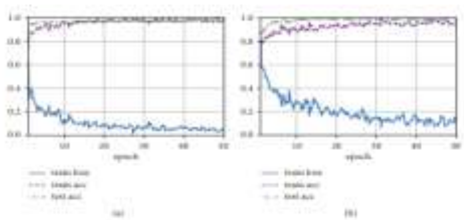

Figure 6: The loss and accuracy in the training and testing processes of the hybrid deep learning model for the TrashNet dataset. (a) The loss and accuracy of category MPP. (b) The loss and accuracy of category CGT.

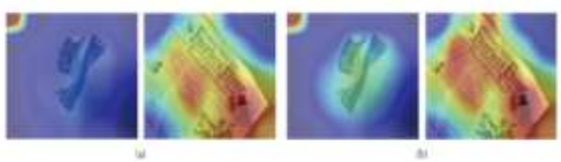

Figure 7: Te CAM of DNN-TC model and the model of this paper in the image of trash class and paper class. (a) The CAM of DNN-TC model. (b) The CAM of hybrid deep learning model.

Conclusion

For the classification of waste, this paper proposed a hybrid deep learning model. CNN is split into two streams for the model.First, we divided category MPP (metal, paper, and plastic class) and category CGT from the experimental dataset TrashNet (cardboard, glass, and trash class). The model's upper stream was created to categorise the image using the MPP or CGT categories.Then, based on the garbage subcategory identified in the top stream's output, we suggested that the lower stream of the model execute a classification. We contrasted the method's predictive performance with that of cutting-edge models to show the validity of the suggested framework.The hybrid deep learning model scored 97.9% in the MPP category, 99.2% in the CGT category, and 98.5% overall. We tested the performance of the hybrid deep learning model using CAM.The model was successfully able to extract visual features, according to experiments.The existing limitations of this paper are acknowledged by the authors. For instance, real systems do not currently use our paradigm. Additionally, because of dataset limitations, our model does not account for garbage categorization against complicated backgrounds.Our future study will include a significant portion devoted to the issue of waste classification in a complicated environment. A unique framework will be developed for further research to improve the model's focus on the key elements of the image.Additionally, the author will test the model on increasingly challenging datasets and real-world systems.

Data Availability

The corresponding author can provide the data that were used to support the paper's conclusions upon request.

Conflicts of Interest

It is stated by the authors that they have no competing interests**.**

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