Dual-Branch CNN for the Identification of Recyclable Materials

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Abstract— **The classification of recyclable materials, and in particular the recovery of plastic, plays an important role in the economy, but also in environmental sustainability. This study presents a novel image classification model that can be efficiently used to distinguish recyclable materials. Building on recent work in deep learning and waste classification, we introduce the so-called "Dual-branch Multi-output CNN", a custom convolutional neural network composed of two branches aimed to i) classify recyclables and ii) distinguish the type of plastic. The proposed architecture is composed of two classifiers trained on two different datasets, so as to encode complementary attributes of the recyclable materials. In our work, the Densenet121, ResNet50 and VGG16 architectures were used on the Trashnet dataset, along with data augmentation techniques, as well as on the WaDaBa dataset with physical variation techniques. In particular, our approach makes use of the joint utilization of the datasets, allowing the learning of disjoint label combinations. Our experiments confirm its effectiveness in the classification of waste material.**

Keywords— Image classification, supervised classification, machine learning

I. INTRODUCTION

Image classification [1] refers to a method that is capable of classifying an image according to its visual content. Although this type of task is effortless for humans, reliable image recognition still poses considerable difficulties for computer vision algorithms [2]. The purpose of this study is to build an algorithm for the automatic classification of potentially recyclable waste items, a task that is significantly challenging due to the state (e.g. level of dirtiness, shape deformation, etc.) of the items during their sorting in waste treatment facilities. A second objective is to further classify the type of plastic, since this particular material includes different types of chemical compound mixtures and, so, different types of plastic used in industry (e.g. PET, PP, PS, HDPE, etc.). Additionally, the fact that current methods for optical identification of recyclable waste are not highly efficient in distinguishing all recyclable materials at once, without the use of hyper-spectral imaging [3, 4, 5] makes our motivation even stronger. Our long-term goal is to increase the productivity and revenue of waste treatment plants. To this end, we build on recent advances in deep learning neural net architectures [6, 7, 8].

In more detail, we receive input images of recyclable materials and aim to classify each one with the use of two labels. The first label distinguishes one of five classes-namely glass, paper, metal, plastic, and trash. The second one categorizes specific "plastic subclasses" - i.e., PET, PE-HD, PP, PS and a non-plastic class. The final output is the characterization of the material with one of these two labels.

To achieve this classification task, we design a novel Dual-Branch Parallel CNN architecture. In our work we integrate several features from two different data sources, so as to facilitate classification with the additional benefit of joint utilization. A key idea is that a combination of the Trashnet dataset (which contains glass, paper, metal, plastic and trash material) [9] and the WaDaBa dataset [10] (which contains different labelled types of plastic, but augmented with non-plastic material in our case) will lead to a more robust model, one with potentially higher classification accuracy compared to using Trashnet alone.

As such, our Dual-Branch Multi-output CNN approach combines two independent separately trained classifiers, one for each branch. One branch is trained with the recyclable waste materials (from Trashnet), and the other with images of plastic types (from the augmented WaDaBa). We base our final predictions on those of the recyclable waste classifier, but increase our confidence on these predictions or revise them completely based on the output of the plastic classifier. For instance, if the "Material classification branch" has a large "confidence" (probability) in classifying an item as "plastic" and the "Plastic classification branch" assigns a large probability in the item being a certain type of plastic, then we may favor this particular class of plastic with increased confidence. Similarly, if the "Mateial branch" predicts some material to be in a specific non-plastic class (e.g., "glass"), and the "Plastic branch" agrees that this material is "non-plastic", then we enhance our confidence on the initial prediction. On the other hand, if the "Material branch" has predicted some non-plastic class with low probability p but the "Plastic branch" predicts a certain type of plastic with a probability larger than p, then we base our final classification on the predictions of the "Plastic branch".

Our "Material classification branch'' is built using a Stacked Ensemble of CNNs aiming to achieve better accuracy with fewer false predictions. By integrating various architectures [11], the Stacked Ensemble learns the optimal combination of predictions from a variety of well-performing machine learning models.

Our problem formulation shares certain characteristics with the incremental learning of networks from diverse datasets that cannot be brought together. This is the case, for instance, in medical multicenter datasets of different modalities, or of the same type but addressing different properties of the population. In these domains, the concept of shared wisdom from the data forms the tradeoff between learning efficiency and privacy level [12, 13]. To this end, the concept of Federated learning implements different training of networks at each data site and then an averaging combination of these networks at the final central point [14]. Instead, the concept of Split learning trains separate networks at each site, up to the level of feature extraction, whereas all networks are combined towards a final centralized classification network [12]. Our approach of Dual-Branch learning builds on these approaches, and formulates different classifier networks as in Federated learning; with adaptive combination at the classifier level, similar to Split learning.

We compare against an architecture that simply employs two independent CNNs, each responsible for the different classification tasks. We conduct a systematic evaluation on well-known benchmark datasets, showing that our approach meets its purpose of increasing classification confidence, and achieves a very robust overall performance, with an overall accuracy of 90.02%.

Our contribution can be summarized as follows:

- We expand on the concept of shared wisdom from data and explore how various datasets can be combined to improve accuracy and create stable network architectures.
- We implement a novel, dual-branch multi-output CNN for recyclable waste classification, with a component that uses multiple source information at the final stage. The need for this component arises from the need to address and exploit the peculiarities of the data, especially the different types of plastics.
- We demonstrate via extensive testing that our approach results to a clear improvement in performance. Specifically, transfer learning is shown to be achieved, and material classification is shown to be significantly improved by exploiting the output of the plastics' classifier, whose performance boosts that of the overall network.
- When tested on data originating from the same dataset used for training (i.e., with a less demanding, non-transfer learning setup), our materials classification branch surpasses the accuracy of state-of-the-art methods for the same benchmark dataset.
- The success of our approach highlights the importance of exploiting information emerging from different attributes and experimental settings.

II. Related Work

Waste classification can be handled in many ways, examining either the civilian's behavior towards circular economy [15] or the operation conditions of the recycling facilities [16]. The main trend in utilizing image classification in the recycle waste industry is focused on the identification of the recyclable waste material and moreover on the type in case of plastic material. The plastic waste recycling and recovery industry has a great impact in the U.S. and Europe [17]. Thus, many attempts have been made mainly in the area of waste material identification using CNNs.

There are, however, four prevailing examples of waste classifying CNNs. The "TrashNet" network identifies waste into five groups of recyclable material and trash [18]. Additionally, Spot-Garbage [19] is a smartphone application that helps users to recognize garbage in the streets of urban centers across India. It uses a CNN called GarbNet, which was trained on an annotated dataset called Garbage in Images. Another similar study uses a multi-layer hybrid deep-learning system (MHS) for the automated disposal of waste by individuals in urban public areas [20]. Finally, CompostNet [21] is an image classifier for meal waste especially classifies images according to how they should be correctly discarded. An architecture with similarities to ours is the two-branch convolutional neural network for remote sensing data classification in [22]. Another network similar to our material classification branch is the multiple Fully Connected SubNetworks (FCSNs) [23].

Finally, there is a rich tradition of computer vision methods for transfer learning and domain adaptation [2, 24]. Transfer learning focuses on deep NNs has recently attracted considerable attention in the community [25, 26]. Fine-tuning a pre-trained network model such as ImageNet on a new dataset is the most popular tactic for information transfer. Methods have been suggested to fine-tune all network parameters [27], just the last few layer parameters [28], or to simply use the pre-trained model as a fixed-feature extractor with a classifier such as SVM at the top [29].

III. Proposed Classification Framework

Our proposed classification framework is the Dual-Parallel CNN for waste Classification, shown in Fig. 1. This includes a Stacked Ensemble of CNNs branch for waste sorting and a classic CNN branch for plastic classifying. In our experiments we pit this against a CNN pipeline, where explicitly after the first CNN predicts waste classes, the second CNN predicts the form of plastic (Fig. 3).

A. Dual-Parallel CNN for recyclable waste classification

The CNN architecture we put forward in this work, consists of two branches corresponding to two independent classifiers, depicted in Fig. 1. The first of these is a dedicated branch for a plastic classifier trained with the WaDaBa dataset, albeit augmented with an extra class consisting of non-plastic images from the Trashnet dataset for the classifying four types of plastic or not plastic at all. For a more detailed composition of the network, we use a CNN network with weights initialized via pretraining on "Imagenet"; and then replace the final fully connected layers with 2 dense layers with 512 neurons. After the convolutional layer, the output gets through a softmax activation function with temperature scaling for neural network calibration and to "soften" the probabilities [30, 31]. The final network is fine-tuned using the WaDaBA images.

The second branch is an independently trained Stacked Ensemble of different CNN architectures, specializing in classifying (potentially recyclable) materials into five classes. This branch was trained on Trashnet. The base-learners are 3 different pretrained CNNs (DenseNet121, ResNet50, VGG16). The outputs of each model can then be combined. We use a straightforward merge of concatenation, where a single 15-element vector is generated from the five class-probabilities predicted by each of the three models. We then use a hidden layer to translate this "input" to the meta-learner and the output layer to produce its own probabilistic prediction. Finally, we create a stacked generalization model based on a list of trained sub-models, as shown in Fig 2.

Each branch performs its respective series of convolution, activation, batch normalization, pooling and drop-out operations until the final output is reached.

Now, it is important to assess the transfer learning capability of a given architecture. To test transfer learning, in one of our experiments we created a mixed test set from the two Datasets for our Dual-Branch CNN. In some detail, the testing set is fed with images from five classes: (a) glass, (b) paper, (c) metal, (d) trash, (e) plastic. These consist of image samples from the TrashNet dataset except for the plastic class which take samples from WaDaBa dataset.

Our experimentation showed that transfer learning cannot occur when using the "Material Branch" alone. The reason behind this is that this "material classifier" branch is trained with TrashNet images that may be labeled as "trash", while they depict plastic, and are thus similar to the plastic images originating from the WaDaBa dataset. Naturally, the Trashnet branch decides that these are "trash", as shown in the confusion matrix we report. This phenomenon mirrors a wider, key problem faced in transfer learning: namely, the challenge to be able to classify correctly images that might look very similar to training data that originated from a class with a different, misleading label.

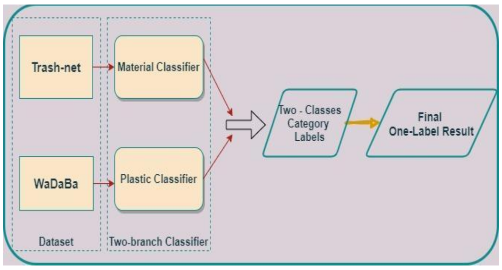

Fig. 1. Dual-Branch Architecture

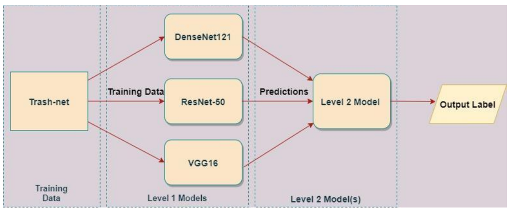

Fig. 2. The "Material Branch" - Trained on Trashnet

To counter this problem, we equip our Dual-Branch CNN with an additional step performed after we receive the two-labels output. In this step we exploit the known fact that we have a classifier specialized in plastic separation, and use this knowledge to increase our confidence in the "material class'' (Trashnet branch) predictions, or even revise these completely, given the output of the "plastic" classifier (WaDaBa branch). Specifically, we convert the double-labeled result of the proposed system into a final one-label result as follows. If the "Material branch" has predicted "plastic", and the "Plastic branch" gives a greater probability for a certain type of plastic, then we assign this probability as the probability of "plastic" - and predict that particular type of plastic. However, if the "Material branch" has predicted any other particular class with probability p, but the "Plastic branch" predicts a certain type of plastic with a greater than p probability, then we base our final classification on this "assumed-to-be-expert-on-plastic" prediction, and assign the material to be classified in the corresponding "plastic type" class predicted by WaDaBa. Finally, if the "Material branch" has predicted the item is in some particular non-plastic class with probability q, while the "Plastic branch" has assigned the item a probability q' ≥ q for it to be in its "non-plastic" category, then we are more confident in identifying the material class as the one predicted by the "Material branch", and produce exactly that class as our final prediction for the input image. In this way, our overall Dual-Branch Architecture allows for the joint utilization of the datasets, and effectively achieves transfer learning.

B. Training Process

First, the distinct branches of the Dual-Branch's architecture are trained on separate training data using fine-tuning that requires a pre-trained model on the same or greater data set. Fine-tune will load the weights of the pre-trained model to substantially minimize the computing time.

The Stacked Ensemble CNN material classifier and the CNN plastic classifier are first trained on separate training sets. More precisely, and similarly to what is suggested in [22], two separate branches are first trained in the first stage of the training process. When the two components are merged in the second stage of the process, the pre-trained models extract the respective classes from the training data pairs, and we obtain the two-class output labels. The training process is described in Table 1.

Table 1. Training process of the Dual-Branch CNN for the classification of waste materials

1. Initialize all weights
2. for #epochs
3. Stage 1:
   - Train the material classifier branch
   - Train the plastic classifier branch
4. for #epochs
5. Stage 2:
   - Merge the separately trained models
   - Test the Dual-Branch CNN

Additionally, we used data augmentation techniques in order to generate samples of images and thus enrich the initial training dataset. The augmentation transformations we use are a) random flipping, b) random rotating, c) gaussian distortion, d) shearing and skewing, e) random zooming in order to render variations within the dataset, so it can correctly generalize the unseen data. All data is scaled to 0−1 in order to increase the speed of convergence. On the other hand, fine-tuning is typically used to transfer a pre-trained model for large-scale data to small-scale and related data. In consideration of the characteristics extracted from each branch which are relevant for a particular branch, we use the transfer learning strategy of [32] to train the two separate branches in a specific and very similar training set.

Finally, we compare the proposed Dual-Parallel CNN with the sequential implementation of the two CNN networks, the first used for material classification and the second one for plastic type categorization as shown in Fig 3.

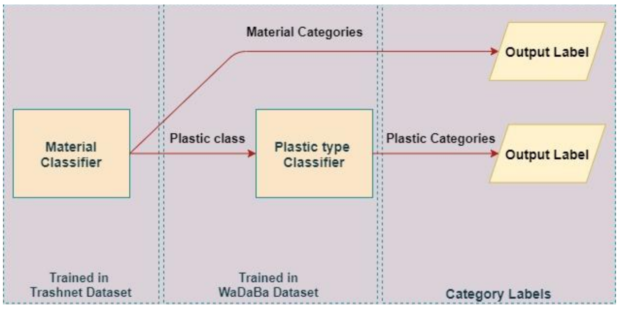

Fig. 3. Sequential CNN Architecture

IV. EXPERIMENTAL EVALUATION

In this section we evaluate the performance of the proposed parallel dual-branch CNN architecture. Our coding used Python and Tensorflow via the Keras high-level application programming interface. We ran our tests on dual Intel i7-9700, 32 GB Ram, with Nvidia GTX 1080 GPUs.

As mentioned earlier, we test our network on two datasets: (a) the Plastic Waste Data Base of Images – WaDaBa: it consists of 3960 images obtained after transformations, such as change of perspective, damage effect, and light sources shifting. The specific categories of plastic waste are: a) PET, b) PE-HD, c) PP, d) PS [9]; and (b) the Augmented TrashNet Dataset: the TrashNet data collection consists of images of six classes: glass, paper, cardboard, plastic, metal and trash. The dataset currently consists of 2527 images [9]. We picked five labels for classification, i.e. Paper, Plastic, Metal, Glass, Trash and used data augmentation that resulted to a dataset of 10,000 images equally divided among the 5 classes.

A. *Parameter Tuning*

The tuning of the various parameters of a deep learning architecture is key to optimize classification performance. We tried three different architectures for our “Plastic branch”. Specifically, we tried the Visual Geometry Group network (VGG16) [33]; the Densely Connected Convolutional Network (DenseNet121) [34]; and the Deep Residual Learning for Image Recognition (ResNet50) [35]. The bottom 3 layers, i.e. full connection, classify, and data input, are removed.

The rate of learning is one of the factors that determines the convergence of speeds that may affect the performance of training. The learning rate is set to 0.01 with Adam's policy [34]. We tested different learning rates on the WaDaBa dataset and established empirically that accuracy is not improved with higher learning rates. Since the fine-tuning strategy can significantly reduce the complexity of the computation, the low-level features are extracted by pre-trained layers, which then fit into the custom layers for the task of classification. In fact, fine-tuning helps to achieve higher classification accuracy and to build a more robust network. As shown in Table 2, the overall accuracy of the WaDaBa dataset classification showed similar accuracy between the three options of different architectures.

B. *Experiments and Results*

The fundamental basis of our formulation explores the utilization of different datasets in the formation of a specific query based on a subclass of data samples. More specifically, we can find available experimental datasets that differ not only in the experimental protocol but also in the classes of interest. In our case, we use one dataset focused on the classification of materials (including plastics in general) and a second dataset addressing the identification of specific plastic subtypes. Success in the latter boosts our confidence in the classification of plastics in the former. Our architecture allows for the joint utilization of the datasets.

To demonstrate these issues, we formulate specific classification problems for comparison. We first test individual classifiers, separately on the two datasets. Then, we also test the sequential training of classifiers on the two datasets and compare the performance to the proposed dual-branch architecture that fuses information from the two datasets, thus boosting the training capacity in the plastics class. We note that our plastic’s subtype classifier exhibits a remarkable performance, a fact which allows our proposed scheme to significantly improve the overall network’s performance in plastics classification, without affecting the performance in the other material types.

In detail, we evaluated the three CNN architectures for the “Plastic branch” with images from the four plastic classes in the WaDaBa dataset, and from an extra class for non-plastic samples taken from TrashNet. The total number of samples are 4234 for the training and 1308 for the testing dataset. The CNN models’ accuracy is demonstrated in Table 2. DenseNet121 is the network exhibiting the highest accuracy. Note that the accuracy of all models surpasses the 75.68% accuracy of the only known-to-date model used on WaDaBa [3]. We use 4-stratified fold validation for generalization. A confusion matrix for DenseNet121 on the WaDaBa dataset described above is shown in Table 3. We observe there that almost all instances from each actual class are mapped to the corresponding predicted classes.

Table 2. Accuracy for the CNN models on WaDaBa dataset

Deep Learning model	4 - fold accuracy
DenseNet121	99.33% (+/- 0.17%)
VGG16	99.25% (+/- 0.30%)
ResNet50	99.12 (+/- 0.17%)

Now, in order to test the Stacked Ensemble CNN used for the “Material branch”, we use 87.5% of the samples in the augmented TrashNet dataset for training and testing the base learners and keep the remaining 12.5% as a hold-out set for testing the Stacked Ensemble CNN. The samples represent the classes ‘Glass’, ‘Metal’, ‘Paper’, ‘Plastic’ and ‘Trash’. We test the pre-trained base learners, and the performance of each of these architectures is shown in Table 4. We then evaluated the “Material branch” model to assess whether it can exhibit a better performance. Its accuracy is 97%, as shown in Table 6; while its corresponding confusion matrix in Table 5. Here again, the algorithm provides a good match between the actual and the predicted class for each instance, while the 4-fold cross validation accuracy remains high to each one of the three proposed deep learning models. We note that the Stacked Ensemble model’s accuracy surpasses, by more than 2%, several state-of-the-art models applied on TrashNet: specifically, an accuracy of 95% is reported in [36] for DenseNet121, while a maximum accuracy of 94% and 95% is reported in [37] for InceptionResNetV2 and DenseNet121 respectively.

Finally, to test the transfer learning ability of our proposed Dual Parallel CNN architecture, and showcase its ability to combine different datasets to improve accuracy, we employ a second, mixed, hold-out set, different to the Hold-Out set #1 mentioned above. This mixed Hold-Out set #2 contains only 411 images, and is built by replacing the plastic images of the original (augmented TrashNet) hold-out set with 154 plastic images originating from WaDaBa; while the 257 images used for the other materials come from TrashNet but are different to the ones used in Hold-Out set #1 above (which had 1250 images in total). As such, this is a rather demanding transfer learning experiment. To accomplish this task, we use the two independently trained networks (branches) as "frozen" classifiers to determine example images and obtain the multi-output classifications. Then, we perform the final one-label classification step to predict the class of the input image. Tables 7 & 8 summarize the performance of the overall classification scheme in material separation and plastic identification, respectively. The overall model's accuracy is 90.02%.

Table 3. Confusion Matrix for DenseNet121 on WaDaBa

	Confusion Matrix: Plastic Type Classifier					
	Predicted labels					
Actual labels		PET	PE_HD	PP	PS	non-plastic
	PET	99.8%		0.2%		
	PE_HD	1.3%	98.7%			
	PP	1.2%		96.9%	1.9%	
	PS			3.8%	96.2%	
	non-plastic					100%

Table 4. Accuracy for the base-learner models on Trash-net

Base-learner model	4-fold Accuracy
DenseNet121	96.73% (+/- 0.59%)
VGG16	96.22% (+/- 0.61%)
ResNet50	96.21% (+/- 0.22%)

Table 5. Confusion Matrix for Material Branch on Hold-out #1

	Confusion Matrix:Material Branch on Hold-Out #1					
	Predicted labels					
Actual labels		glass	metal	paper	plastic	trash
	glass	94.0%	2.4%	1.6%	2.0%	
	metal	1.2%	96.8%	0.4%	1.6%	
	paper	0.4%		98.0%	0.8%	0.8%
	plastic	3.2%		2.0%	94.0%	0.8%
	trash					100%

Table 6. Accuracy of the Material Branch on Hold-Out #1

Stacked Ensemble CNN	4 - fold accuracy: 97%

By contrast, Table 9 demonstrates the independent performance of the material classifier (i.e., the "Trashnet branch"). In particular, we observe the inability of the material branch to correctly identify several plastic items, that are erroneously classified as trash, paper, or metal. This underscores the need for our proposed extra step, the one that combines the two results into one final output, resulting to the much improved performance observed in Table 7. Intuitively, the final step manages to enhance the performance of the material classifier, based on the excellent performance of the "Plastic branch" in plastics' separation.

Table 7. Confusion Matrix of the Dual-Branch net on Hold-Out #2

	Confusion Matrix: Dual-Branch Architecture Final Outcome (when tested on mixed Hold-Out set #2)					
	Predicted labels					
Actual labels		glass	metal	paper	plastic	trash
	glass	92.8%	2.9%		2.9%	1.4%
	metal	3.9%	94.1%	2.0%		
	paper	1.4%		90.5%		8.1%
	plastic			1.9%	97.4%	0.6%
	trash	11.1%	4.8%	14.3%	4.8%	65.1%

Table 8. Confusion Matrix of the Plastic Branch on Hold-Out #2

	Confusion Matrix: Plastic Branch on mixed Hold-Out #2					
	Predicted labels					
Actual labels		PET	PE_HD	PP	PS	non-plastic
	PET	100%				
	PE_HD		100%			
	PP			100%		
	PS				100%	
	non- plastic					100%

Table 9. Confusion Matrix for the Material Branch on Hold-Out #2

	(independent) Material Branch on Hold-Out #2					
	Predicted labels					
Actual labels		glass	metal	paper	plastic	trash
	glass	92.8%	2.9%		2.9%	1.4%
	metal	3.9%	94.1%	2.0%		
	paper	1.4%		90.5%		8.1%
	plastic	1.9%	17.5%	24.0%	27.9%	28.6%
	trash	11.1%	4.8%	14.3%	4.8%	65.1%

V. Conclusions and Future Work

In this paper we present a dual-branch CNN architecture for the classification of recyclables, which achieves incremental learning from disjoint datasets. Our architecture takes advantage of the combined knowledge of its sub-nets across the various datasets, with local training only on the site of each dataset. Thus, we can effectively learn from multiple sources and accumulate knowledge without mingling the data samples. The combination scheme at the classification level exploits the individual outcomes of sub-nets in a way that increases confidence in the final decision-making process. Our results indicate that we can indeed make effective use of the independent datasets, so as to achieve strong classification performance. Moreover, our classifiers outperform state-of-the-art ones used on our evaluation datasets. In subsequent stages of this research, we intend to use this approach in real-time applications, as an adaptively modified federated learning scheme.

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