

Hybrid cnn–densenet121 architecture for intelligent waste classification in sustainable smart cities

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Abstract. The growing volume of waste produced around the world has posed serious problems for recycling and environmental sustainability. Correct waste classification is a key to successful waste recycling, and the current type of systems remains dependent on manual classification, which is time-consuming and prone to errors. Thus, waste classification automation has become a significant field of study. This paper proposes a deep-learning hybrid model for waste classification. The proposed system combines a four-layer CNN and a DenseNet121 model to obtain both detailed visual features and higher-level patterns of waste images. The TrashNet dataset is used to train and test the model and consists of six classes of recyclable waste. The findings indicate that the proposed hybrid model has better performance compared to a single model system, as combining the proposed CNN with DensNet121 enabled an efficient waste classification. This research supports the development of intelligent recycling systems that enhance the sustainability and efficiency of waste management practices.

1 Introduction

Human beings generate large volumes of waste every day, putting great stress on the environment and posing challenges for waste-management systems around the world. It is estimated that in a single year, approximately 2.01 billion tons of municipal solid waste are produced and that at least 33% of this waste is not disposed of in an environmentally secure way, even by conservative estimates. In addition, the current garbage production in the world is estimated to increase to approximately 3.40 billion tons by 2050, compared to 2.01 billion tons generated today [1]. The recycling of 1 ton of paper waste will save the equivalent of 17 trees, and greenhouse gas emissions would be reduced to 12,400 m³ [2]. Most of the wastes, which can be reformed and reused as raw materials in other supply chains, end up in the landfills rather than being converted into raw materials, which would be a very inefficient economic approach. The impact of such poor waste management can affect the economy, environment, and health of people [3]. Recycling is turning out to be a part of a sustainable society. Nevertheless, the total process of recycling comes with many unseen costs because of sorting, classification, and processing of the recyclable items. Thus, the creation of automated recycling systems has become very useful to contemporary industrial and information societies. These systems have the potential to provide the world with not only significant environmental impact, but significant economic rewards as well [4]. Today, the primary flaw of traditional systems is that they mainly use manual separation for material sorting. Consequently, such methods can be inefficient, laborintensive and subject to human error. With the increasing global focus on sustainability and a circular economy, there is a

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growing need for smart and scalable solutions that can make recycling processes more efficient, more accurate, and less harmful to the environment. [5]. Among the most developed methods to classify solid waste, there is the deep learning algorithm that is grounded on Convolutional Neural Networks (CNNs) [6]. CNNs are extensively used in image recognition applications and are able to assign meaningful labels to the input images automatically. Even though deep learning remains an area of active research, it has already passed the stage of laboratory research and entered commercial life, changing the work of many industries [7]. Among different CNN networks, DenseNet (Densely Connected Convolutional Networks) [8] is one of the numerous CNN networks that have recently received a lot of attention because of its high performance despite a relatively small number of parameters. DenseNet121 employs densely connected layers, which enhance gradient flow, feature extraction, and, ultimately, classification accuracy. This paper introduces a smart waste classification system that uses a hybrid CNN- DenseNet121 as the main classification model to identify different types of recyclable materials. A 4-layer CNN is proposed to work in parallel with the DensNet21 follower by concatenation of features. In addition, the proposed model is systematically compared with several state-of-the-art deep learning models to highlight its advantages in terms of classification accuracy, computational efficiency, and overall reliability. The results demonstrate the potential of intelligent, data-driven recycling systems to improve sustainable waste management in urban environments and support the larger vision of future smart cities.

2 Related work

Several studies have investigated smart waste recycling. For example, He et al. [9] explored automated waste classification using a custom CNN and contemporary pretrained deep learning networks in the TrashNet data set. An adapted AlexNet was trained directly using dropout, data augmentation, and learning-rate scheduling to reach an overall maximum accuracy of 79.94% with a combination of categorical loss and partial augmentation. In 2021, Ozdemir et al. examined how machine learning can be used to improve recycling methods by detecting and classifying waste automation [10]. Several machine learning algorithms are reviewed in the context of the recycling application, which proves their ability to categorize waste materials with an acceptable precision. The results of the experiments have shown that machine-learning-based systems can substantially reduce the number of people involved and help implement more sustainable waste-management policies. The authors concluded that machine learning is an effective answer to intelligent recycling systems, but more data and data heterogeneity are needed. A review has been made by Wanjun Xial et al. in 2022, on the use of machine learning (ML) and deep learning (DL) methods in municipal solid waste management (MSWM) between 2000 and 2020 [11]. More than 200 studies are reviewed that involve the entire MSWM pipeline, such as waste generation predictions, optimal collection and transportation, waste classification, recycling, and landfill operations. The review highlights the suitability of ML models, including artificial neural networks (ANNs), support vector machines (SVMs), random forests, and CNNs, for modeling the intricate nonlinear relationships inherent in waste management systems. Furthermore, Keskin et al. in 2023, retrained a number of CNN models, such as MobileNet, Xception, ResNet50, and DenseNet121, on the six waste categories [2]. DenseNet121 performed best with 95% accuracy. The results show that although scratch-trained CNNs have limitations in their performance, pretrained deep learning models, especially DenseNet121, can significantly improve performance and may significantly benefit automated recycling systems. Sharma et al. tested CNN, ResNet50, DenseNet121, MobileNetV2 and SVM models using a labeled Kaggle data set of six types of wastes [12]. The best accuracy of (93%) was obtained in ResNet50 compared to DenseNet121 and MobileNetV2 (89%), and the worst among all was

the traditional SVM. The results also proved that deep neural networks greatly contribute to image-based waste classification and provide a scalable path to develop intelligent waste classification systems. In 2024, Kant et al. fine-tuned the DenseNet121 model on an augmented Kaggle dataset to classify waste into six categories [13]. Their model achieves (88%) accuracy after being modified with a pretrained architecture to add normalization layers, dense layers, and dropouts. Also, their model shows that it worked well with cardboard, paper, and metal, but it has poor performance with the trash category due to the scarcity of information and visual proximity to other classes. Training curves exhibit slight overfitting, and the confusion matrix indicates the existence of certain misclassification trends. Hossen et al. introduce a deep-learning model known as RWC-Net (recyclable waste classification network), which is used to categorize recyclable waste into six categories using the TrashNet dataset [14]. RWC-Net uses auxiliary branches to combine elements of DenseNet201 and MobileNet-v2, the model achieves an accuracy of 95.01 with five-fold cross-validation and data augmentation. The work concluded that RWC-Net has potential in automated waste sorting, but future research should increase the diversity of datasets and deal with real-life challenges like cluttered scenes and other types of waste.

3 Methodology

The analysis is performed on the Kaggle platform [15] using a TensorFlow environment, with a GPU T4 x2 to speed up computation.

3.1 Data collection and pre-processing

The proposed model is trained on the TrashNet database. The dataset is publicly available from GitHub [16]. It comprises 2,527 images divided into six classes: paper (594 images), glass (501 images), plastic (482 images), metal (410 images), cardboard (403 images), and trash (137 images). Figure 1 shows samples of these images. The resolution of each image is (512 × 348) pixels. In this study, we employed a 70% of the dataset for training, and 15% for validation and testing. To increase the number of images, data augmentation methods are used during the training process. These methods aim to enhance the variety of the training data artificially through the creation of manipulated representations of the original images without altering the content of the image by using shifting, zooming, horizontal flips, brightness adjustment, and rotation of 20°, to improve the generalization capacity of the model and to reduce the chance of over-fitting, by providing a more stable and effective training. Also, the augmentation process is applied to the trash class separately to increase the image up to 400 images to make the training process more effective and balanced.

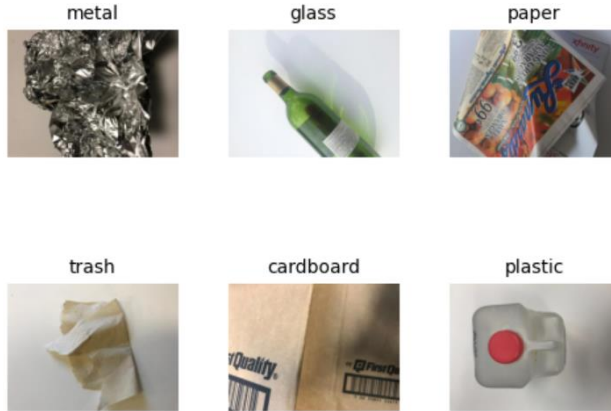


Fig. 1: Sample images of TrashNet dataset

3.2 Proposed 4-layer cnn

The input to the proposed model is an image of size ($224 \times 224 \times 3$). The first stage of the proposed architecture consists of a four-layer CNN. This CNN comprises four convolutional blocks, each consisting of a convolutional layer followed by batch normalization, a ReLU activation, and a max-pooling operation. Batch normalization is used to stabilize training and accelerate convergence, while ReLU activation enhances learning efficiency by mitigating the vanishing-gradient problem. Following the convolutional stages, the resulting feature maps are flattened and passed to a fully connected layer with 64 neurons. To reduce overfitting, a dropout layer with a rate of (0.5) is applied. Finally, a softmax output layer is used to produce class probability distributions for the target categories. The convolutional stages are followed by the flattening of the feature maps, after which they are subjected to a fully connected layer containing 64 neurons. A rate of (0.2) dropout layer is implemented to prevent overfitting. The last layer of this branch is a softmax layer that generates class probabilities.

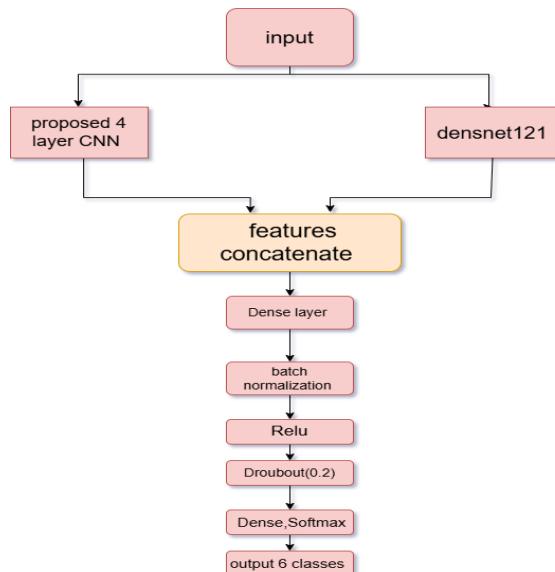


Fig. 2: Proposed Model Architecture

3.3 Densenet sub-model

DenseNet-121 is a deep convolutional neural network designed to improve accuracy while remaining efficient. Its main idea is dense connectivity, where each layer receives the feature maps of all preceding layers and passes its output to all subsequent layers. This direct flow of information helps the network preserve important details as it gets deeper and makes learning more stable. Although the model has 121 layers, it avoids unnecessary complexity by reusing features instead of learning the same patterns multiple times. Early layers capture simple visual information, while deeper layers build on these features to learn more complex representations. This structure allows DenseNet-121 to achieve strong performance with fewer parameters, making it a reliable choice for demanding image classification tasks.

3.4 Feature concatenation and classification

The feature outputs from the custom CNN branch and the DenseNet121 branch are concatenated along the feature dimension to form a unified feature representation. This fusion integrates low-level and high-level features, allowing the classifier to combine complementary information for improved prediction accuracy. The combined feature vector is fed into a fully connected layer with 128 neurons, followed by batch normalization and a ReLU activation function. To further improve generalization performance, a dropout layer with a rate of (0.2) is applied. Finally, a softmax classification layer is employed to generate probability distributions over the six target classes.

4 Result and discussion

4.1 Training procedure

Each branch (the proposed CNN branch and Densnet121) was trained from scratch for 70 epochs with a batch size equal to 32. The optimization is performed using the AdamW optimizer [17] with a small learning rate (1×10^{-4}) and a weight decay coefficient of (1×10^{-5}) so that it encourages stable convergence and minimizes overfitting. To enhance performance, early stoppage is also used. Figure 3 illustrates the training accuracy and loss curves of the DenseNet121 model, while Figure 4 presents the corresponding accuracy and loss curves of the proposed hybrid model.

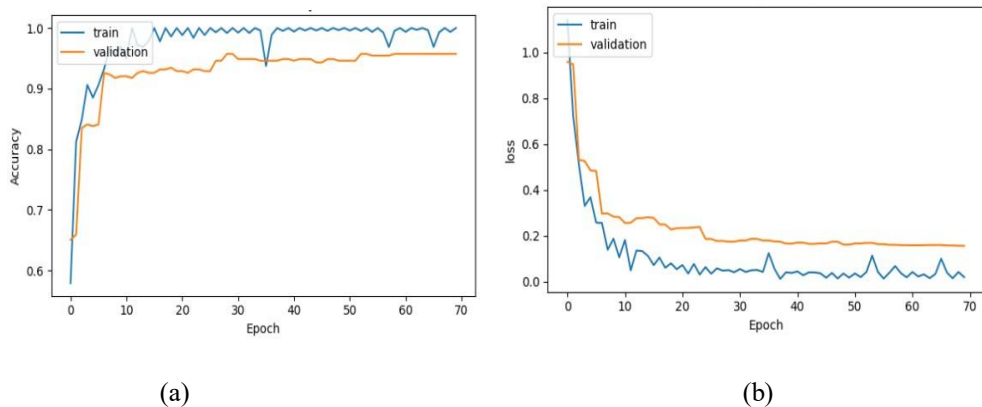


Fig. 3: Proposed model training performance: (a) Average accuracy per epoch (b) Loss values per epoch

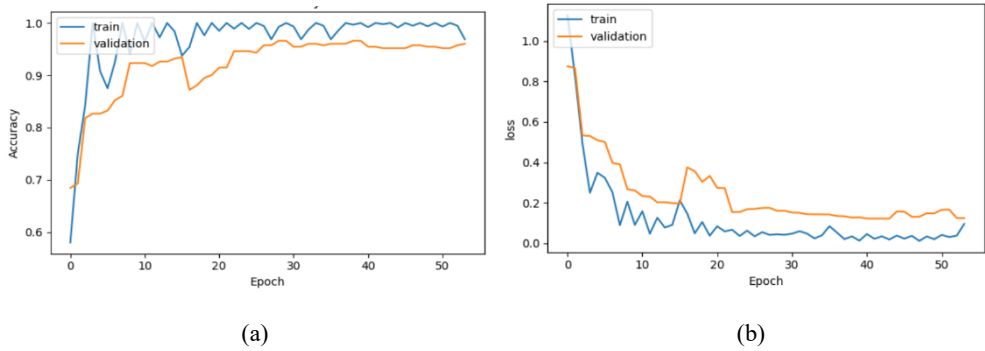


Fig. 4: Densen121 model training performance: (a) Average accuracy per epoch (b) Loss values per epoch

From Table 1, we see that adding a simple four-layer CNN to the DenseNet model, using a concatenation approach, improves performance. Compared with prior work, this result demonstrates a clear improvement [2], [12], [13], using the same DenseNet121 model that illustrate in Table 2.

Table 1. Results of proposed model accuracies

Model	F1-score	Test Accuracy
Four Layer CNN	0.69	0.69
DenseNet121	0.95	0.95
Combined model	0.96	0.96

Table 2. Comparison with state-of-the-art on TrashNet dataset.

Authors	Type of Dataset	DenseNet121 test accuracy
Keskin et al. [2]	2527, image of TrashNet dataset	95%
Sharma et al. [12]	2527, image of TrashNet dataset	89%
Kant et al. [13]	2467, image of TrashNet dataset	88%

4.2 Model evaluation

4.2.1 classification results

As the results of the evaluation provided in Table III indicate, the model has remarkable abilities in terms of separating different types of waste with a high level of accuracy. This system has an overall accuracy of 96% on a total of 384 samples, and it is this level of reliability and strength of the algorithm that was used to process

different data points that indicates that the system is healthy. Upon a critical examination of the individual classes, it is possible to note that the model worked outstandingly well with Paper and Cardboard. It is important to note that the highest Recall of 1.00, or the model identified all single cases of cardboard, without a false alarm, was achieved in the Cardboard category. At the same time, the category of Paper had a precision of 0.99, which is essentially a perfect result in the success rate of having the items that were considered as paper, and the rate of false positives was practically nonexistent. Additionally, with F1-scores of 0.97 and 0.95 for Metal and Glass, respectively, the performance in these two categories was consistently strong. This suggests that the model's feature extraction process is highly successful in identifying the special qualities of these materials. Even the 22-sample low-support category of the trash had a respectable F1-score of 0.93. Given the small amount of data available for this category, the result is still impressive, even though its Recall (0.91) was marginally lower than that of other classes. Finally, the value of the Macro Average and the Weighted Average are equal to 0.96, reflecting the stability of the model. This balance demonstrates that the model is balanced and is not biased to a specific class, including those that have more samples.

Table 3. Classification Report Evaluation.

Class	Precision	Recall	F1-score	Support
Cardboard	0.97	1.00	0.98	61
Glass	0.97	0.93	0.95	76
Metal	0.95	0.98	0.97	62
Paper	0.99	0.98	0.98	90
Plastic	0.93	0.95	0.94	73
Trash	0.95	0.91	0.93	22
Accuracy		0.96		384
Macro Avg	0.96	0.96	0.96	384
Weighted Avg	0.96	0.96	0.96	384

4.2.2 Confusion Matrix

As the confusion matrix represented in Figure 5 indicates, the proposed model can identify six types of waste. The model has a Remarkable performance under the cardboard category (61/61), where there are no mistakes in classifying all samples. The paper class also has a very high percentage of correct predictions, as the sample is only two misclassifications, indicating high discriminative ability. The glass group is also very accurate, with the majority of the samples correctly recognized and a few mixed with metal and plastic. In the case of metal, the model works quite well, with just a single example being incorrectly recognized as plastic. The plastic

group is generally performing well, but some of them are identified as glass, metals, or paper, which creates the possibility of visual similarity between the materials. The trash category has the least number of samples, but the majority are predicted right, and only two samples in the trash category are wrongly identified as cardboard and metal. The few misclassifications are mostly between the visually related materials, and this implies that there are still regions where the classification of the classes can be enhanced.

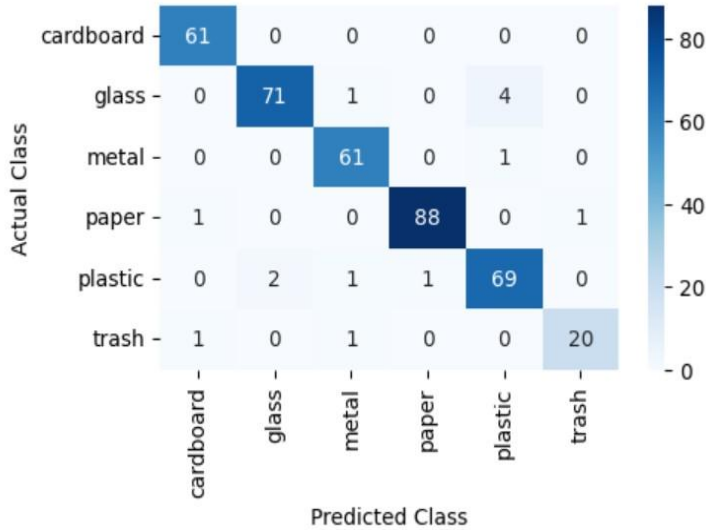


Fig. 5: confusion matrix of proposed model

5 Conclusion

The paper introduced a hybrid deep learning model that enhanced the performance of automated waste classification systems. The offered solution combined a four-layer Convolutional Neural Network (CNN) with the use of the DenseNet121 structure, which allowed obtaining the low-level spatial features and high-level semantic representations. This architectural design increased the discriminative ability of this model to various types of waste with a high level of computational efficiency. The model proposed was tested on TrashNet data, and the overall accuracy of the classification was 96%. Overall, the experimental findings support the claim that the combination of a lightweight CNN with DenseNet121 is an efficient approach to improve the performance of the classification and, at the same time, does not lead to the excessive complexity of the model. proposed framework is a valid and scalable solution to the intelligent waste sorting application, and it also helps to improve the development of data-driven solutions to sustainable waste management and modern recycling processes, especially in the context of smart cities.

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