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Comparative analysis of the classification of recyclable wastes

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Abstract

The classification of recycling wastes is of great importance both environmentally and economically. Correct classification of recyclable wastes such as packaging wastes increases the efficiency of the recycling process. This classification process can be done according to the raw material type, colour, shape, size and source of the waste. Correct classification of recycling wastes also provides economic benefits by ensuring more efficient use of resources. The traditional waste classification method involves manually sorting waste into different categories. This method requires a lot of labour and is time consuming. The traditional waste classification method is also prone to human error, which can lead to contamination of recyclable materials. Deep neural networks can quickly identify different types of recyclable materials by analysing images of waste materials. Thus, it can increase efficiency and reduce pollution by sorting them appropriately. In this study, an experimental study was carried out on a data set consisting of 6 classes and 2527 images under the name of "Garbage classification". In this study, a comparative analysis was carried out using the Convolutional Neural Network architectures Resnet101, Convnext and Densenet121. As a result of this study, Resnet101 architecture was more successful than other architectures with an accuracy rate of 97.72%.

Keywords: Classification of Waste; Resnet101; Densenet121; CNN; Deep Learning; Artificial Intelligence

1. Introduction

As a result of population growth, urbanisation and industrialisation, which have been going on for many years throughout the world, a significant amount of resources are used. As a result, large amounts of waste are generated. Increasing waste accumulation has a very harmful effect on both people and the environment. The fact that all of these wastes remain in landfills and cannot be reused, combined with the presence of materials such as plastics that remain in nature forever, creates an extremely dangerous situation for all living things [1]. The construction of high-rise buildings after the forests are cleared, the increase in industrial wastes with the rapid growth of factories and the habit of indiscriminate disposal of wastes into the environment contribute to serious environmental problems that will affect us both today and in the future [2].

Recycled materials have become increasingly popular in recent years as they offer a more environmentally friendly alternative to conventional materials [3]. By using recycled materials, we can reduce the amount of waste going to landfills and conserve natural resources. The search for an automated method for recycling, in a society that values industry and knowledge, the aforementioned is of considerable value [4]. The effects of the situation are not limited to the environmental field, but also extend to social aspects. The economic impact also proves to be favourable.

There is a significant demand for a method that can help to categorise waste that is suitable for recycling in some way. Recent developments in deep learning have contributed to meeting this demand. As a result of these developments there have been several practical applications in augmented computer vision. Driven by extensive data analysis, particularly in relation to object recognition and detection [5], this field is focused on identifying and categorising objects within a given system. Litter can be effectively identified and classified using advanced computer deep learning algorithms in combination with labelled data [6]. Classification of recyclable objects can be done accurately with visual tools.

Instead of relying on traditional visual learning and feature extraction methods, deep learning has more advantages. Deep learning uses large amounts of data to predetermine which features and design elements to extract. This approach gives deep learning a greater potential for learning and adaptation compared to its traditional counterparts [7].

In this study, a dataset containing six waste classes was used. This dataset consists of images showing the appropriate classification of cardboard, paper, glass, plastic, metal and rubbish waste.

The problem of waste management is becoming more and more serious as time passes. In order to address this issue, studies on waste categorisation in the literature have been reviewed.

Yıldız et al. used deep learning and machine learning techniques on a dataset consisting of 6 classes and 2527 images. In the hybrid model they proposed, DenseNet20+DVM model was the prominent model with an accuracy of 89.70% [2]. Sürücü and Ecemiş, working with the same dataset, aim to automatically classify garbage in their study using transfer learning model. Using different transfer learning methods, the Resnet50-V2 model outperformed the other models with an accuracy of 97.07% [8]. In the study conducted by Meng et al. on the same dataset, a convolutional neural network was used to classify garbage. XDenseNet was created to classify visually obtained images. The accuracy rate of the model in the test data set is up to 94.1% [7]. In the study by Rismiyati et al. VGG16, ResNet-50 and Xception models were used. In the study where transfer learning method was also used, it is seen that the Xception model achieved the highest accuracy with 88% [9]. In the study by Meng and Chu, the data set consisting of 2527 images in the convolutional neural network was increased to 10108 images with the flip and rotation method. As a result of the classification, the ResNet50 model was 95.35% successful [4].

In this study, Fu et al. designed a new garbage sorting system based on deep learning. This system has Raspberry Pi 4B hardware and a camera. Transfer learning based classification and an improved MobileNetV3 model were proposed. The proposed system had a success rate of 92.62% [10].

Yang et al. used different methods to improve the robustness of the model and to obtain fast and accurate results using algorithm and data enhancement based on YOLO-V5. Images were created and classified with a camera placed on a garbage container. A 94.5% success rate was achieved with YOLO-V5 [11].

In this study, Yang et al. designed a new incremental learning framework GarbageNet. In addition, a memory pool and a metric-based classifier were developed. To improve the capacity of the model without retraining, 43 classes were evaluated using a dataset of 19459 images. It achieved a best performance of 96.96% with an acceptable extraction rate, outperforming all other valid methods [6].

In the study by Yang and Li, an application was developed for users to easily recognise garbage. They aimed to classify garbage through neural network. The success rate of the system named WaNet was 96.10% [3].

In their study, Cao and Xiang performed a classification study based on transfer learning using a convolutional neural network on imagenet dataset. As a result, an accuracy of 93.2% was achieved [12].

2. Materials and methods

2.1. Data Set

The dataset used to classify the waste in this study was obtained from the Kaggle website, which is open to all users [13]. This dataset is called "Garbage Classification". It contains a total of 6 classes. There are 2527 different images in the dataset, 403 in cardboard class, 410 in metal class, 482 in plastic class, 594 in paper class, 501 in glass class and 137 in rubbish class. The class distribution is given graphically in Figure 1.

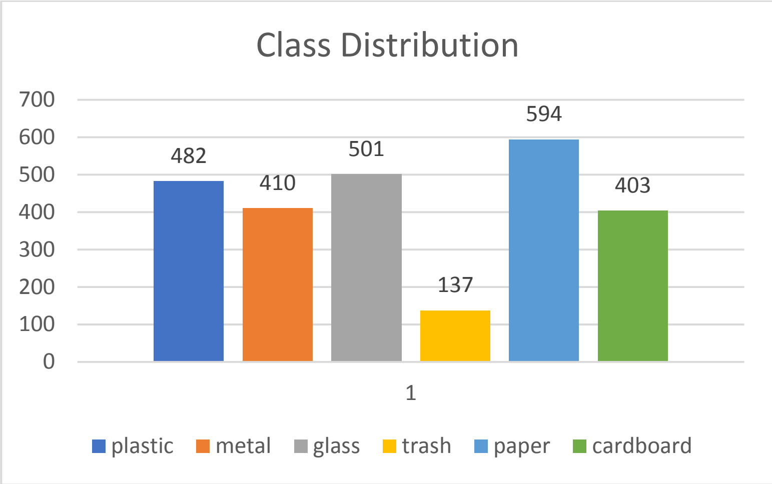

Fig. 1. Class distribution.

2.2. Convolutional neural network (CNN)

CNN consists of various parameters and layers that can be trained. Thanks to its layered structure, the determination of features is more successful and gives more effective results [14]. CNN architecture consists of three main components. These components are convolution, pooling and fully connected layer [5]. During the convolution layer, input data are filtered and features are obtained. Thus, feature maps are created that enable the learning of regional models. Figure 2 illustrates how the architecture can learn more complex objects, such as cats [15] [16], using hierarchically learnt local features. The pooling layer is used to materialise the attributes. The size is reduced through sampling, which also reduces the number of parameters. This leads to a faster learning process. By using a pre-trained model, the model can build on the knowledge already acquired through previous training [16]. In the fully connected layer, the output value is determined according to the neuron inputs of the previous layers [17]. The fully connected layer can also be used to target optimisation. Although CNN architecture is effective for visuals, it is not always sufficient for text-based analyses.

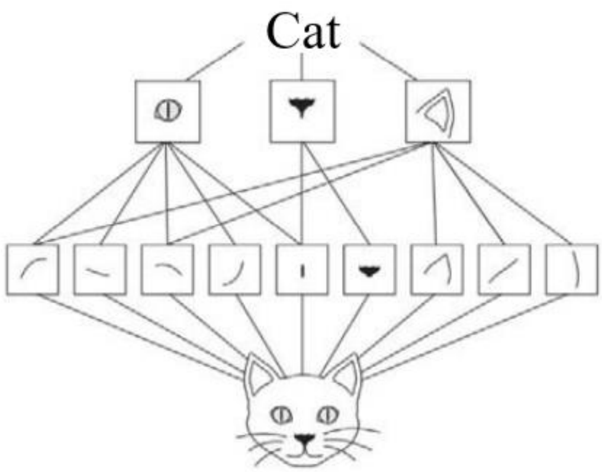

Fig. 2. High level object detection from learned local patterns [16].

2.3. Resnet101 architecture

ResNet is a class of neural networks designed to enhance traditional CNNs. One of the main features that distinguishes ResNets from others is the use of jump connections. This allows for a smaller network size compared to traditional CNNs while maintaining similar performance levels. Although jump connections can be used in any neural network architecture, they are particularly useful in CNNs as they allow feature maps to be reused between layers at different locations [18]. Another important difference between ResNet and previous models is the increased depth of the network. ResNet is one of the pioneering algorithms in incorporating batch normalisation. The network requires input images of size 224×224×3 [2].

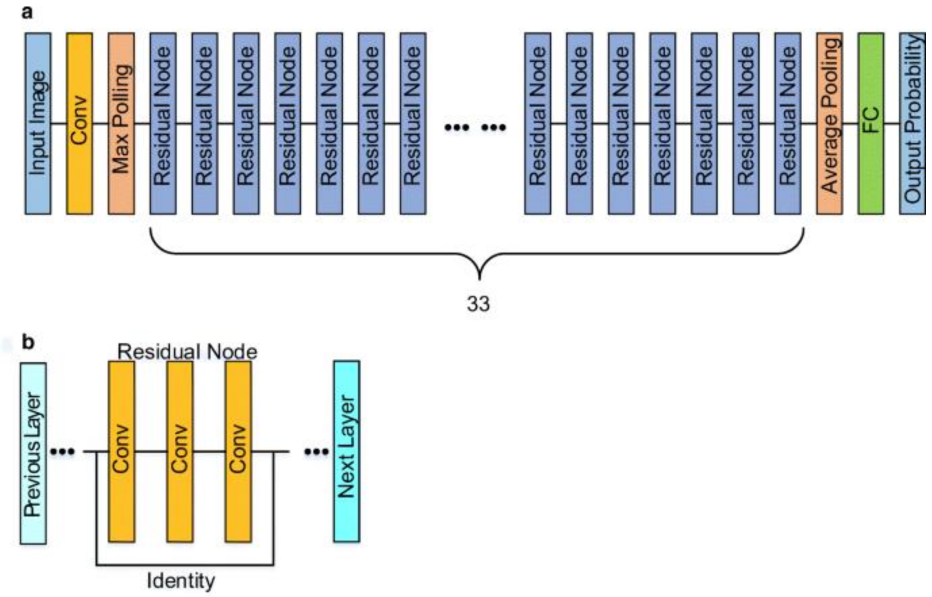

Fig. 3. Resnet101 architecture [19].

Figure 3 shows the Resnet101 architecture. A: Schematics of the ResNet101 architecture, which included 33 residual nodes in total. B: The residual node served as building block for the ResNet101 architecture [19].

In its entirety, ResNet-101 comprises 104 convolutional layers. Within this architecture there are a total of 33 blocks consisting of layers. Of these 33 blocks, 29 of them directly use the output of the previous block. These connections, called residual connections, contain residuals that are used as the primary operand in the resulting aggregation. The output of each block is combined to obtain the input to the next block. The remaining four blocks use the output of the previous block to generate their own outputs. After the convolution layer, there is a next step known as the chunk normalisation layer. This layer performs a convolution operation using a 1x1 filter size and a certain number of steps [20]. The output of this normalisation process is then added to the output of the previous block using the sum operator.

2.4. Convnext architecture

The study titled "ConvNext for the 2020s" published by Liu et al. in 2022 proposes a model inspired by the architectural structure known as Vision Transformers (VIT) [21] [22]. The model, called ConvNext, was classified as a pure CNN model in the study and showed more successful results than VIT architectures. The ConvNext model is characterised by blending the ResNet model with the design and techniques of the VIT architecture family. It results in a modernised and improved form. To address the linearity issue, the developed CNN model incorporates activation functions [23]. Specifically, an architectural update has been made by replacing the traditional choice of ReLU activation function with GeLU (Gaussian Error Linear Unit) in this model. Figure 4 shows an illustration of the Convnext architecture.

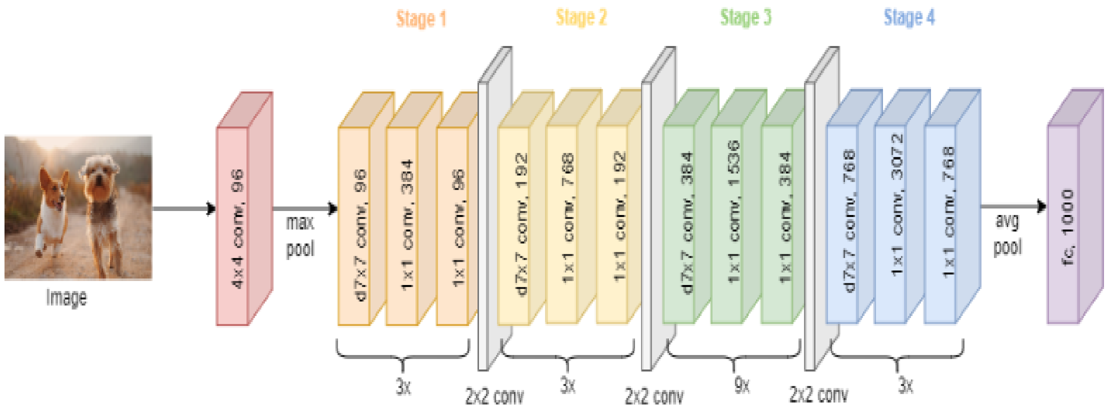

Fig. 4. Convnext architecture [24].

In terms of classification, Convnext exhibits superior performance compared to YOLO's Darknet53. ConvNeXt incorporates the Large Core Sizes optimisation method inspired by the design strategy used by Liu et al [21]. In Swin Transformer, this optimisation method has developed the concepts of Inverse Bottleneck, Deep Convolution and resnet50. As a result, ConvNeXt outperforms Swin Transformer and is able to achieve more successful results in object classification tasks. In object detection, YOLO is hampered by its single-stage detector, making it less effective in processing small objects. To address this limitation, we need higher attribute resolution and a larger detection area to improve its multi-scale target detection capability. Based on ConvNeXt, we increase the feature resolution by modifying the first subsampling layer. In addition, the ConvNeXt Block incorporates coordination attention to improve the network's ability to detect fine features.

2.5. Densenet121 architecture

In the field of deep learning, DenseNet121 is a CNN model that has attracted much attention. This model was introduced in 2016 by Gao Huang, Zhuang Liu, Laurens van der Maaten and Kilian Q. Weinberger in their paper "Densely Connected Convolutional Networks" [25]. The main goal of DenseNet is to streamline the training process of deep networks while at the same time improving their performance. It achieves this by utilising a unique connection structure. A notable feature of DenseNet is that the combined outputs from previous layers are incorporated into the inputs of subsequent layers. Unlike traditional CNN models, which typically combine layers sequentially, DenseNet establishes connections between each layer, the outputs of all previous layers and its own input. This integration, called "heavy coupling", facilitates a more comprehensive flow of information throughout the network. The Densenet121 architecture is shown in figure 5.

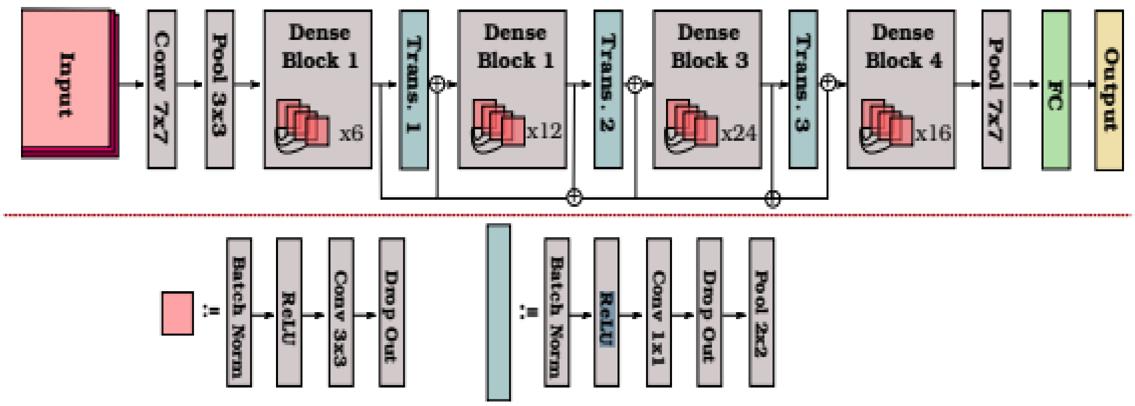

Fig. 5. Densenet121 architecture [26].

DenseNet121 is a complex model consisting of a total of 121 layers. These layers consist of a large number of interconnected smaller layers connected by dense links. This unique structure has the dual effect of reducing the total number of parameters in the network and increasing the efficiency of the training process. It strengthens the model against overlearning [27]. The architecture of DenseNet121 is characterised by its impressive achievements, especially in areas such as object detection, object classification, face recognition and various image processing. Some notable advantages of using DenseNet121 can be listed as follows. The training process is accelerated due to the ease of back propagation with gradients. As the network becomes more complex and interconnected, it becomes increasingly robust to overlearning [28]. The network can improve its performance while minimising the number of parameters required by making complex connections.

3. Experimental methods

In the experimental study, studies were carried out on the data set with Resnet101, Convnext and Densenet121 CNN architectures. These architectures were tested on the cloud servers of the google colab platform with RAM and GPU weight. In Python environment, numpy, pandas, pytorch and albumentations libraries were used. 20% of the images were allocated as test and 80% as training. As training data, there are 385 images from plastic class, 328 images from metal class, 400 images from glass class, 110 images from garbage class, 475 images from paper class and 322 images from cardboard class. The aim is to draw more accurate conclusions on data that the model has never seen. With 10 epochs and 16 batchsize, the training process was completed in 26 minutes 10 seconds for Resnet101, 29 minutes 32 seconds for Convnext and 35 minutes 11 seconds for Densenet121. Thanks to the jumping connections of Resnet101, incoming data is transferred faster from the lower layer to the higher layer. Thus, the process is faster than other architectures. Since the number of connections is denser in Densenet121, the calculation and result are later. Table 1 shows the accuracy rates of the results obtained from CNN architectures.

Table 1. Accuracy rates from CNN architectures (%).

Resnet101	Convnext	Densenet121
97.72	95.54	96.08

After the CNN architectures were trained, Resnet101 was the most accurate with 97.72% accuracy. Resnet101 was followed by Densenet121 with 96.08% and Convnext with 95.54%. The complexity matrices of CNN architectures are given in Table 2, Table 3 and Table 4.

Table 2. Resnet101 confusion matrix.

	plastic	metal	glass	trash	paper	cardboard
plastic	**378**		9	2		
metal		**328**		2		
glass	4		**389**	2		
trash	3		2	**104**		
paper					**462**	9
cardboard					13	**313**

Table 2 shows that Resnet101 CNN architecture has an accuracy rate of 98.41%. Resnet101 model predicted 1974 images correctly and 46 images incorrectly from 2020 images. Resnet101 model correctly predicted 378 images from 385 images for plastic class, 4 images as glass and 3 images as trash class. Resnet101 model predicted all 328 images correctly for the metal class. Resnet101 model correctly predicted 389 images out of 400 images for glass class, 9 images as plastic and 2 images as trash class.

Table 3. Convnext confusion matrix.

	plastic	metal	glass	trash	paper	cardboard
plastic	**363**	1	10	3	1	
metal	3	**326**	2	1		
glass	13		**386**	2		

trash	6	1	2	**101**	2	6
paper				2	**455**	17
cardboard				1	17	**299**

When Table 3 is analysed, it is seen that the accuracy rate of Convnext CNN architecture is 96.63%. Convnext model predicted 1930 images correctly and 90 images incorrectly from 2020 images. Convnext model correctly predicted 363 images from 385 images for plastic class, 13 images as glass, 3 images as metal and 6 images as trash class. For the metal class, Convnext model correctly predicted 326 images from 328 images, incorrectly predicted 1 image as plastic and 1 image as trash class. For the glass class, Convnext model correctly predicted 386 images out of 400 images, incorrectly predicted 10 images as plastic, 2 images as trash and 2 images as metal class.

Table 4. Densenet121 confusion matrix.

	plastic	metal	glass	trash	paper	cardboard
plastic	**371**	2	17	1		3
metal	2	**324**	2	3	1	
glass	10	1	**380**	1		1
trash	2	1	1	**104**	1	1
paper				1	**457**	12
cardboard					16	**305**

Table 4 shows that the accuracy rate of the Densenet121 CNN architecture is 97.11%. Densenet121 model predicted 1941 images correctly and 79 images incorrectly from 2020 images. Densenet121 model correctly predicted 371 images from 385 images for plastic class, 10 images as glass, 2 images as metal and 2 images as trash class. Densenet121 model correctly predicted 324 images from 328 images for metal class, incorrectly predicted 2 images as plastic, 1 image as glass and 1 image as trash class. Densenet121 model correctly predicted 380 images out of 400 images for glass class, incorrectly predicted 17 images as plastic, 1 image as trash and 1 image as metal class.

As an example, Figure 6 shows the classification image for control purposes after the process with Resnet101 architecture.

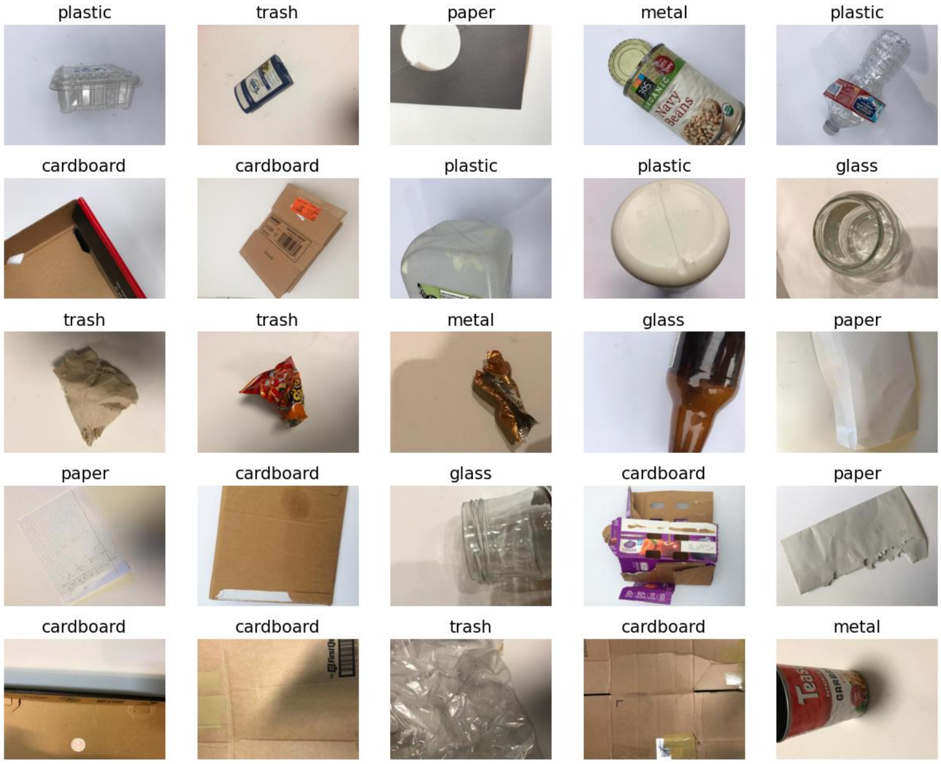

Fig. 6. Resnet101 classification image.

Table 5 shows a comparative table of the study and other studies.

Table 5. Comparison table of the same and similar studies.

Study Name	Method	Accuracy Ratio (%)
Yıldız et al., 2023 [2]	DenseNet20+DVM	89.70
Sürücü and Ecemiş, 2022 [8]	Resnet50-V2	97.07
Meng et al., 2020 [7]	XDenseNet	94.10
Rismiyati et al., 2020 [9]	Xception	88.00
Meng and Chu 2020 [4]	ResNet50	95.35
Fu et al., 2021 [10]	MobileNetV3	92.62
Yang et al., 2021 [11]	Yolo-V5	94.50
Yang et al., 2021 [6]	GarbageNet	96.96
Yang and Li, 2020 [3]	WaNet	96.10
Cao ve Xiang, 2020 [12]	Inception V3	93.20
This study	**Resnet101**	**97.72**
This study	**Convnext**	**95.53**
This study	**Densenet121**	**96.08**

The data set used in the studies of Yıldız et al, Sürücü and Ecemiş, Meng et al, Rismiyati et al, Meng and Chu in Table 5 is the same as the data set of our study. Other studies were conducted with different data sets. As can be seen from Table 5, the Resnet101 architecture used in our study was more successful than both the studies on the same data set and the other studies. The fact that the Resnet101 architecture is more successful than the others can be explained by the fact that the network goes deeper and adds the output of the previous layers directly to its history. Thanks to the 101 layer of Resnet, more accuracy gains have been obtained from the significantly increased depth by preventing data corruption problems during image processing.

4. Conclusion

In today's world, deep learning has proven to be highly effective in image processing and classification. Deep learning techniques have been applied with great success in various sectors such as health, agriculture, energy and industry. Training deep learning techniques on a variety of datasets, including images or other types of data, allows them to effectively learn complex patterns and features that cannot be recognised by conventional methods. Detection of such discriminations can be difficult using traditional techniques. Integrating deep learning approaches into waste classification systems improves their efficiency and accuracy. Ultimately, it encourages the proper management and recycling of various waste materials. The act of classifying landfill waste involves sorting it into different waste types and then incorporating it into the recycling system. This process is critical to minimise environmental impact, conserve natural resources and enable longer life and economic utilisation of waste. By recycling waste, the depletion of essential natural resources required for the production of new products is prevented. In addition, the recycling process enables the use of recycled materials instead of raw materials, resulting in significant energy savings and no reduction in greenhouse gas emissions during production. It helps the global effort to combat climate change. In the study, results from 3 different CNN architectures were obtained. The results obtained were compared and Resnet101 architecture stood out as more successful than other architectures with an accuracy rate of 97.72%. In addition, we get faster results with Resnet101 compared to other architectures. The classification and recycling of garbage waste is a vital issue not only today but also tomorrow. In future studies, we think that big data analytics can be used to better understand waste streams and consumer habits. In this way, we aim to develop more strategic approaches to reduce waste generation and improve sorting processes.

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References

[1] C. Hark and S. Kiziloluk, ‘Geri Dönüştürülebilir Atiklarin Siniflandirilmasi’, Accessed: May 11, 2023. [Online]. Available: https://www.researchgate.net/publication/366153733

[2] E. N. Yildiz *et al.*, ‘Önerilen Derin Öğrenme ve Makine Öğrenmesi Tabanlı Hibrit Model ile Çevresel Atıkların Sınıflandırılması’, *Fırat Univ. J. Eng. Sci.*, vol. 35, no. 1, pp. 353–361, Mar. 2023, doi: 10.35234/FUMBD.1230982.

[3] Z. Yang and D. Li, ‘WasNet: A Neural Network-Based Garbage Collection Management System’, *IEEE Access*, vol. 8, pp. 103984–103993, 2020, doi: 10.1109/ACCESS.2020.2999678.

[4] S. Meng and W. T. Chu, ‘A Study of Garbage Classification with Convolutional Neural Networks’, *Indo - Taiwan 2nd Int. Conf. Comput. Anal. Networks, Indo-Taiwan ICAN 2020 - Proc.*, pp. 152–157, Feb. 2020, doi: 10.1109/Indo-TaiwanICAN48429.2020.9181311.

[5] Y. Lecun, Y. Bengio, and G. Hinton, ‘Deep learning’, *Nat. 2015 5217553*, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.

[6] J. Yang, Z. Zeng, K. Wang, H. Zou, and L. Xie, ‘GarbageNet: A Unified Learning Framework for Robust Garbage Classification’, *IEEE Trans. Artif. Intell.*, vol. 2, no. 4, pp. 372–380, Aug. 2021, doi: 10.1109/TAI.2021.3081055.

[7] S. Meng, N. Zhang, and Y. Ren, ‘X-DenseNet: Deep Learning for Garbage Classification Based on Visual Images’, *J. Phys. Conf. Ser.*, vol. 1575, no. 1, p. 012139, Jun. 2020, doi: 10.1088/1742-6596/1575/1/012139.

[8] A. Makalesi, S. Sürücü, and İ. N. Ecemiş, ‘Garbage Classification Using Pre-Trained Models’, *Mayıs 2022 Eur. J. Sci. Technol. Spec. Issue*, vol. 36, no. 36, pp. 73–77, 2022, doi: 10.31590/ejosat.1103628.

[9] Rismiyati, S. N. Endah, Khadijah, and I. N. Shiddiq, ‘Xception Architecture Transfer Learning for Garbage Classification’, *ICICoS 2020 - Proceeding 4th Int. Conf. Informatics Comput. Sci.*, Nov. 2020, doi: 10.1109/ICICoS51170.2020.9299017.

[10] B. Fu, S. Li, J. Wei, Q. Li, Q. Wang, and J. Tu, ‘A Novel Intelligent Garbage Classification System Based on Deep Learning and an Embedded Linux System’, *IEEE Access*, vol. 9, pp. 131134–131146, 2021, doi: 10.1109/ACCESS.2021.3114496.

[11] G. Yang *et al.*, ‘Garbage Classification System with YOLOV5 Based on Image Recognition’, *2021 6th Int. Conf. Signal Image Process. ICSIP 2021*, pp. 11–18, 2021, doi: 10.1109/ICSIP52628.2021.9688725.

[12] L. Cao and W. Xiang, ‘Application of Convolutional Neural Network Based on Transfer Learning for Garbage Classification’, *Proc. 2020 IEEE 5th Inf. Technol. Mechatronics Eng. Conf. ITOEC 2020*, pp. 1032–1036, Jun. 2020, doi: 10.1109/ITOEC49072.2020.9141699.

[13] ‘Garbage Classification | Kaggle’. https://www.kaggle.com/datasets/asdasdasasdas/garbage-classification (accessed May 21, 2023).

[14] G. Çınarer , K. Kılıç and T. Parlar , "A Deep Transfer Learnıng Framework For The Stagıng Of Dıabetıc Retınopathy", Journal of Scientific Reports-A, no. 051, pp. 106-119, Dec. 2022
[15] F. Chollet, 'Deep Learning with Python, Second Edition', *Deep Learning with Python*, 2021. https://www.manning.com/books/deep-learning-with-python-second-edition (accessed May 21, 2023).
[16] E. Somuncu and N. A. Atasoy, 'Realization of character recognition application on text images by convolutional neural network', *J. Fac. Eng. Archit. Gazi Univ.*, vol. 37, pp. 17–27, 2022, doi: 10.17341/gazimmfd.866552.
[17] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, 'A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects', *IEEE Trans. Neural Networks Learn. Syst.*, vol. 33, no. 12, pp. 6999–7019, Dec. 2022, doi: 10.1109/TNNLS.2021.3084827.
[18] M. Shafiq and Z. Gu, 'Deep Residual Learning for Image Recognition: A Survey', *Appl. Sci. 2022, Vol. 12, Page 8972*, vol. 12, no. 18, p. 8972, Sep. 2022, doi: 10.3390/APP12188972.
[19] F. Li *et al.*, 'Deep learning-based automated detection of glaucomatous optic neuropathy on color fundus photographs', *Graefe's Arch. Clin. Exp. Ophthalmol.*, vol. 258, no. 4, pp. 851–867, Apr. 2020, doi: 10.1007/S00417-020-04609-8/FIGURES/4.
[20] A. Demir, F. Yilmaz, and O. Kose, 'Early detection of skin cancer using deep learning architectures: Resnet-101 and inception-v3', *TIPTEKNO 2019 - Tip Teknol. Kongresi*, vol. 2019-January, Oct. 2019, doi: 10.1109/TIPTEKNO47231.2019.8972045.
[21] Z. Liu, H. Mao, C.-Y. Wu, C. Feichtenhofer, T. Darrell, and S. Xie, 'A ConvNet for the 2020s'. pp. 11976–11986, 2022. Accessed: Jul. 20, 2023. [Online]. Available: https://github.com/facebookresearch/ConvNeXt
[22] X. Zhai, A. Kolesnikov, N. Houlsby, and L. Beyer, 'Scaling Vision Transformers'. pp. 12104–12113, 2022.
[23] E. Yüzgeç *et al.*, 'Alzheimer ve Parkinson Hastalıklarının Derin Öğrenme Teknikleri Kullanılarak Sınıflandırılması Classification of Alzheimer's and Parkinson's Diseases Using Deep Learning Techniques', *Fırat Üniversitesi Müh. Bil. Derg. Araştırma Makal.*, vol. 35, no. 2, pp. 473–482, 2023, doi: 10.35234/fumbd.1234638.
[24] 'ConvNeXt'. https://tech.bertelsmann.com/en/blog/articles/convnext (accessed Jul. 26, 2023).
[25] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, 'Densely Connected Convolutional Networks'. pp. 4700–4708, 2017. Accessed: Jul. 25, 2023. [Online]. Available: https://github.com/liuzhuang13/DenseNet.
[26] N. Radwan, 'Leveraging Sparse and Dense Features for Reliable State Estimation in Urban Environments', 2019, doi: 10.6094/UNIFR/149856.
[27] M. Chhabra and R. Kumar, 'A Smart Healthcare System Based on Classifier DenseNet 121 Model to Detect Multiple Diseases', *Lect. Notes Networks Syst.*, vol. 339, pp. 297–312, 2022, doi: 10.1007/978-981-16-7018-3_23/FIGURES/6.
[28] X. Zhang, X. Chen, W. Sun, and X. He, 'Vehicle Re-Identiication Model Based on Optimized DenseNet121 with Joint Loss', doi: 10.32604/cmc.2021.016560.