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Improvement of EfficientNet in medical waste classification

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Abstract:

In recent years, medical waste has gained attention due to its hazardous nature, complexity, and high cost of manual sorting and management. Therefore, it is crucial to develop classification systems that are accurate and efficient. This study analyzes various deep learning models for medical waste classification, compares their accuracies in image recognition, and provides an in-depth analysis of EfficientNet, a classification model that is well-suited to handle large amounts of waste mixing. EfficientNet's superior performance can be adapted to numerous potential scenarios in medical waste, and its improved performance is also very promising in the field of medical waste classification. The data demonstrate its significant advantages over other models, indicating broad application prospects and economic benefits.

Keywords: EfficientNet, Medical waste classification, Deep learning, Significant advantage

1. Introduction

In recent years, with the outbreak of COVID-19 and its mutant plants, medical waste disposal has increasingly become a thorny issue. Medical institutions generate a large amount of medical waste every day, which puts considerable pressure on medical waste disposal. Since manual sorting of medical waste is a labor-intensive and time-consuming process, it is highly likely to cause human error under high workload. At the same time, medical waste is characterized by spatial contamination, acute infection and latent infection, in which the residual germs carried are extremely hazardous [1], which can directly endanger human health or cause more serious consequences by contaminating the soil, waters, and atmosphere, etc. [2]. Therefore, the traditional waste treatment methods (mainly focusing on incineration and landfill) and manual operations are no longer able to meet the current needs, for which an accurate classification system is needed to link the follow up medical waste treatment process and to reduce human errors. To solve this problem, computer vision-based medical waste classification using machine learning and deep learning models is more suitable for large cardinal numbers and multiple types of medical waste. Therefore, we introduce the EfficientNet model in the image classification session, which improves the classification quality with lower complexity compared to models with similar classification performance. This is possible because EfficientNet performs optimized network expansion with predefined complexity [3]. Also, the improved model based on EfficientNet has more significant advantages in terms of accuracy and recognition speed. Section 2 introduces related medical waste classification techniques, Section 3 presents EfficientNet and its improved model, Section 4 reports the data and experimental results obtained, and Sections 5 and 6 conclude the paper by summarizing its content and presenting future outlook.

2. Overview of Medical Waste Segregation Technologies

2.1 *Basic classification and identification techniques for medical waste*

The classification of medical waste primarily focuses on identifying individual small items, such as gloves, gauze, tweezers, syringes, bags, and bottles. A small number of classifications are based on the national identification of the five major categories of medical waste: infectious waste, injurious waste, pathologic waste, pharmaceutical waste, and chemical waste. To recognize small targets, Jiale Chu[5] and others developed a program using the improved ResNet-50 model to identify medical waste images. Zhehua Zhou[6] created a medical waste sorting garbage can that uses a machine vision-based sorting system and a classification model, Medwaste-R, to achieve photographic recognition and initial waste classification. A. Bruno[3] and colleagues achieved accurate classification using an improved EfficientNet deep learning model trained on an existing database of single-target images. Yuchao Chen[7] and colleagues achieved recognition and classification using machine vision. They pre-processed the images and then utilized the MobileNet model. T

Mythili[8] and coworkers designed a deep neural network waste classification function of the Enhanced Segmentation Network (EnSegNet). Haiying Zhou[10] et al. based on the ResNeXt deep neural network, designed a classification model suitable for practical applications; ANH H. VO[9] improved the ResNext model and designed a deep neural algorithm DNN-TC, which improves the prediction performance; Adedeji and Wang [4] proposed an intelligent classification method using ResNet. To recognize large targets, Yupeng Mou[11] introduced the attention mechanism and improved the activation function based on the YoloV4 model. This modification resulted in better performance for both small target classification and large category recognition.

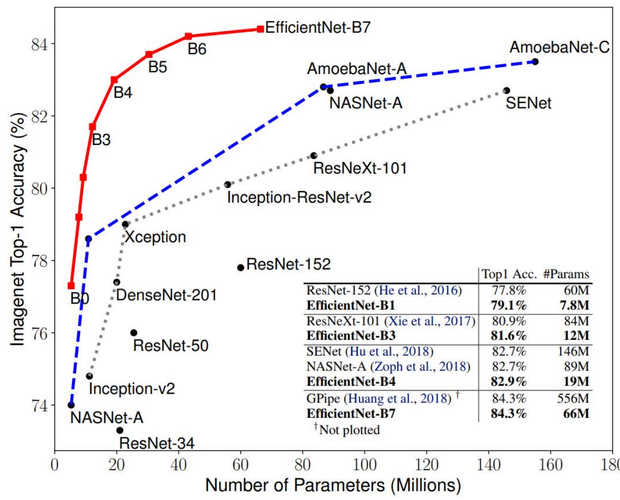
2.2 *Advantages and disadvantages of prior art*

Most medical waste classification techniques rely on machine vision and use classification methods based on existing databases of medical waste images. These methods are trained using appropriate machine learning and deep learning models. However, the basic neural network has deficiencies in data performance for different models, affecting both recognition accuracy and speed. For instance, Haiying Zhou et al. reported significantly lower accuracy based on the ResNext deep neural network model compared to ANH H. VO et al.'s improved ResNext model, which achieved 98% recognition accuracy. Most current deep learning models have high accuracy, but they require significant amounts of data to be processed, leading to increased hardware requirements. This is not ideal given the current high pressure on medical waste images. Based on existing deep learning models, it is necessary to improve a model that is suitable and efficient for the medical waste classification scenario.

3. EfficientNet model and its improvement

3.1 *Principles and model structure of EfficientNet*

This study focuses on a basic CNN network model that is very suitable for the field of medical waste classification: EfficientNet[12]. The model was proposed by Google and its underlying network architecture was designed using neural architecture search. EfficientNet differs from traditional convolutional neural networks in that it does not rely on conventional improvements in model depth and width to enhance performance. Instead, it utilizes simple and efficient composite coefficients to balance the depth, width, and input image resolution of the network.



[12]Figure 1. Model Size vs. ImageNet Accuracy

The figure above compares the image recognition accuracy and number of parameters of the EfficientNet network from B0 to B7 with other models. It is evident that the EfficientNet model outperforms other models in both recognition accuracy and data processing efficiency. This results in a significant increase in recognition speed and accuracy while reducing the amount of data processed.

A constructive analysis of the model follows:

3.1.1 *Optimization of objectives*

Define ConvNets as:

$$\mathcal{N} = \bigoplus_{i=1\ldots s} \mathcal{F}_i^{L_i}\left(X_{(H_i,W_i,C_i)}\right) \tag{1}$$

The convolution block $\mathcal{F}_i^{L_i}$ is denoted by $\mathcal{F}_i$ repeated L_i times, while (H_i,W_i,C_i) denotes the height, width, and number of channels of the ith stage. $\bigoplus\limits_{i=1\ldots s}$ denotes the sequential connection of multiple stages. The algorithm aims to optimize the network structure $\mathcal{N}$ by finding the scaling ratios for depth L_i, width C_i, and resolution (H_i,W_i,C_i). The scaling is done in these dimensions to obtain the optimal network structure. Control coefficients d,w,r are introduced to scale L_i, C_i, (H_i,W_i,C_i). However, the computational resources are finite while the combinations of d,w,r are infinite. Therefore, the optimization objective is to maximize the model's accuracy for any given resource constraint, which is formulated as an optimization problem.

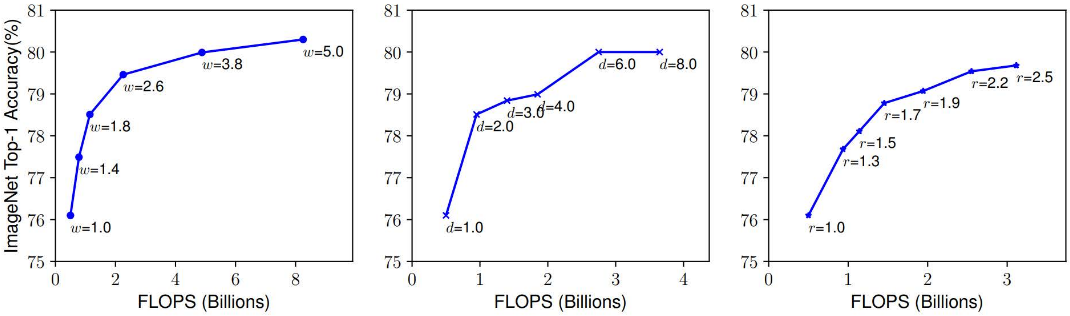
$$\underset{d,w,r}{max}?\ Accuracy(N(d,w,r))$$

$$s.t. N(d,w,r) = \underset{i=1\ldots s}{?}\ ?\widehat{\mathcal{F}}_i^{d\cdot\hat{L}_i}\left(X_{?r\cdot\hat{H}_i, r\cdot\hat{W}_i, w\cdot\hat{C}_i?}\right)(2)$$

$$Memory(N) \leqslant target\_memory$$

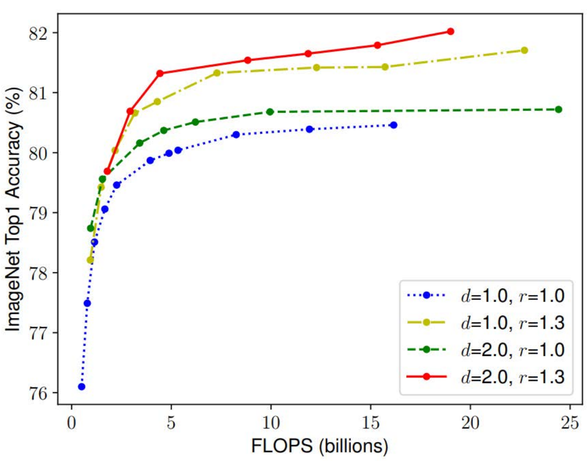
$$FLOPS(N) \leqslant target\_flops$$

Scaling a single dimension increases the accuracy, but as magnification increases, the boost becomes smaller until saturation.



[12]Figure 2 Scaling Up a Baseline Model with Different Network Width (w), Depth (d), and Resolution (r) Coefficients.

For combined amplification, accuracy gain saturates more slowly than a single dimensional boost when increasing depth or resolution at the same time, and at the same FLOPS.



[12]Figure 3 Scaling Network Width for Different Baseline Net-works.

Therefore, the scaling dimensions are not independent of each other. To coordinate and balance these dimensions simultaneously, a composite scaling model is introduced. The model defines the composite coefficient φ, which balances the width, depth, and resolution of the network.

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The constant α,β,γ, which determines how resources are allocated to network depth, width, and resolution, is determined through a small grid search. The user-specified coefficient φ is used to control the model's increase in accordance with the increase in resources. Additionally, the restriction $\alpha\cdot\beta^2\cdot\gamma^2\approx 2$ ensures that FLOPS grows according to 2^{φ}. The optimal composite scaling can be determined by finding $\alpha,\beta,\gamma,\varphi$.

3.1.2 *algorithmic architecture*

The EfficientNet modeling algorithm is based on Mnas-Net. The baseline is identified as EfficientNet-B0.

[12]Table 1 EfficientNet-B0 baseline network

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

The process was divided into two steps:

I. $\varphi=1$ remains unchanged. Assuming the resources are scaled up by a factor of two, a grid search is performed on α,β,γ using Equation $(2)(3)$ to determine the optimal value $\alpha=1.2,\beta=1.1,\gamma=1.15$ for EfficientNet-B0 under the given constraints.

II. To obtain EfficientNet-B0 to B7, fix the three values mentioned above and extend the baseline using different φ.

3.1.3 *comparison experiment*

The EfficientNet series outperforms other models in terms of accuracy while also being significantly smaller in size than models with the same accuracy.

[12]Table 2 EfficientNet Performance Results on ImageNet (Russakovsky et al., 2015).

Model	Top-1 Acc.	Top-5 Acc.	#Params	Ratio-to-EfficientNet	#FLOPs	Ratio-to-EfficientNet
EfficientNet-B0	**77.1%**	**93.3%**	**5.3M**	**1x**	**0.39B**	**1x**
ResNet-50 (He et al., 2016)	76.0%	93.0%	26M	4.9x	4.1B	11x
DenseNet-169 (Huang et al., 2017)	76.2%	93.2%	14M	2.6x	3.5B	8.9x
EfficientNet-B1	**79.1%**	**94.4%**	**7.8M**	**1x**	**0.70B**	**1x**
ResNet-152 (He et al., 2016)	77.8%	93.8%	60M	7.6x	11B	16x
DenseNet-264 (Huang et al., 2017)	77.9%	93.9%	34M	4.3x	6.0B	8.6x
Inception-v3 (Szegedy et al., 2016)	78.8%	94.4%	24M	3.0x	5.7B	8.1x
Xception (Chollet, 2017)	79.0%	94.5%	23M	3.0x	8.4B	12x
EfficientNet-B2	**80.1%**	**94.9%**	**9.2M**	**1x**	**1.0B**	**1x**
Inception-v4 (Szegedy et al., 2017)	80.0%	95.0%	48M	5.2x	13B	13x
Inception-resnet-v2 (Szegedy et al., 2017)	80.1%	95.1%	56M	6.1x	13B	13x
EfficientNet-B3	**81.6%**	**95.7%**	**12M**	**1x**	**1.8B**	**1x**
ResNeXt-101 (Xie et al., 2017)	80.9%	95.6%	84M	7.0x	32B	18x
PolyNet (Zhang et al., 2017)	81.3%	95.8%	92M	7.7x	35B	19x
EfficientNet-B4	**82.9%**	**96.4%**	**19M**	**1x**	**4.2B**	**1x**
SENet (Hu et al., 2018)	82.7%	96.2%	146M	7.7x	42B	10x
NASNet-A (Zoph et al., 2018)	82.7%	96.2%	89M	4.7x	24B	5.7x
AmoebaNet-A (Real et al., 2019)	82.8%	96.1%	87M	4.6x	23B	5.5x
PNASNet (Liu et al., 2018)	82.9%	96.2%	86M	4.5x	23B	6.0x
EfficientNet-B5	**83.6%**	**96.7%**	**30M**	**1x**	**9.9B**	**1x**
AmoebaNet-C (Cubuk et al., 2019)	83.5%	96.5%	155M	5.2x	41B	4.1x
EfficientNet-B6	**84.0%**	**96.8%**	**43M**	**1x**	**19B**	**1x**
EfficientNet-B7	**84.3%**	**97.0%**	**66M**	**1x**	**37B**	**1x**
GPipe (Huang et al., 2018)	84.3%	97.0%	557M	8.4x	-	-

We omit ensemble and multi-crop models (Hu et al., 2018), or models pretrained on 3.5B Instagram images (Mahajan et al., 2018).

3.2 *Potential Applications of EfficientNet in Medical Waste Sorting*

EfficientNet has high accuracy and low data volume, making it suitable for efficiently processing a large number of medical waste images in a short period of time. This is particularly relevant given the current high pressure on medical waste classification due to outbreaks of infectious diseases. Meanwhile, the EfficientNet model is highly feasible for preliminary waste sorting in the early stage as it does not require high hardware, resulting in lower costs for waste sorting equipment. Different EfficientNet network models can be adapted to different garbage classification modes, including single target recognition, different target recognition of the same type, and different type recognition. This makes EfficientNet widely applicable. Therefore, EfficientNet is a powerful tool in the field of medical waste segregation.

3.3 *Improving methods and strategies*

EfficientNet has been applied and improved for single-target recognition in the field of medical waste. For instance, [3]Bruno A et al. adapted the final fully-connected layer of the EfficientNet-B0 model to fit the required output size for medical waste image recognition. However, EfficientNet has multiple advantages, including its ability to handle multi-target mixed images. Therefore, the model can be adjusted for both training methods and convolution formats.

4. Applications and Experiments

4.1 *Data integration*

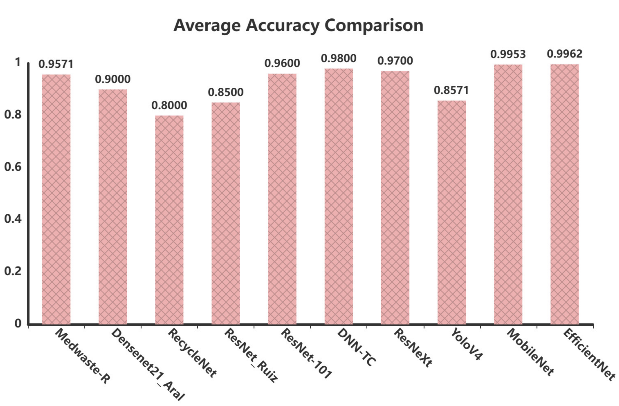

Figure 4 Comparison of average accuracy of different models

Figure 4 displays the average accuracy of medical waste image recognition across different models. It is evident that the recognition accuracy is nearly perfect when using the EfficientNet model.

Table 3 Comparison of single target recognition accuracy.

Class	EfficientNet	MobileNet	YoloV4	ResNeXt	ResNet-50	Medwaste-R
Gloves	**1.0**	0.9815	0.92	0.93	0.95	\
Gauzes	**0.9891**	\	\	0.98	\	0.98
Caps	**1.0**	\	0.85	0.98	\	0.84

Table 3 shows a comparison of the accuracy of different models for different target recognition. While some models are not supported by data, we can still find that EfficientNet has been able to achieve basically no error in ordinary target recognition.

4.2 *Improving the performance of EfficientNet-B0 model on medical waste classification task*

[3] Table 4 Performance of Improved EfficientNet

Class	Precision	Recall	F1-Score	Support
Gauzes	0.98913	0.97849	0.98378	93
Gloves	0.99209	0.99603	0.99406	252
Med Cap	1.00000	1.00000	1.00000	57
Med Glasses	1.00000	1.00000	1.00000	93
Shoe Cover	0.99265	1.00000	0.99631	135
Test Tube	1.00000	1.00000	1.00000	54
Urine Bag	1.00000	0.97778	0.98876	45
Accuracy			0.99451	729
Macro avg	0.99627	0.99319	0.99470	729
Weighted avg	0.99452	0.99451	0.99450	729

Table 4 shows the recognition accuracy of Bruno A[3] et al.'s improved model based on EfficientNet-B0 for image sets.

4.3 *summarize*

Figure 4 shows that the EfficientNet model outperforms other models in terms of average accuracy, indicating its superior comprehensive performance. Although the difference in the average accuracy may not be significant, it can be magnified when dealing with a large amount of medical waste image data in real-world scenarios. Table 3 demonstrates that the EfficientNet model has achieved near-perfect recognition accuracy for common single targets. Additionally, as shown in Table 4, the improved EfficientNet-B0 also has a very high accuracy in recognizing some unusual medical waste, which means that the improved EfficientNet-B0 is also highly adaptable for complex types of object recognition.

5. Synthesis and outlook

5.1 *Comprehensive evaluation of EfficientNet*

EfficientNet-B0 demonstrates high recognition accuracy and faster speed in medical waste classification. The model also exhibits strong generalization ability, making the EfficientNet family adaptable to various scenarios. However, there are few existing medical waste datasets, and there is still a lack of photo data in specific medical scenarios. This makes the training volume of the model insufficient and its stability uncertain. Additionally, there are limited applications of the EfficientNet model, and its universal adaptability in multi-objective and multi-scenario situations, such as medical waste classification, is not well-established.

5.2 *Limitations of current research and possible future research directions*

Currently, with the continuous progress of science and technology, the world has entered the era of interconnected big data. Medical devices and treatment methods are constantly developing. The lack of medical-related photo data can hinder the significant improvement of model learning ability. Therefore, in the future, the general trend for medical waste classification will be to network for data set sharing and to train a universal medical waste classification model. At the same time, the current classification of medical waste relies mainly on machine vision to capture image data. The quality of image data captured in the early stages directly affects subsequent image recognition and classification work. Therefore, targeted development of machine vision in the field of medical waste will have a positive impact on classification efficiency. Finally, to enhance the efficiency and accuracy of image recognition, preliminary image preprocessing is necessary. This simplifies subsequent model operations and reduces the number of image processing steps required.

5.3 *Further optimization of the EfficientNet model*

To further improve EfficientNet for medical waste classification, the focus should be on optimizing the combination of large category classification and small target recognition. The accumulation and complexity of a large amount of waste can cause the classification efficiency of a single small target and small category identification to become very low, which is not suitable for the medical pressure caused by the large population base. The combination of identifying small targets and classifying them on a larger scale will not only enhance classification efficiency but also have a positive impact on waste treatment connections. EfficientNet's migration learning and information extraction abilities have not been fully developed, and there are currently fewer models based on EfficientNet. However, if applied to classification tasks in various scenarios with large amounts of data, its performance will be well demonstrated. Also, there are clear directions for improving the performance and architecture of the model, such as the EfficientNetV2 model proposed by Mingxing Tan[13] et al. The proposed method effectively addresses several issues, including slower training with larger input resolutions, deep depth wise convolution is slower in shallow layers of the network, and scaling each stage of the network with the same scaling factor is suboptimal. Additionally, an efficient and improved asymptotic training method is suggested to enhance the overall performance of the original model. In summary, the combination of the improved EfficientNet architecture and advancements in classification applications will likely lead to the robust development of medical waste classification in the future.

6. Conclusion

This study summarizes the main classification methods and model architectures in the field of medical waste classification. A deep learning network model with high performance, EfficientNet, is found to be very suitable for this field. The architecture and advantages of this model are analyzed in depth and compared with other models applied in this field. It is found that EfficientNet has good potential for development due to its high accuracy and ability to perform well with low data volume. It has a high potential economic value in terms of practical data and operability. Finally, the optimization and future development trends of the improved EfficientNet are presented.

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