

# 7~8차시. Mobile Unet

MobileUnet

# 논문보기



# 구글 검색

- [arXiv.org](#)

unet paper

전체 이미지 동영상 지도 쇼핑 더보기 설정 도구

검색결과 약 961,000개 (0.38초)

arxiv.org > cs ▾ 이 페이지 번역하기

**U-Net: Convolutional Networks for Biomedical Image ...**

2015. 5. 18. - In this **paper**, we present a network and training strategy that relies on the strong use of data augmentation to use the available annotated ...

O Ronneberger 저술 - 2015 - 16753회 인용 - 관련 학술자료

함께 검색한 항목

arXiv.org > cs > arXiv:1505.04597

Computer Science > Computer Vision and Pattern Recognition

[Submitted on 18 May 2015]

## U-Net: Convolutional Networks for Biomedical Image Segmentation

Olaf Ronneberger, Philipp Fischer, Thomas Brox

There is large consent that successful training of deep networks requires many thousand annotated training samples. In this paper, we present a network and training strategy that relies on the strong use of data augmentation to use the available annotated samples more efficiently. The architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization. We show that such a network can be trained end-to-end from very few images and outperforms the prior best method (a sliding-window convolutional network) on the ISBI challenge for

Search... All fields Search  
Help | Advanced Search

**Download:**

- PDF
- Other formats (license)

Current browse context: cs.CV  
< prev | next >  
new | recent | 1505  
Change to browse by:

# 구글 스칼라 검색

- [scholar.google.com](https://scholar.google.com)
- 이 두 가지 방법으로 대부분 무료로 볼 수 있다.

The screenshot shows a Google Scholar search results page for the query "unet". The search bar at the top contains "unet". Below the search bar, there is a sidebar with filters: "학술자료" (Academic Journals), "모든 날짜" (All dates), "2020년부터" (From 2020), "2019년부터" (From 2019), "2016년부터" (From 2016), and "기간 설정..." (Set date). There are also filters for "관련도별 정렬" (Sort by relevance) and "모든 언어" (All languages), with "한국어 웹" (Korean Web) selected. At the bottom of the sidebar, there are two checked checkboxes: "특허 포함" (Include patents) and "서지정보 포함" (Include citation information).

The main search results area displays the following entries:

- H-DenseUNet: hybrid densely connected UNet for liver and tumor segmentation from CT volumes**  
X Li, H Chen, X Qi, Q Dou, CW Fu... - IEEE transactions on ..., 2018 - ieeexplore.ieee.org  
Liver cancer is one of the leading causes of cancer death. To assist doctors in hepatocellular carcinoma diagnosis and treatment planning, an accurate and automatic liver and tumor segmentation method is highly demanded in the clinical practice. Recently, fully ...  
☆ 368회 인용 관련 학술자료 전체 9개의 버전
- Nas-unet: Neural architecture search for medical image segmentation**  
Y Weng, T Zhou, Y Li, X Qiu - IEEE Access, 2019 - ieeexplore.ieee.org  
Neural architecture search (NAS) has significant progress in improving the accuracy of image classification. Recently, some works attempt to extend NAS to image segmentation which shows preliminary feasibility. However, all of them focus on searching architecture for ...  
☆ 47회 인용 관련 학술자료 전체 2개의 버전
- RIC-Unet: An improved neural network based on U-net for nuclei segmentation in**

# Mobile-Unet

- 두 가지 방법으로 다 무료로 볼 수 없다. (올라와 있지 않음)
- 대학생이라면, 학교 도서관과의 제휴로, 학교 IP에 한해, 논문을 다운 받을 수는 있다.
- 일반인이라면, 이 방법은 불가능

The screenshot shows the homepage of SAGE journals. The top navigation bar includes the SAGE journals logo, a search bar, a browse menu, resources, access options, sign in, and institution links. A large banner image of a textured fabric is visible. Below the banner, the journal title 'Textile Research Journal' is displayed, along with an impact factor of '1.926'. The main content area features a research article titled 'Mobile-Unet: An efficient convolutional neural network for fabric defect detection' by Junfeng Jing, Zhen Wang, and Matthias Rätsch. The article was first published on May 29, 2020, and is a research article. It includes a DOI link (<https://doi.org/10.1177/0040517520928604>). To the right of the article details is an 'Altmetric' badge showing 0 interactions and a lock icon.

SAGE journals

Search Browse Resources Access Options:

Sign In Institution

1.926

Textile Research Journal

Journal Home Browse Journal Journal Info Stay Connected Submit Paper

**Mobile-Unet: An efficient convolutional neural network for fabric defect detection**

Junfeng Jing , Zhen Wang, Matthias Rätsch, more... Show all authors

First Published May 29, 2020 | Research Article | Check for updates

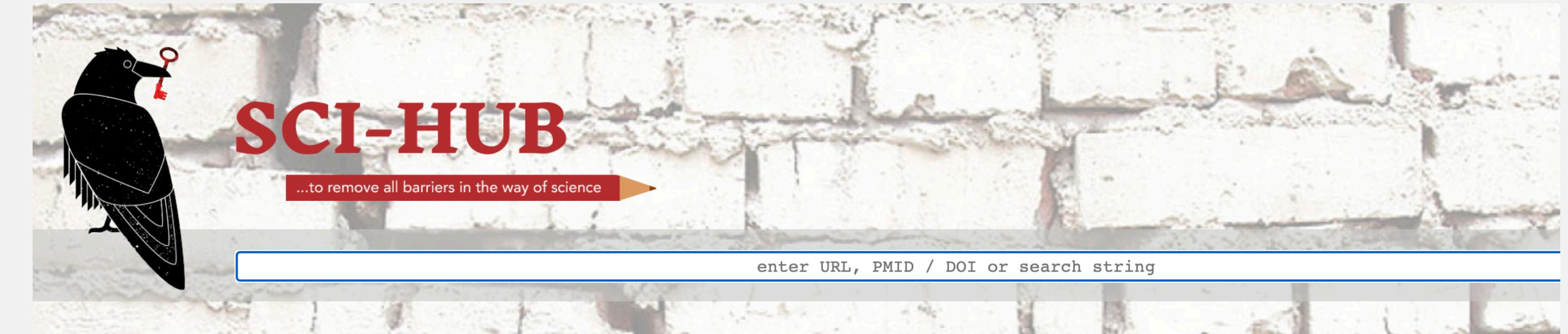
<https://doi.org/10.1177/0040517520928604>

[Article information](#)

**Abstract**

Deep learning-based fabric defect detection methods have been widely investigated to improve production efficiency and product quality. Although deep learning-based methods have proved to be powerful tools for classification and segmentation, some key issues remain to be addressed when applied to real applications.

# SCI-HUB



- <https://sci-hub.tw/>
- 10.1177/0040517520928604

The image shows a detailed view of a research article on the Sci-Hub platform. The article title is "Mobile-Unet: An efficient convolutional neural network for fabric defect detection". It is authored by Junfeng Jing (with an ORCID icon), Zhen Wang, and Matthias Rätsch, and is a "Research Article". The article was first published on May 29, 2020. A blue link provides the DOI: <https://doi.org/10.1177/0040517520928604>. Below the article title, there is a "Article information" section and a large "Abstract" section. The abstract discusses the development of a deep learning-based fabric defect detection system using Mobile-Unet, highlighting its efficiency and product quality. The text is cut off at the bottom.

Home Browse Journal ▾ Journal Information

**Mobile-Unet: An efficient convolutional neural network for fabric defect detection**

Junfeng Jing , Zhen Wang, Matthias Rätsch, more

First Published May 29, 2020 | Research Article

<https://doi.org/10.1177/0040517520928604>

[Article information ▾](#)

**Abstract**

Deep learning–based fabric defect detection has been widely used due to its high efficiency and product quality. Although deep learning models have achieved great success in classification and segmentation, some key issues still remain to be solved, such as how to effectively extract features from complex fabric images and how to deal with the variation of illumination and texture. In this paper, we propose a mobile convolutional neural network (Mobile-Unet) for fabric defect detection. The proposed Mobile-Unet consists of a symmetric encoder-decoder structure and a skip connection. The encoder is composed of four stages, each of which contains two residual blocks. The decoder is composed of three stages, each of which contains two residual blocks. The skip connection connects the encoder and the decoder. The proposed Mobile-Unet is trained on a dataset of fabric images with defects. The experimental results show that the proposed Mobile-Unet can achieve high accuracy and efficiency in fabric defect detection. The proposed Mobile-Unet is also compared with other state-of-the-art methods, such as U-Net, SegNet, and DeepLabv3+. The results show that the proposed Mobile-Unet outperforms other methods in terms of both accuracy and efficiency.

# SCI-HUB

- DOI 번호로 검색 가능
- <https://ko.wikipedia.org/wiki/%EC%82%AC%EC%9D%B4%ED%97%88%EB%BC%8C>
- 관심있다면, 위키를 읽어보길..

The screenshot shows the Sci-Hub interface. At the top left is the Sci-Hub logo (a black horse head with a red key) and the text "sci-hub to open science". Below the logo is a "save" button with a downward arrow icon. To the right of the logo is a "Check for updates" button with a circular progress bar icon.

The main content area displays an article record:

**Original article**

**Mobile-Unet: An efficient convolutional neural network for fabric defect detection**

Jing, J., Wang, Z., Rätsch, M., & Zhang, H. (2020). *Mobile-Unet: An efficient convolutional neural network for fabric defect detection*. *Textile Research Journal*, 004051752092860. doi:10.1177/0040517520928604

url to share this paper:  
[sci-hub.tw/10.1177/0040517520928604](https://sci-hub.tw/10.1177/0040517520928604)

downloaded on 2020-05-30

Sci-Hub is a project to make knowledge free.  
[support →](#)

updates on twitter

created by

**Junfeng Jing<sup>1</sup> , Zhen Wang<sup>1</sup>, Huanhuan Zhang<sup>1</sup>**

# Mobile-Unet



# Abstract

- Deep learning-based fabric defect detection methods
- 해결하고자 하는 문제
  - 더 높은 실시간 성능이 필요
  - 비정상 샘플의 개수가 정상 샘플 개수에 비해 아주 적어서, 트레이닝 할 데이터 자체가 적다.

## Abstract

Deep learning–based fabric defect detection methods have been widely investigated to improve production efficiency and product quality. Although deep learning–based methods have proved to be powerful tools for classification and segmentation, some key issues remain to be addressed when applied to real applications. Firstly, the actual fabric production conditions of factories necessitate **higher real-time performance of methods**. Moreover, fabric defects as abnormal samples are very rare compared with normal samples, which results in data imbalance. It makes model training based on deep learning challenging. To solve these problems, an extremely efficient convolutional neural network, Mobile-Unet, is proposed to achieve the end-to-end defect segmentation. The median frequency balancing loss function is used to overcome the challenge of sample imbalance. Additionally, Mobile-Unet introduces depth-wise separable convolution, which dramatically reduces the complexity cost and model size of the network. It comprises two parts: encoder and decoder. The MobileNetV2 feature extractor is used as the encoder, and then five deconvolution layers are added as the decoder. Finally, the softmax layer is used to generate the segmentation mask. The performance of the proposed model has been evaluated by public fabric datasets and self-built fabric datasets. In comparison with other methods, the experimental results demonstrate that segmentation accuracy and detection speed in the proposed method achieve state-of-the-art performance.

# Abstract

- 볼링공을 생산하는 업체
  - 볼링공을 생산할 때, 검수 과정을 딥러닝 기반으로 자동화하고자 할 때, 데이터가 필요
  - 현재 불량률이 1% 정도
  - 10000개의 이미지를 얻었을 때, 그 중 100개 만이 불량인 이미지

## Abstract

Deep learning-based fabric defect detection methods have been widely investigated to improve production efficiency and product quality. Although deep learning-based methods have proved to be powerful tools for classification and segmentation, some key issues remain to be addressed when applied to real applications. Firstly, the actual fabric production conditions of factories necessitate **higher real-time performance of methods**. Moreover, fabric defects as abnormal samples are very rare compared with normal samples, which results in data imbalance. It makes model training based on deep learning challenging. To solve these problems, an extremely efficient convolutional neural network, Mobile-Unet, is proposed to achieve the end-to-end defect segmentation. The median frequency balancing loss function is used to overcome the challenge of sample imbalance. Additionally, Mobile-Unet introduces depth-wise separable convolution, which dramatically reduces the complexity cost and model size of the network. It comprises two parts: encoder and decoder. The MobileNetV2 feature extractor is used as the encoder, and then five deconvolution layers are added as the decoder. Finally, the softmax layer is used to generate the segmentation mask. The performance of the proposed model has been evaluated by public fabric datasets and self-built fabric datasets. In comparison with other methods, the experimental results demonstrate that segmentation accuracy and detection speed in the proposed method achieve state-of-the-art performance.

# Abstract

- Mobile-Unet은 end-to-end defect segmentation을 달성하기 위한 극도로 효율적인 CNN
  - 1의 문제를 해결하기 위해, depth-wise separable convolution 도입
  - 2의 문제를 해결하기 위해, median frequency balancing loss 도입
  - 둘 다 기존에 있는 것들

## Abstract

Deep learning-based fabric defect detection methods have been widely investigated to improve production efficiency and product quality. Although deep learning-based methods have proved to be powerful tools for classification and segmentation, some key issues remain to be addressed when applied to real applications. Firstly, the actual fabric production conditions of factories necessitate **higher real-time performance of methods**. Moreover, fabric defects as abnormal samples are very rare compared with normal samples, which results in data imbalance. It makes model training based on deep learning challenging. To solve these problems, an extremely efficient convolutional neural network, Mobile-Unet, is proposed to achieve the end-to-end defect segmentation. The median frequency balancing loss function is used to overcome the challenge of sample imbalance. Additionally, Mobile-Unet introduces depth-wise separable convolution, which dramatically reduces the complexity cost and model size of the network. It comprises two parts: encoder and decoder. The MobileNetV2 feature extractor is used as the encoder, and then five deconvolution layers are added as the decoder. Finally, the softmax layer is used to generate the segmentation mask. The performance of the proposed model has been evaluated by public fabric datasets and self-built fabric datasets. In comparison with other methods, the experimental results demonstrate that segmentation accuracy and detection speed in the proposed method achieve state-of-the-art performance.

# Abstract

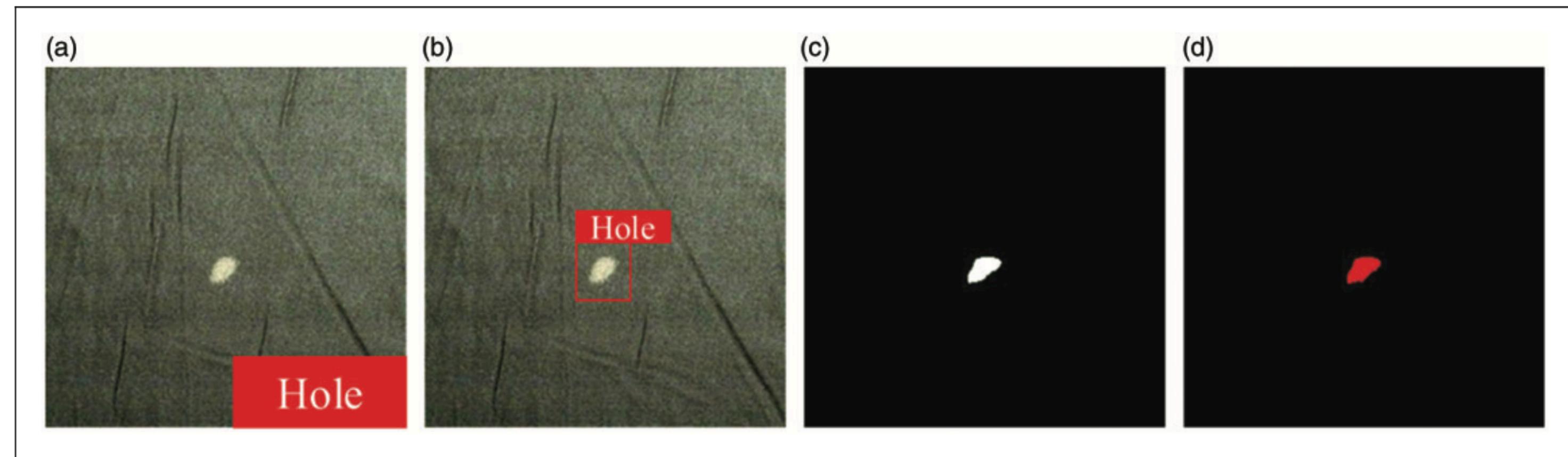
- Encoder, Decoder 구조의 네트워크
  - 인코더에 MobileNetV2 feature extractor 도입
  - 이게 전이학습을 사용하는 요소.
  - 디코더에 다섯개의 컨볼루션 네트워크 도입
  - 맨 마지막에 softmax 레이어 도입

## Abstract

Deep learning-based fabric defect detection methods have been widely investigated to improve production efficiency and product quality. Although deep learning-based methods have proved to be powerful tools for classification and segmentation, some key issues remain to be addressed when applied to real applications. Firstly, the actual fabric production conditions of factories necessitate **higher real-time performance of methods**. Moreover, fabric defects as abnormal samples are very rare compared with normal samples, which results in data imbalance. It makes model training based on deep learning challenging. To solve these problems, an extremely efficient convolutional neural network, Mobile-Unet, is proposed to achieve the end-to-end defect segmentation. The median frequency balancing loss function is used to overcome the challenge of sample imbalance. Additionally, Mobile-Unet introduces depth-wise separable convolution, which dramatically reduces the complexity cost and model size of the network. It comprises two parts: encoder and decoder. The MobileNetV2 feature extractor is used as the encoder, and then five deconvolution layers are added as the decoder. Finally, the softmax layer is used to generate the segmentation mask. The performance of the proposed model has been evaluated by public fabric datasets and self-built fabric datasets. In comparison with other methods, the experimental results demonstrate that segmentation accuracy and detection speed in the proposed method achieve state-of-the-art performance.

# Introduction

- 기존에 Fabric 결함 감지를 찾아냈던 방법들
- 딥러닝 기반 결함 감지 방법
  - CNN 기반 방법 여러가지의 소개
- U-Net의 초반부를 MobileNetV2로 교체하겠다.
  - real-time application 및 better feature extraction 간의 균형 맞추기



**Figure I.** Four levels of defect detection: (a) defect classification; (b) defect location; (c) defect segmentation; (d) defect semantic segmentation.

# Introduction

- Contributions
  - end-to-end 네트워크
  - 더 적은 파라미터. 온라인. (속도 및 실시간)
  - 샘플 간의 불균형 해소방안. (불균형 해소 방안)

1. Different from traditional algorithms for defect classification or defect location, Mobile-Unet is a novel **end-to-end** defect segmentation network that achieves pixel-level fabric defect classification.
2. Compared with extant methods, Mobile-Unet has **fewer model parameters** and can significantly shorten detection time. It is also more suitable for **online automated detection**.
3. In order to solve the imbalance between defective and non-defective samples, **a cross-entropy loss function weighted with median frequency balancing** is used to improve the convergence speed and detection accuracy of the model.

# Proposed Model

- 사전 트레이닝 단계
  - MoibleNetV2
    - 결함 분류기
- 시맨틱 세그먼테이션 단계
  - 첫 다섯 컨볼루션을 인코더로, 디코더로서, 다섯 개의 디콘볼루션 도입

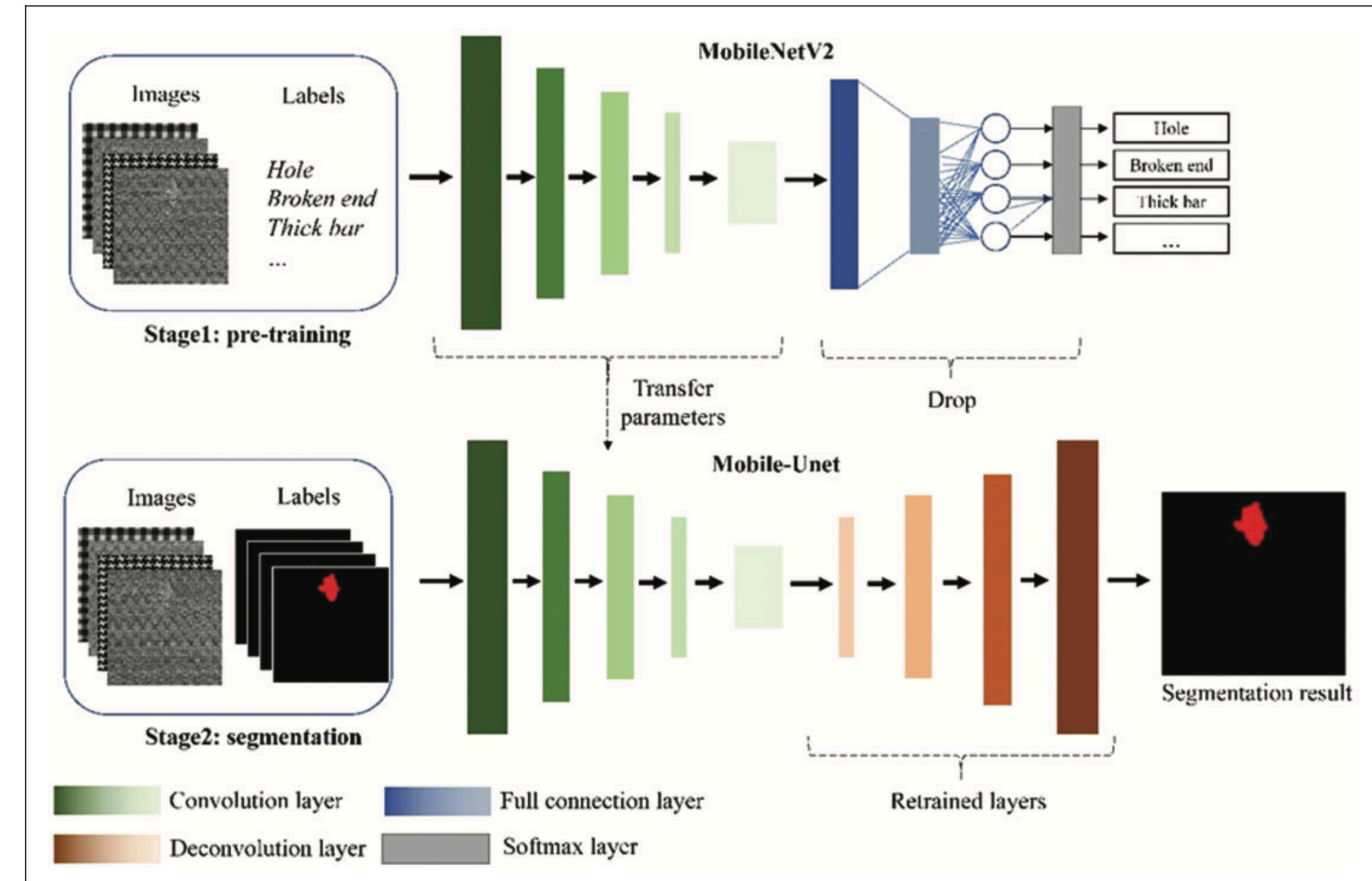


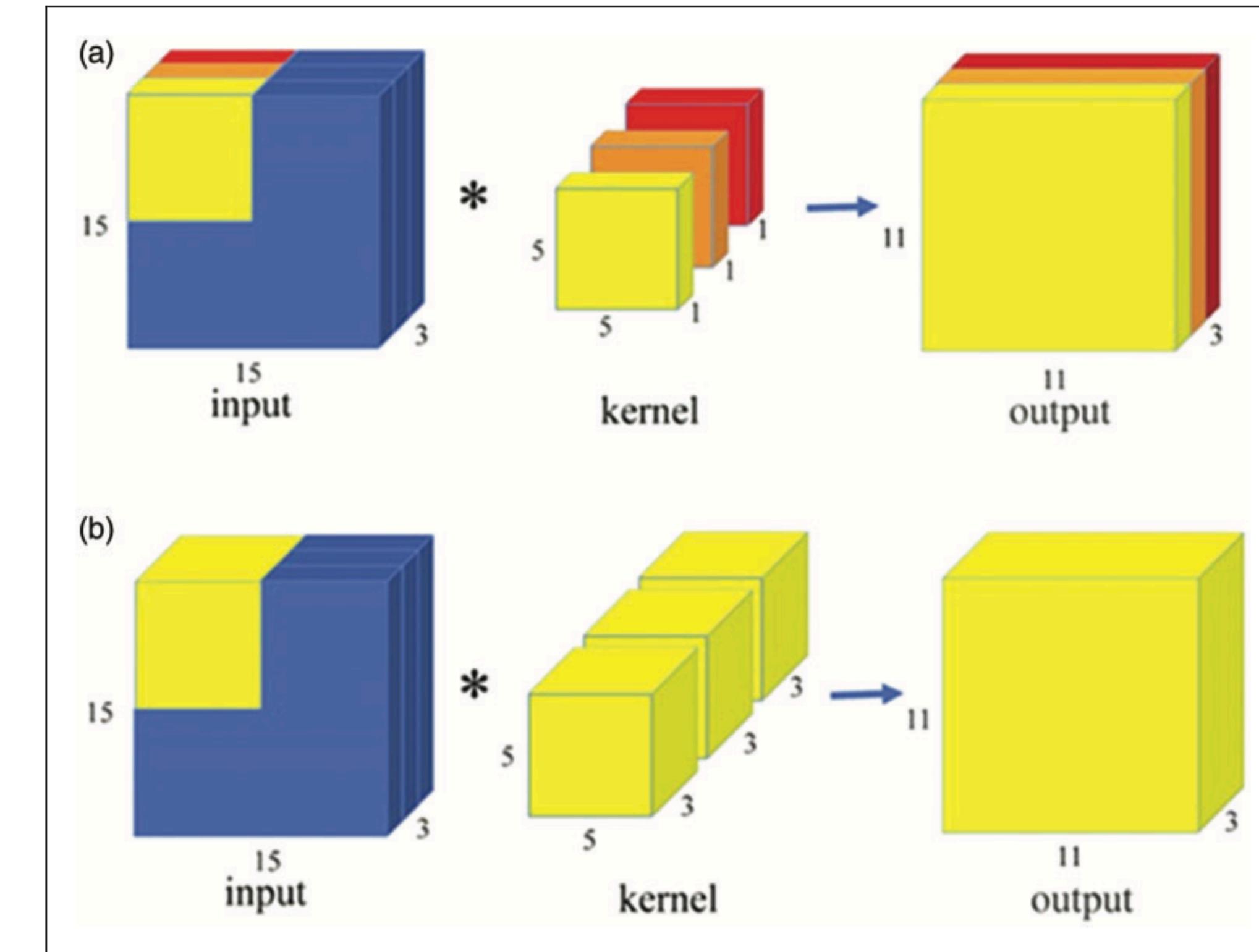
Figure 2. Process of our method.

relationship between the two stages is illustrated in Figure 2. The pre-training stage (stage 1 in Figure 2) comprises training MobileNetV2 for defect classification, and the input of the network is the defect image

# Proposed Model

## 사전 트레이닝 단계

- MobileNetV2
  - 경량 CNN을 위한 depthwise. separable convolutions 사용
  - depthwise separable convolutions.
  - real-time tasks에서 널리 도입됨
  - 이유
    - 더 적은 파라미터
    - 계산량이 적다.

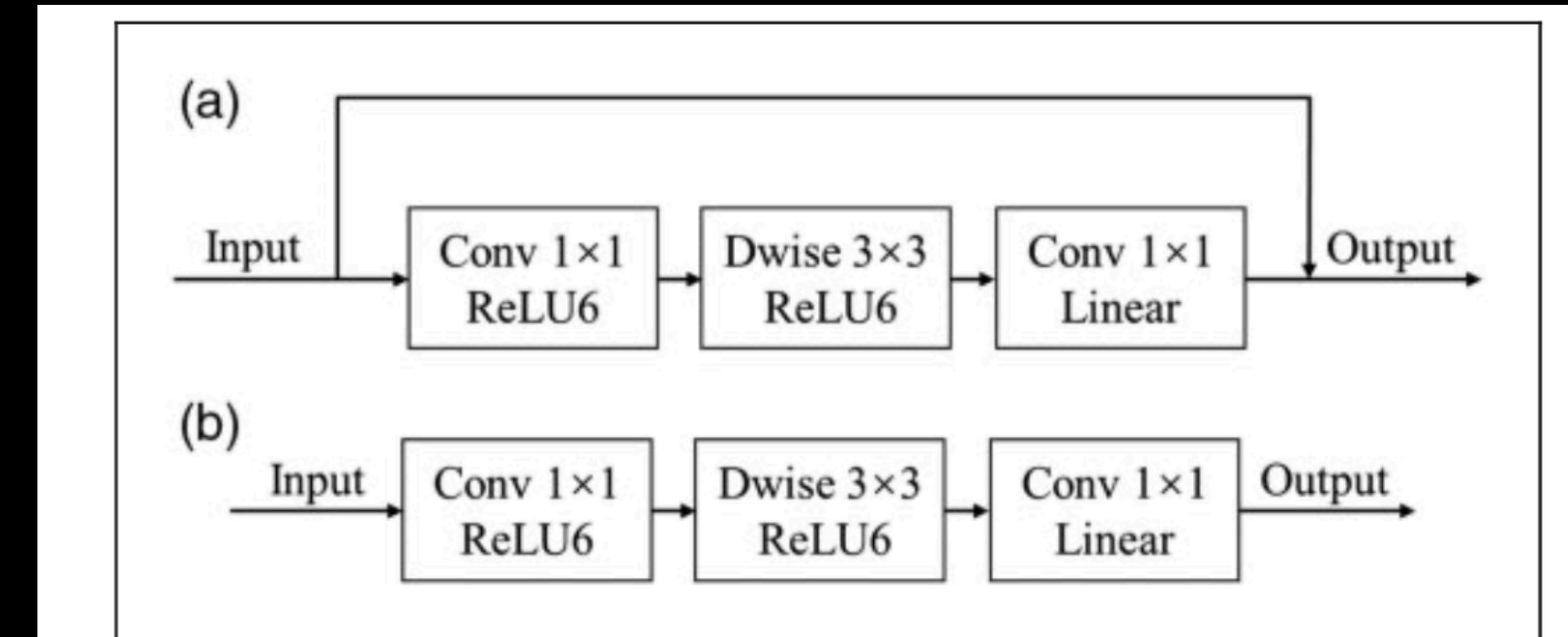


**Figure 3.** Two types of convolution using three kernels to transform a  $15 \times 15 \times 3$  image into an  $11 \times 11 \times 3$  image: (a) depth-wise convolution; (b) standard convolution.

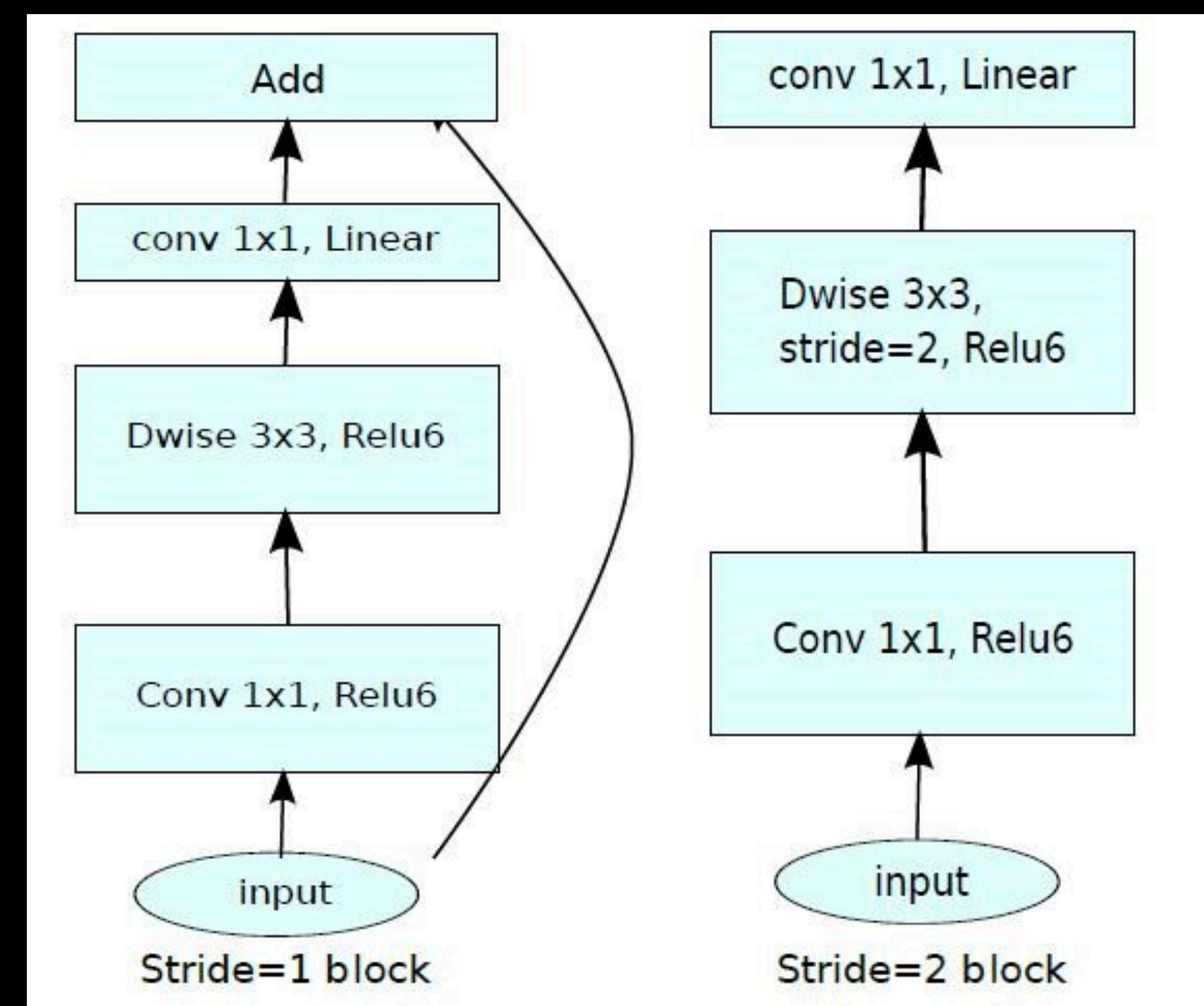
# Proposed Model

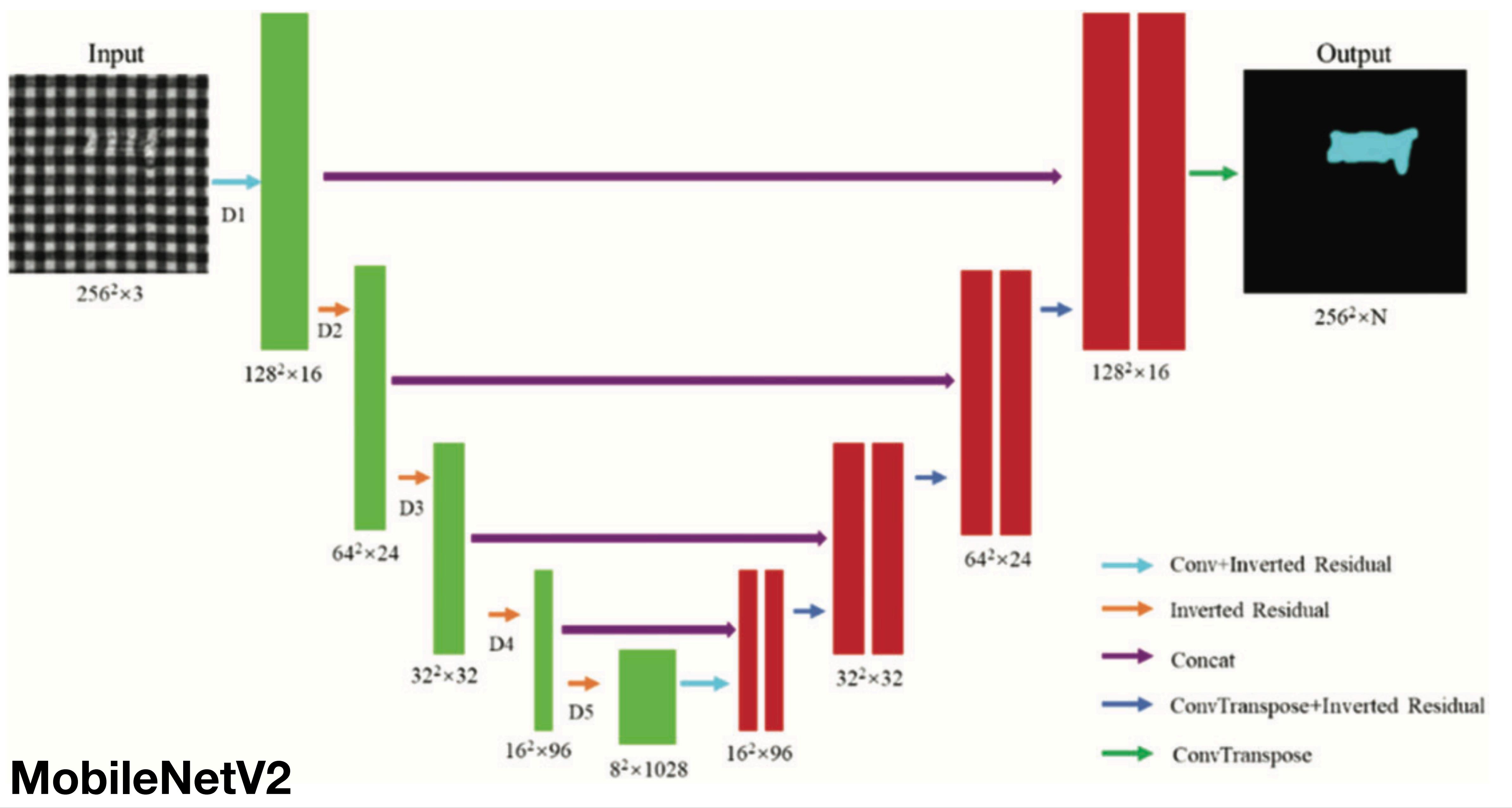
## 사전 트레이닝 단계

- inverted residual blocks.
  - 하나는 stride가 1인 residual 블록.
  - 다른 하나는 stride가 2인 다운사이징을 위한 블록.
  - 두 타입의 블록 모두는 세 레이어로 구성
    - 1x1 컨볼루션 레이어. ReLU 6.
    - 3x3 깊이별 컨볼루션 레이어
    - 1x1 컨볼루션 레이어. 활성화 함수 없음



**Figure 4.** Inverted residual blocks: (a)  $\text{stride} = 2$  block; (b)  $\text{stride} = 1$  block.





**Figure 5.** Architecture of Mobile-Unet.



**Table I.** The structural configuration of MobileNetV2

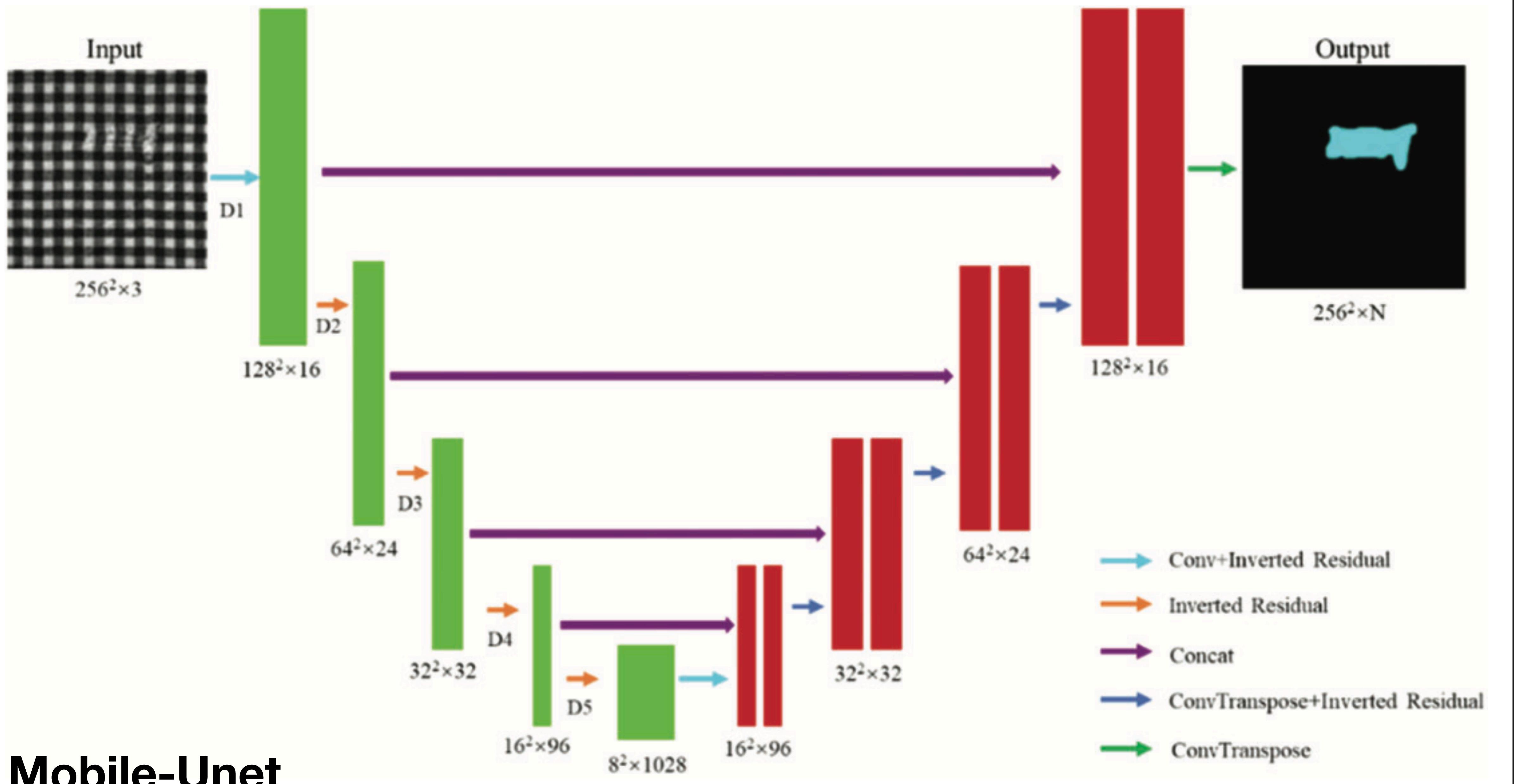
Layers	Input size	Operation	t	k	n	s	Output size
Input image	—	—	—	—	—	—	(3,256,256)
D1	(3,256,256)	Conv + BN + ReLU6 Inverted residual	— 1	3 —	1 1	— 1	(16,128,128)
D2	(16,128,128)	Inverted residual	6	—	2	2	(24,64,64)
D3	(24,64,64)	Inverted residual	6	—	3	2	(32,32,32)
D4	(32,32,32)	Inverted residual	6	—	4	2	(96,16,16)
D5	(96,16,16)	Inverted residual Inverted residual Inverted residual	6 6 6	— — 3	3 1 1	2 1 —	(128,8,8)
CI	1280	Linear	—	—	—	—	N

**MobileNetV2**

16<sup>2</sup>×96      8<sup>2</sup>×1028      16<sup>2</sup>×96

→ ConvTranspose

**Figure 5.** Architecture of Mobile-Unet.



**Figure 5.** Architecture of Mobile-Unet.

**Table 2.** Definition and operation of each layer of Mobile-Unet

Layer	Input	Output	Output size	k	s	t
Input image	—	—	(3,256,256)	—	—	—
D1	Input image	X1	(16,128,128)	—	—	—
D2	X1	X2	(24,64,64)	—	—	—
D3	X2	X3	(32,32,32)	—	—	—
D4	X3	X4	(96,16,16)	—	—	—
D5	X4	X5	(1280,8,8)	—	—	—
ConvTranspose1	X5	L1	(96,16,16)	4	—	2
Inverted Residual1	L1 + X4	L2	(96,16,16)	—	6	1
ConvTranspose2	L2	L3	(32,32,32)	4	—	2
Inverted Residual2	L3 + X3	L4	(32,32,32)	—	6	1
ConvTranspose3	L4	L5	(24,64,64)	4	—	2
Inverted Residual3	L5 + X2	L6	(24,64,64)	—	6	1
ConvTranspose4	L6	L7	(16,128,128)	4	—	2
Inverted Residual4	L7 + X1	L8	(16,128,128)	—	6	1
ConvTranspose5 + SoftMax	L8	Output	(N,256,256)	4	—	2

## Mobile-Unet

10<sup>-3</sup> × 908<sup>2</sup> × 102810<sup>-3</sup> × 90

→ ConvTranspose

**Figure 5.** Architecture of Mobile-Unet.

# Proposed Model

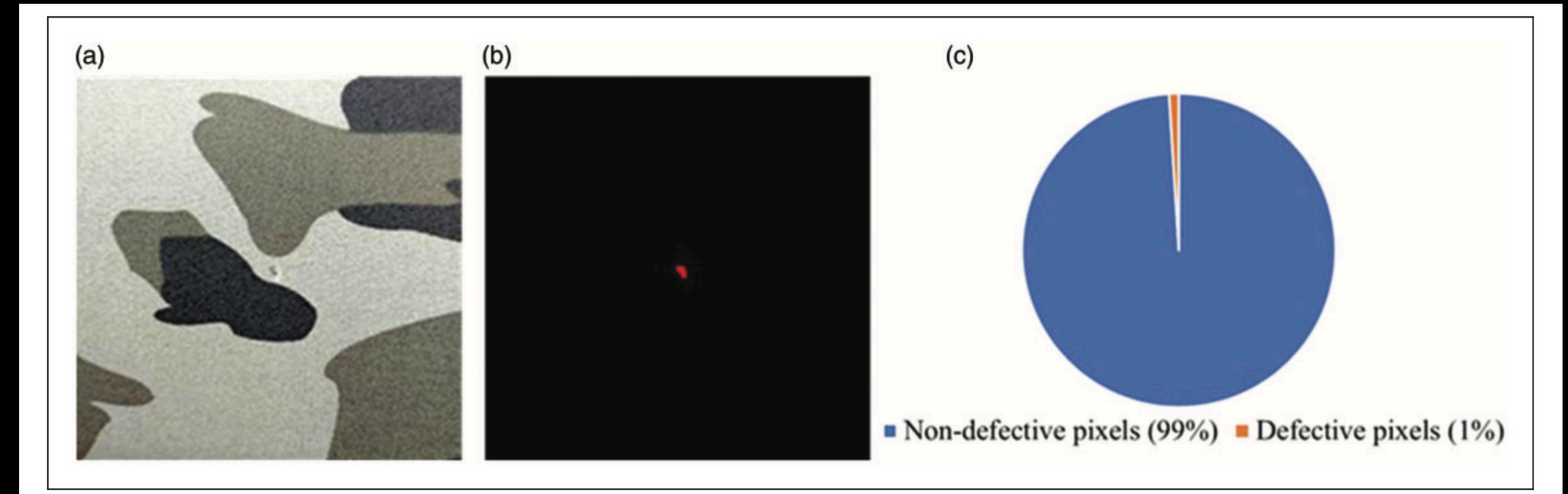
## 개선된 손실 함수

- 결합 비율이 아주 낮은 문제를 해결하자.

$$\text{Loss} = -\frac{1}{N} \sum_{n=1}^N \sum_{c=1}^C w_c l_c^{(n)} \log(p_c^{(n)})$$

$$w_c = \frac{\text{median}(\{f_c | c \in C\})}{f_c}$$

- $N$ : 트레이닝 샘플의 픽셀 수
- $w_c$ : 클래스  $c$ 의 가중치
- $f_c$ : 클래스  $c$ 에 있는 픽셀의 frequency
- $p_c^{(n)}$ : 클래스  $c$ 에 있는 픽셀  $n$ 의 softmax 확률
- $l_c^{(n)}$ : 클래스  $c$ 에 대한 샘플  $n$ 의 해당되는 라벨 (one-hot 인코딩)
- $C$ : 모든 클래스의 세트



**Figure 6.** Imbalanced number of defects and background pixels: (a) original images; (b) ground truth; (c) comparison of the number of defective and non-defective pixels.

shows the imbalance in the number of defects and background pixels. An ordinary loss function may cause the network to fall into local optimum. In order to solve the sample imbalance problem, an improved cross-entropy loss with median frequency balancing weights (CE-MFB)<sup>34</sup> is used. The class loss is weighted by the ratio of the median class frequency in the training set and the actual class frequency. The improved cross-

# Proposed Model

## 개선된 손실 함수

- 결함 비율이 아주 낮은 문제를 해결하자.

$$Loss = -\frac{1}{N} \sum_{n=1}^N \sum_{c=1}^C w_c l_c^{(n)} \log(p_c^{(n)})$$

$$w_c = \frac{\text{median}(\{f_c | c \in C\})}{f_c}$$

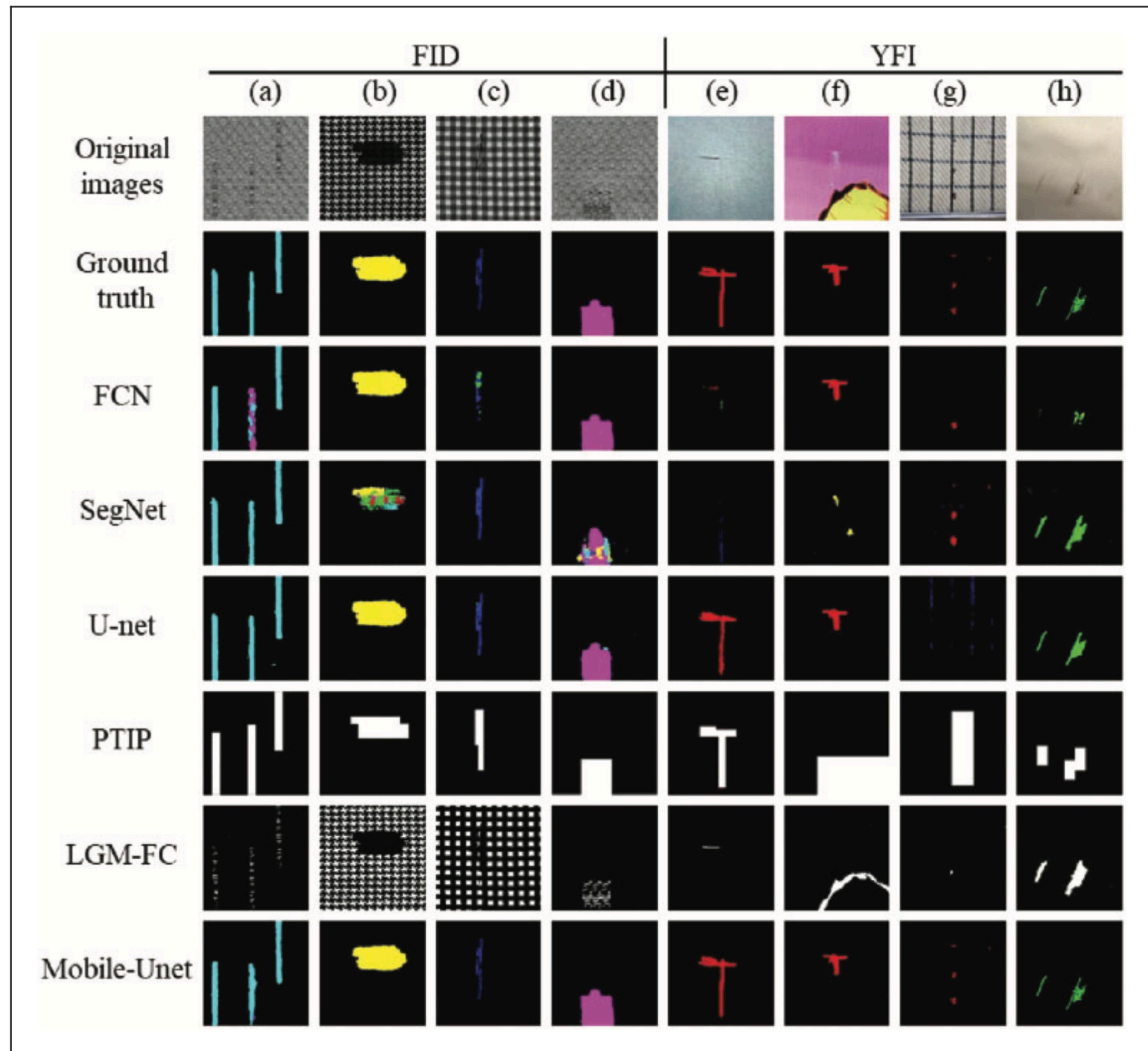
- $N$ : 트레이닝 샘플의 픽셀 수
- $w_c$ : 클래스  $c$ 의 가중치
- $f_c$ : 클래스  $c$ 에 있는 픽셀의 frequency
- $p_c^{(n)}$ : 클래스  $c$ 에 있는 픽셀  $n$ 의 softmax 확률
- $l_c^{(n)}$ : 클래스  $c$ 에 대한 샘플  $n$ 의 해당되는 라벨 (one-hot 인코딩)
- $C$ : 모든 클래스의 세트

```
def _compute_cross_entropy_mean(class_weights, labels, softmax):
    cross_entropy = -tf.reduce_sum(
        tf.multiply(labels * tf.log(softmax), class_weights),
        reduction_indices=[1])

    cross_entropy_mean = tf.reduce_mean(
        cross_entropy, name='xentropy_mean')
    return cross_entropy_mean
```

shows the imbalance in the number of defects and background pixels. An ordinary loss function may cause the network to fall into local optimum. In order to solve the sample imbalance problem, an **improved cross-entropy loss with median frequency balancing weights (CE-MFB)<sup>34</sup>** is used. The class loss is weighted by the ratio of the median class frequency in the training set and the actual class frequency. The improved cross-

# 결과



# 실습 Session

4. Mobile-Unet.ipynb

Mobile-Unet

# 딥러닝을 도와주는 보조도구



<https://deepcognition.ai/>

딥러닝 GUI

<https://github.com/lutzroeder/netron>

딥러닝 GUI 분석기