Mobilenet v2 Architecture

- MobileNet-v2 is a convolutional neural network that is 92 layers deep. The network has pretrained version which trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224.

- It's one of the applications of Depth-wise Separable Convolutional Neural Networks

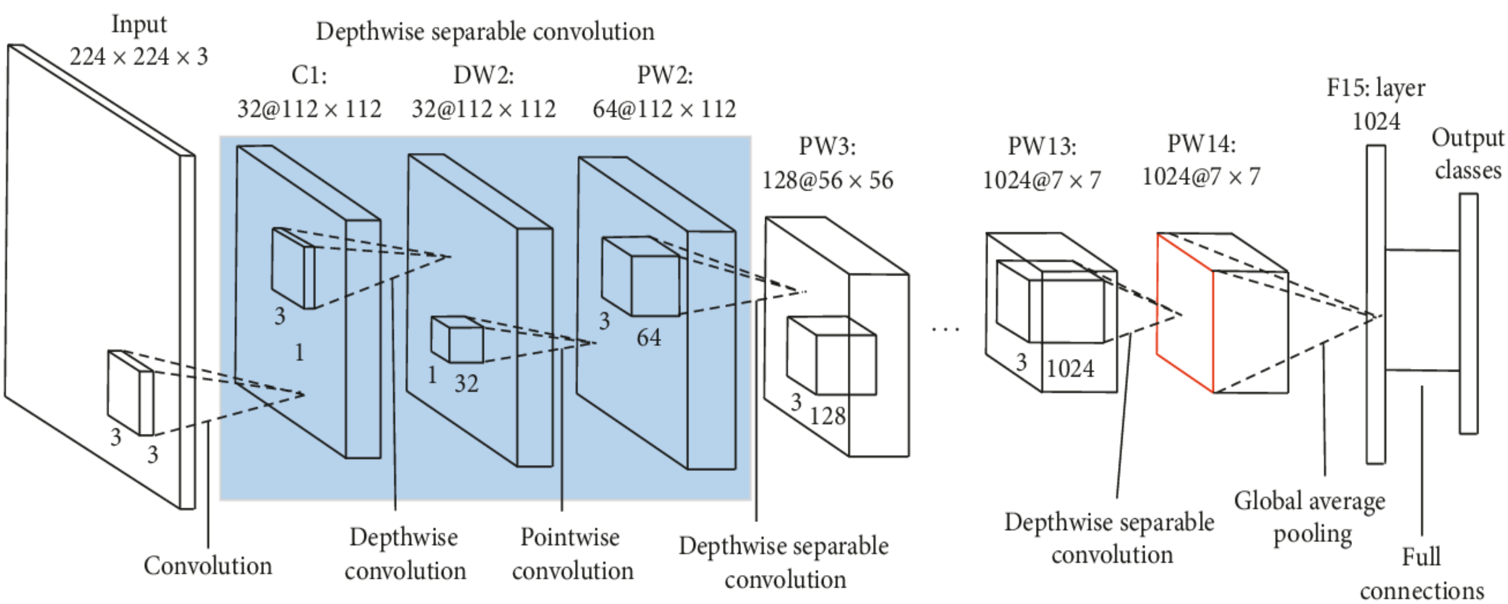
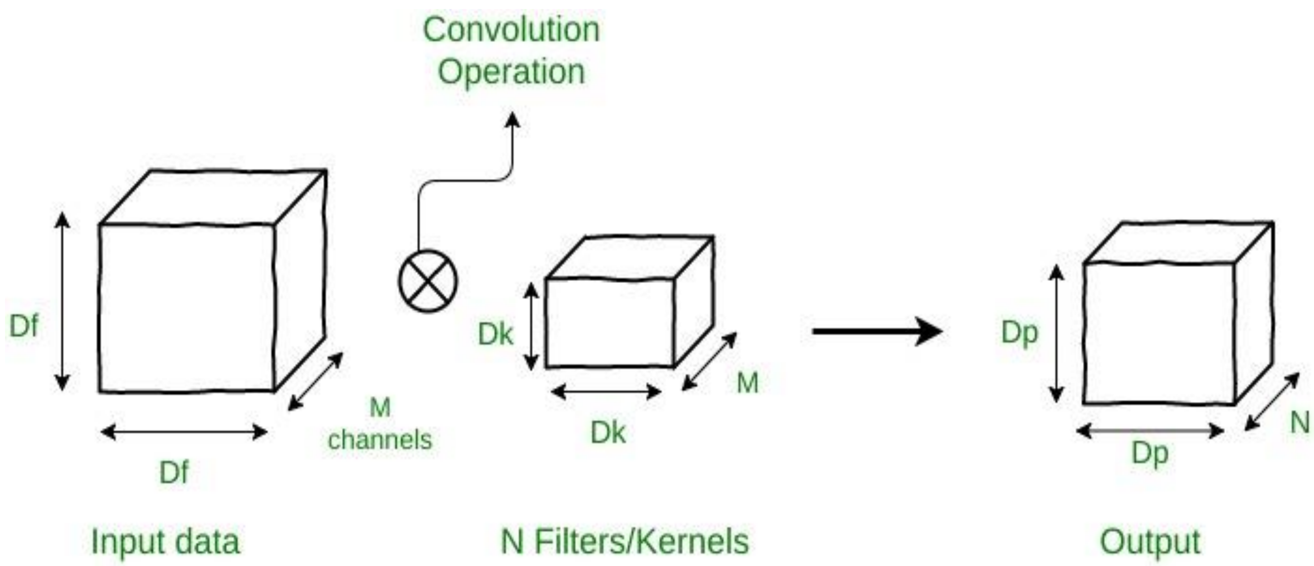


FIGURE 1: Architecture of MobileNet.

Understanding Normal Convolution operation



- Suppose there is an input data of size **Df x Df x M**, where **Df x Df** can be the image size and **M** is the number of channels (3 for an RGB image). Suppose there are **N** filters/kernels of size **Dk x Dk x M**. If a normal convolution operation is done, then, the output size will be **Dp x Dp x N**.

- *The number of multiplications in 1 convolution operation = size of filter =* ***Dk x Dk x M***

- *the total number of multiplications become* ***N x Dp x Dp x (Multiplications per convolution)***

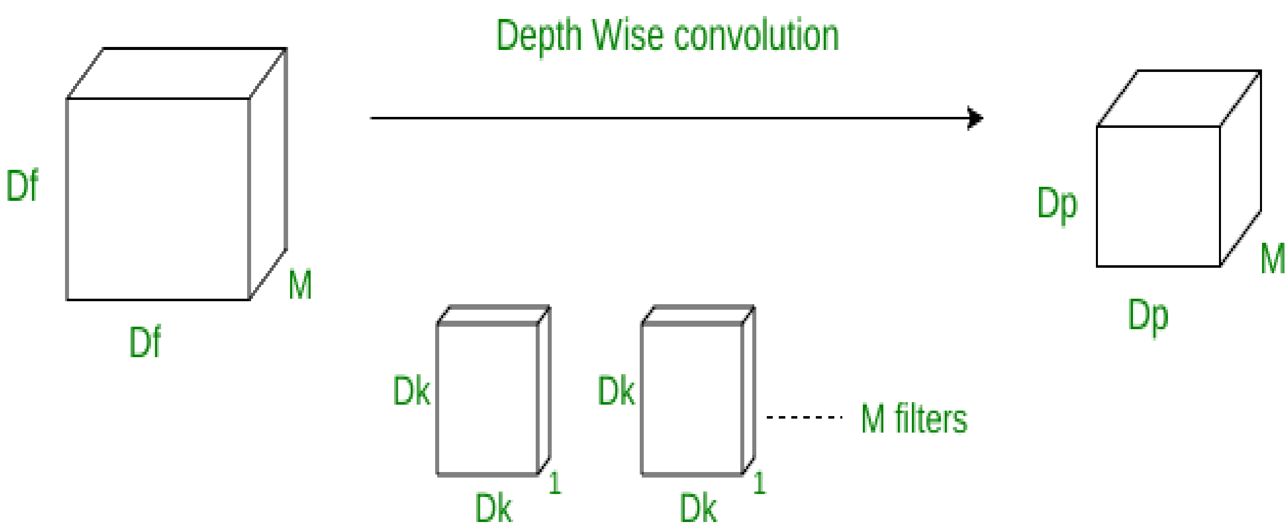
- ***Total no of multiplications = N x Dp^2 x Dk^2 x M***

Depth-Wise Separable Convolutions

- *This process is broken down into 2 operations :*
    - *Depth-wise convolutions*
    - *Point-wise convolutions*

1-DEPTH WISE CONVOLUTION :

In ***depth-wise operation***, convolution is applied to a **single channel** at a time unlike standard CNN's in which it is done for all the M channels. So here the filters/kernels will be of size **Dk x Dk x 1**. Given there are M channels in the input data, then M such filters are required. Output will be of size **Dp x Dp x M**.

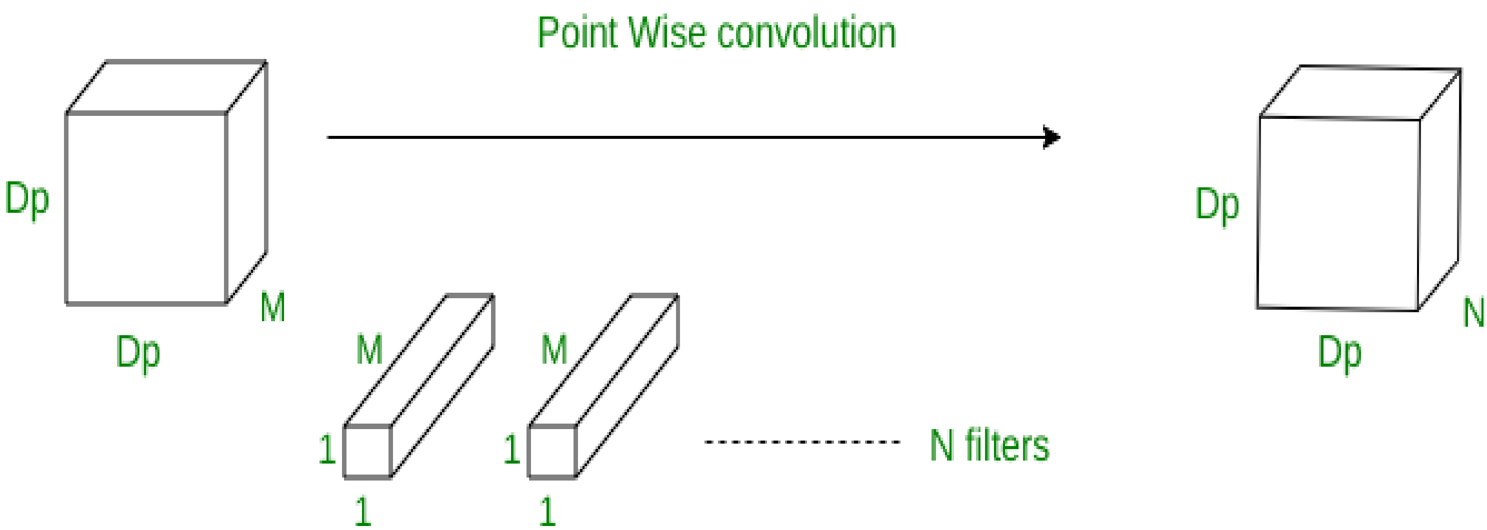


Cost of this operation:

- A single convolution operation require **Dk x Dk** multiplications.
- Since the filter are slided by **Dp x Dp** times across all the M channels, the total number of multiplications is equal to **M x Dp x Dp x Dk x Dk**
- So for depth wise convolution operation, **Total no of multiplications = M x Dk^2 x Dp^2**

2-POINT WISE CONVOLUTION :

In ***point-wise operation***, a **1×1 convolution** operation is applied on the M channels. So the filter size for this operation will be **1 x 1 x M.** Say we use N such filters, the output size becomes **Dp x Dp x N**.



Cost of this operation:

- *A single convolution operation require **1 x M** multiplications.*
- Since the filter is being slided by **Dp x Dp** times, *the total number of multiplications is equal **to M x Dp x Dp x (no. of filters)***
- So for point wise convolution operation, ***Total no of multiplications = M x Dp^2 x N***

Therefore, for overall operation:

- *Total multiplications = Depth wise conv. multiplications + Point wise conv. multiplications*
- *Total multiplications* ***= M * Dk² * Dp² + M * Dp² * N = M * Dp² * (Dk² + n)***
- So for depth wise separable convolution operation, *Total no of multiplications* ***= M x Dp² x (Dk² + N)***

Comparison between the complexities of these types of convolution operations

Type of Convolution	***Complexity***
Standard	*N x Dp² x Dg² x M*
Depth wise separable	*M x Dp² x (Dk² + N)*

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Complexity of depth wise separable convolutions
--------------------------------------------------   =  RATIO ( R )
       Complexity of standard convolution
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Ratio(R) = 1/N + 1/Dk²

As an example, consider N = 100 and Dk = 512. Then the ratio R = 0.010004

This means that the depth wise separable convolution network, in this example, performs 100 times lesser multiplications as compared to a standard constitutional neural network.

This implies that we can deploy faster convolution neural network models without losing much of the accuracy.