

# FLOWER RECOGNIZER FOR MOBILE APPLICATION

LORENZO PIROLA - MAT. 816418  
MATTEO ROMANATO - MAT. 816852  
YOUSSEF KARRATI - MAT. 817435

# **Outline**

- 
- 1. Introduction**
  - 2. Dataset**
  - 3. Models**
  - 4. Models compression**
  - 5. Conclusions**

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- 
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# Introduction

## Objective

The aim of the **project** was to create a model suitable to a **mobile context** that can recognize **flowers** from images.

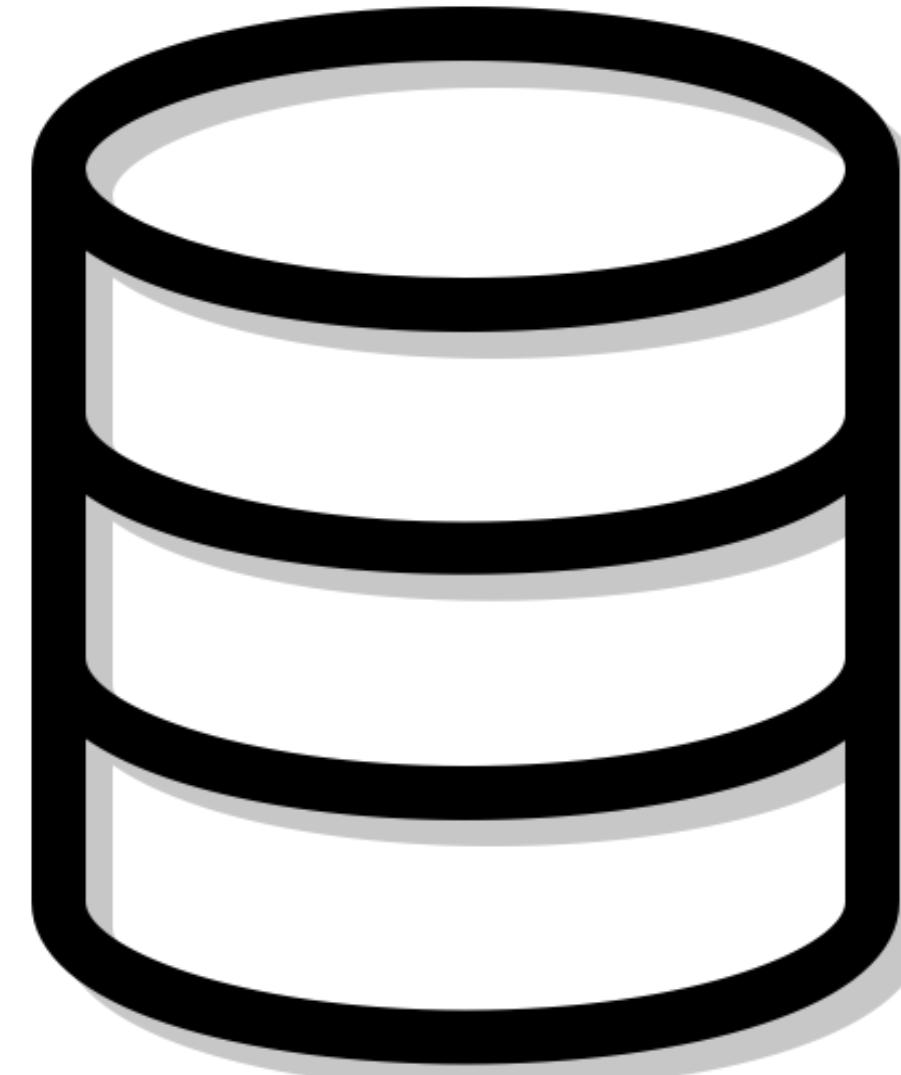
For the creation of the model three different architectures were chosen for comparison as starting point: MobileNetV2, DenseNet-121 and EfficientNet-B0.



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- 
1. Introduction
  2. **Dataset**
  3. Models
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# Dataset



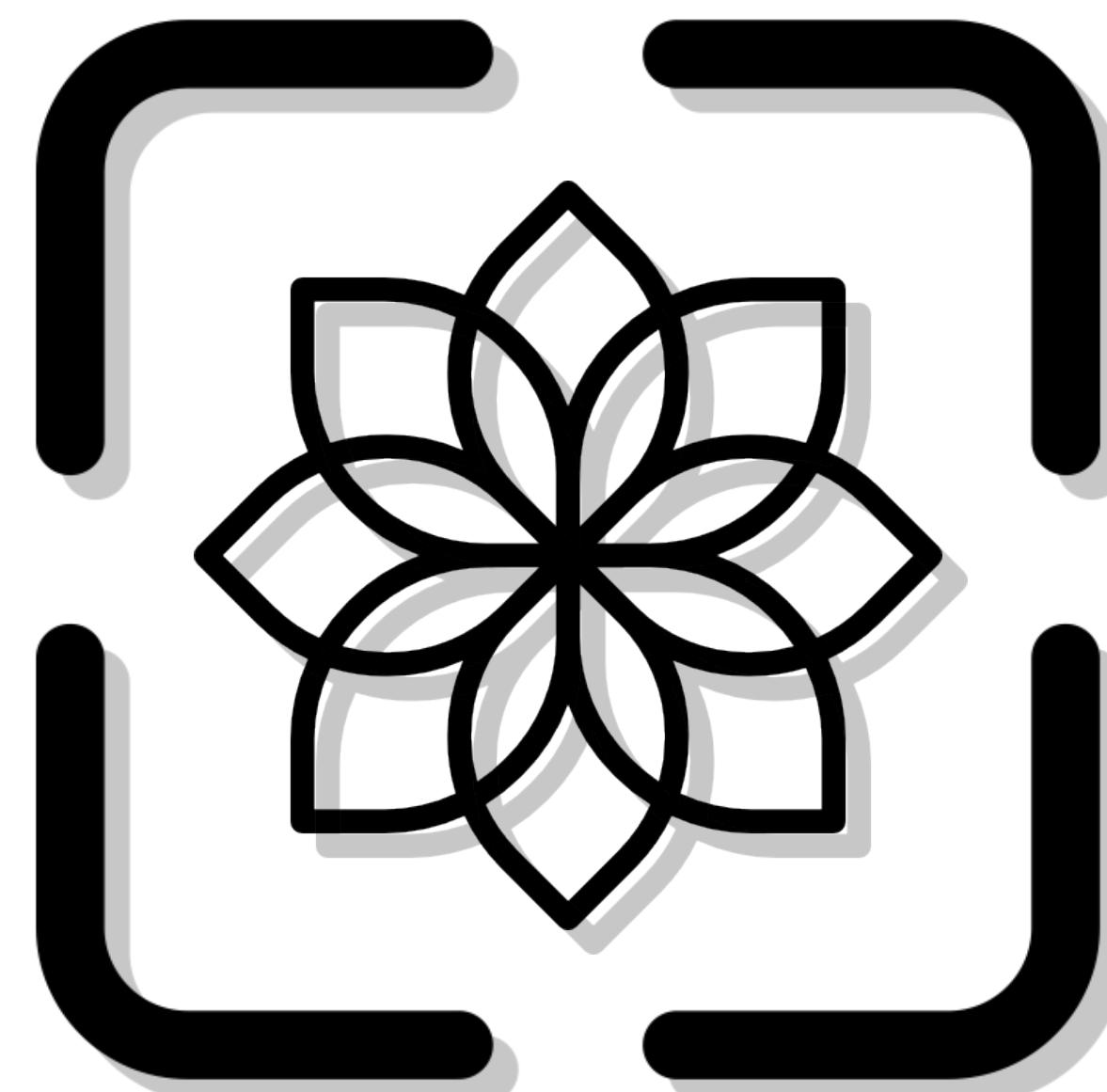
The **dataset** used contains 8189 images of flowers commonly found in the UK, belonging to 102 different classes. It was divided into:

- **Train set** using 80% of the available images (5284)
- **Test set** using the remaining 20% of the images (1638)
- **Validation test** was created using 20% of train set images (1267)

# Preprocessing

## Normalization

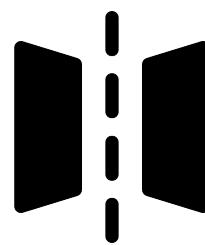
- **MobileNetV2**: rescales pixels in a range between -1 and 1
- **DenseNet-121**: rescales pixels in a range between 0 and 1 and normalizes channels with respect to the ImageNet dataset
- **EfficientNet-B0**: converts from RGB to BGR and normalizes channels with respect to the ImageNet dataset



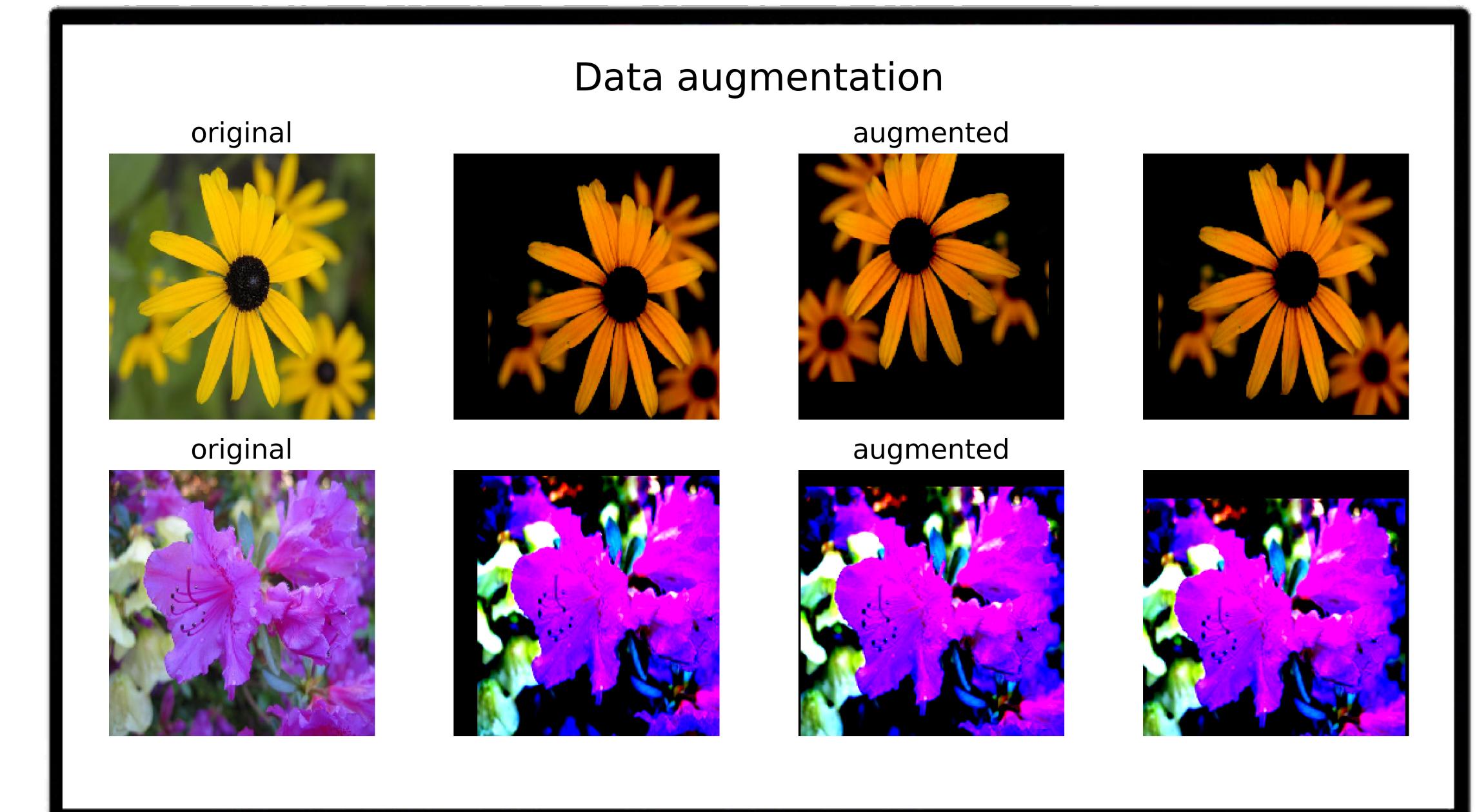
# Preprocessing

Data set

## Data augmentation



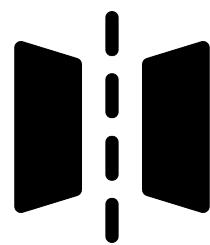
Width shifting and height shifting



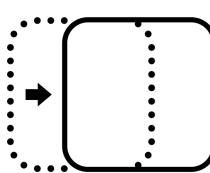
# Preprocessing

Dataset

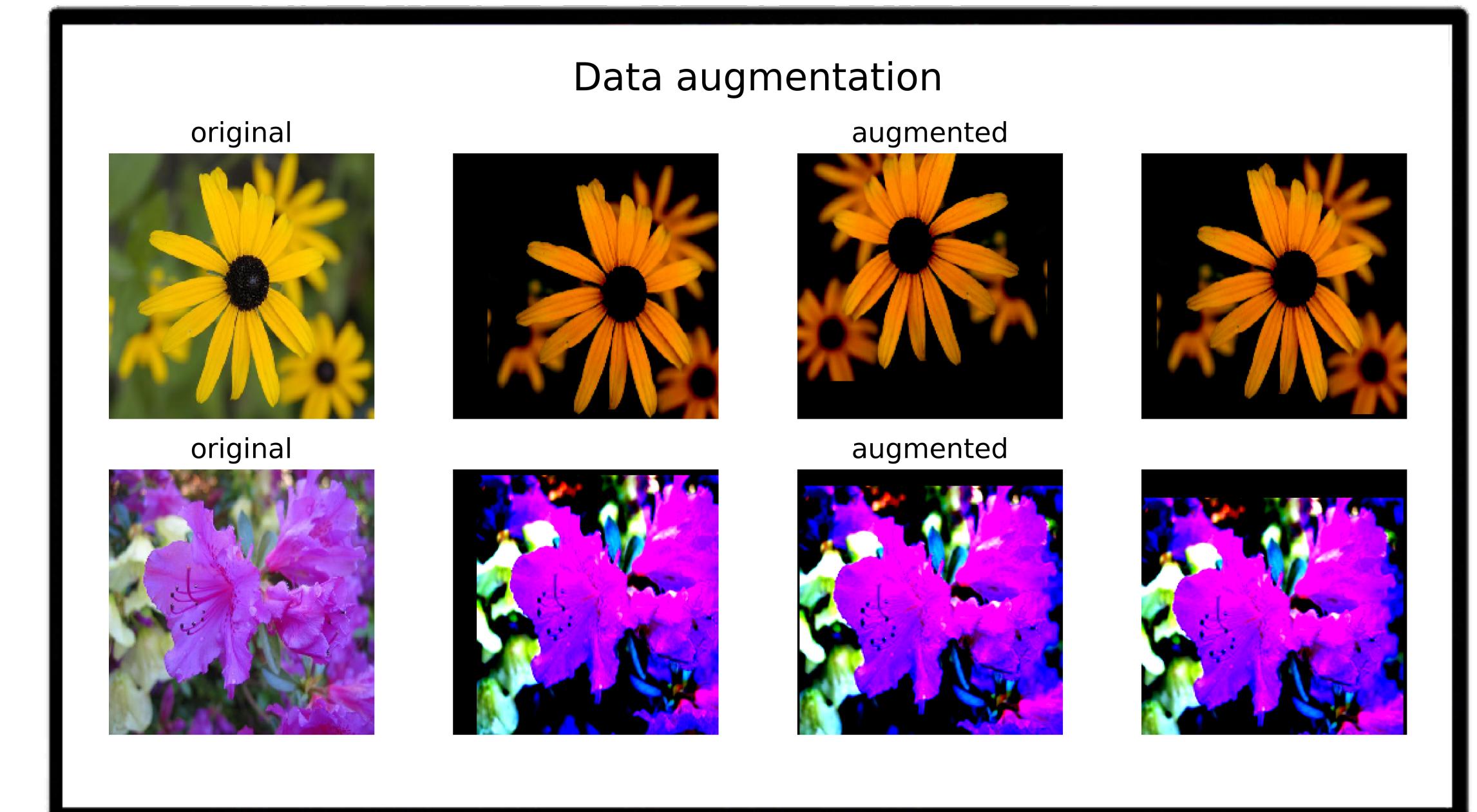
## Data augmentation



Width shifting and height shifting



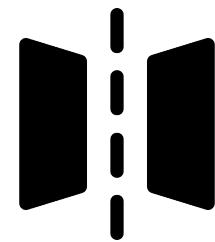
Horizontal flipping



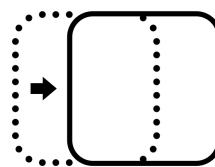
# Preprocessing

Data set

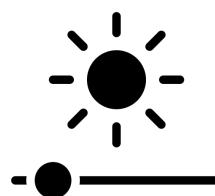
## Data augmentation



Width shifting and height shifting



Horizontal flipping



Brightness

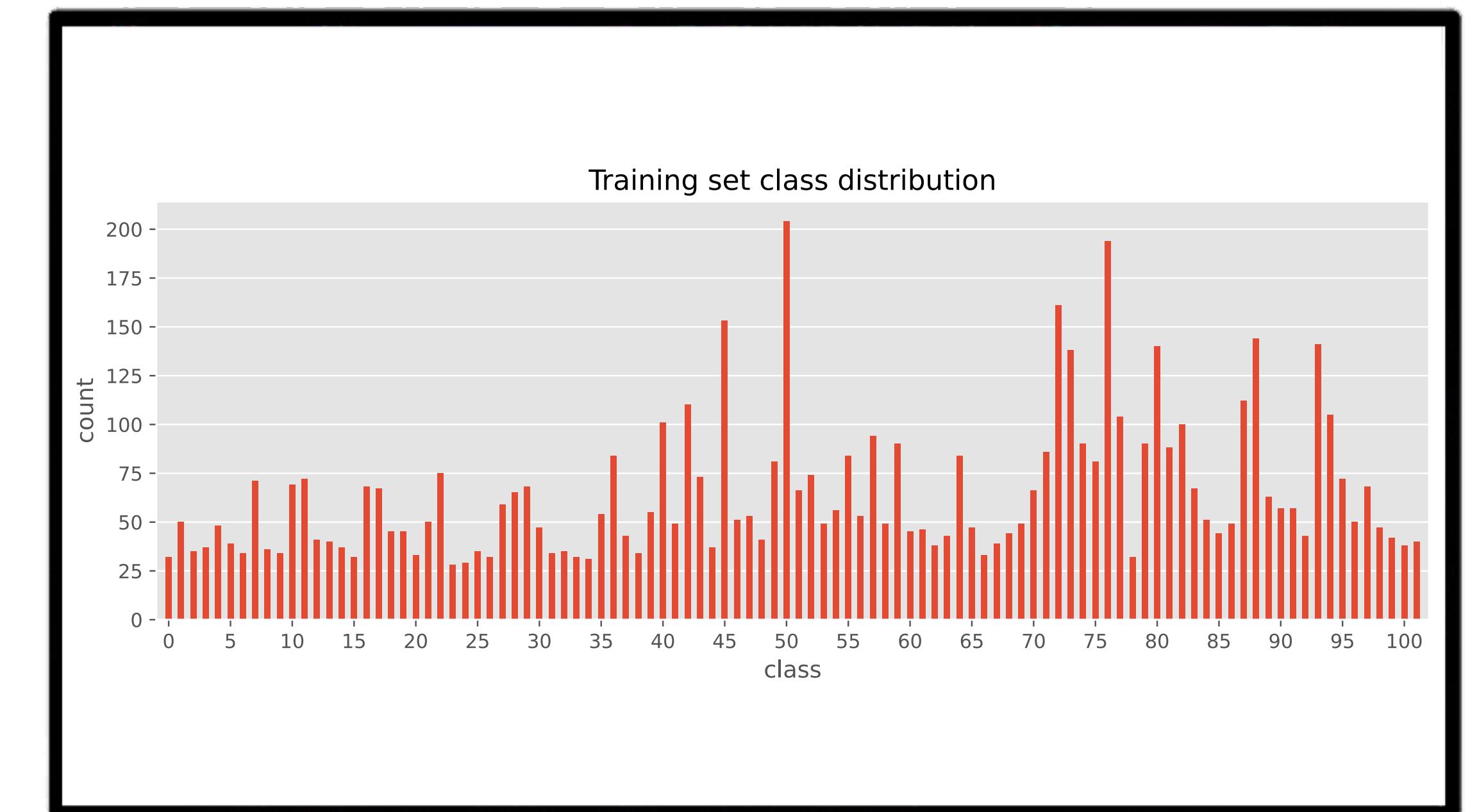


# Preprocessing

## Class weight balancing



**Weight-balancing** approach in the loss function to overcome the problem of **unbalanced dataset**.



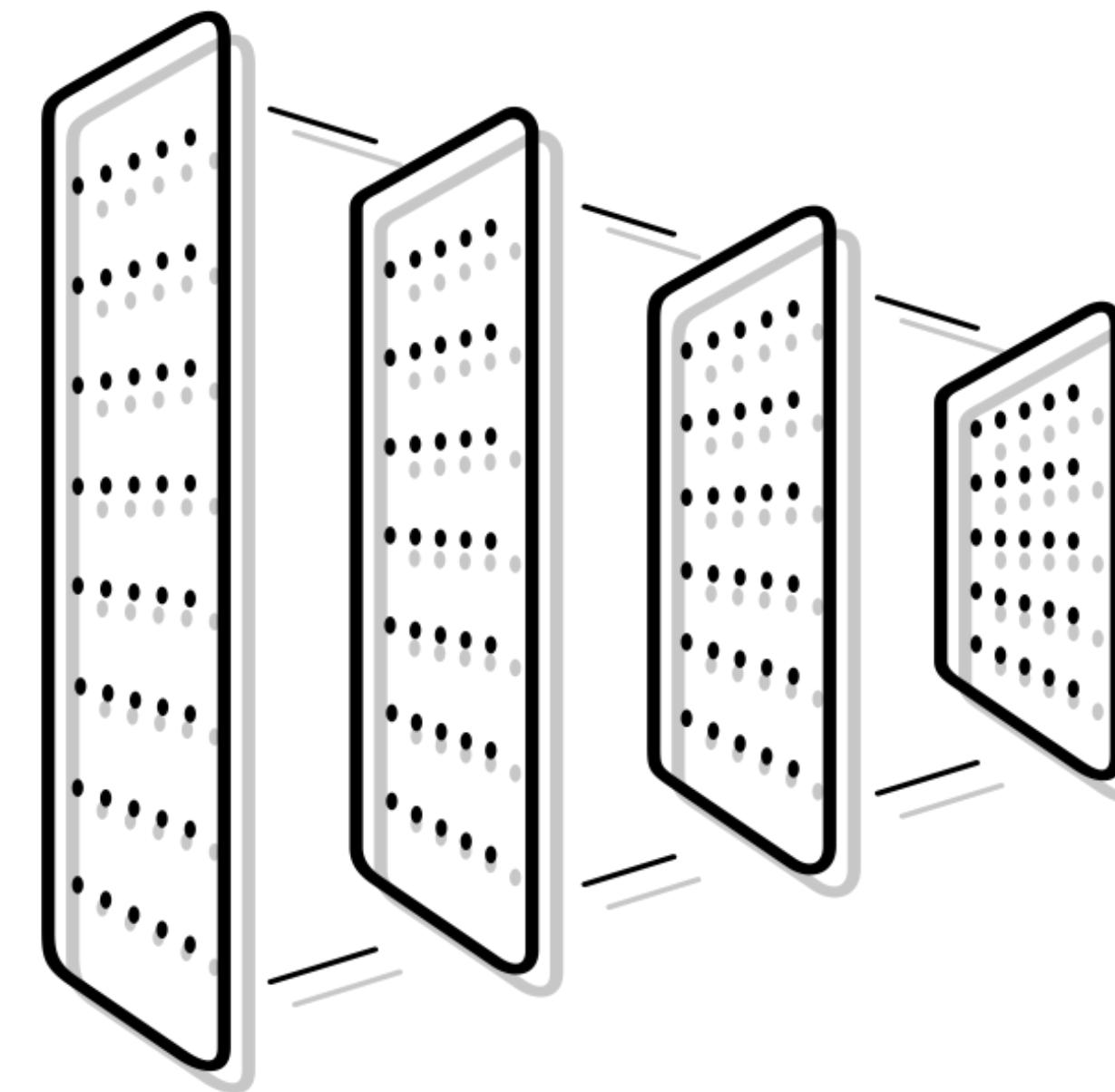
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- 
1. **Introduction**
  2. **Dataset**
  3. **Models**
  4. **Models compression**
  5. **Conclusions**

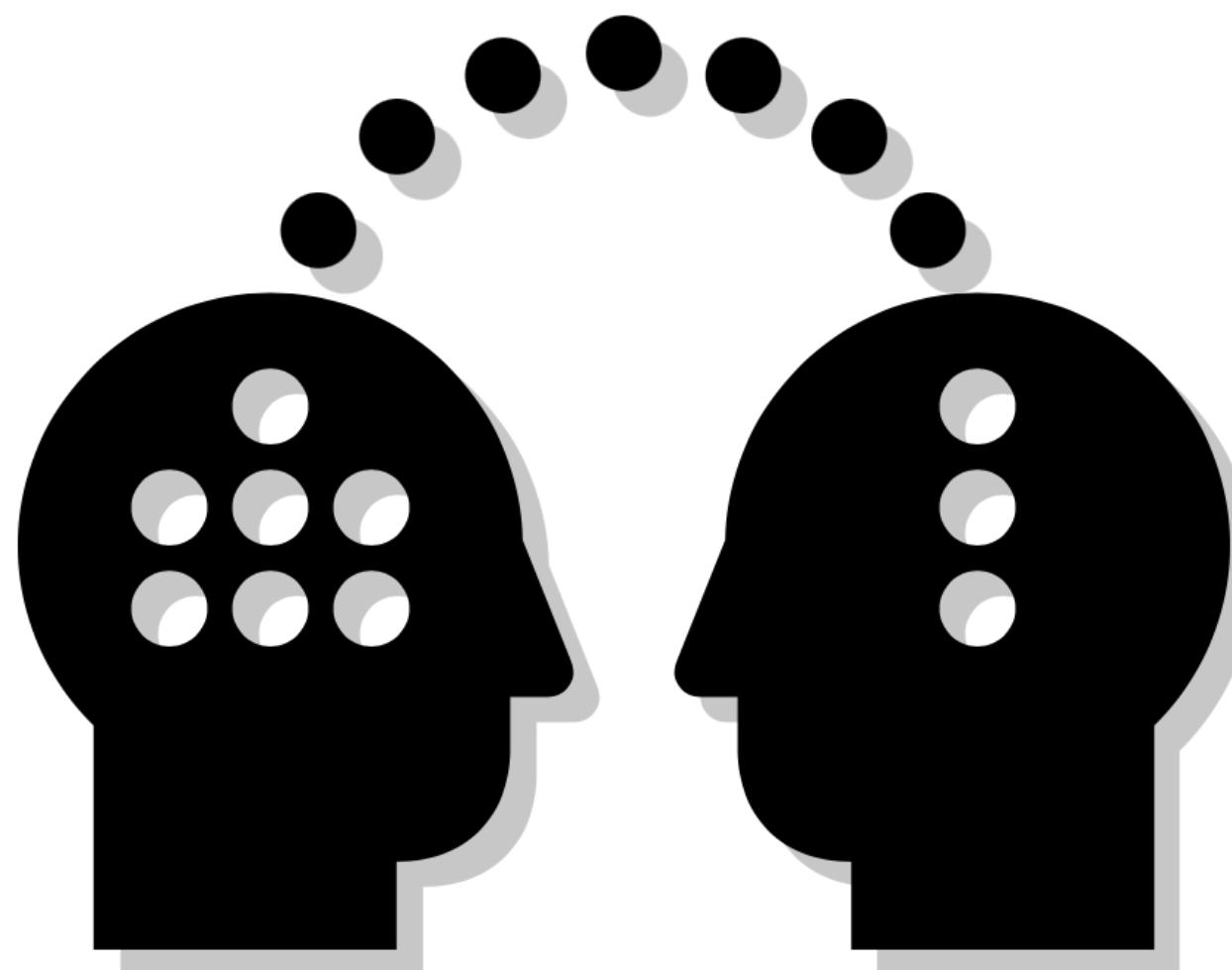
# Models

## Architectures

- MobileNetV2
- DenseNet-121
- EfficientNet-B0



# Models



## Transfer learning

It was used a **fine-tuning** techniques due to the features of the dataset.  
Cut on the **last layer** provided the best performance.

# Models

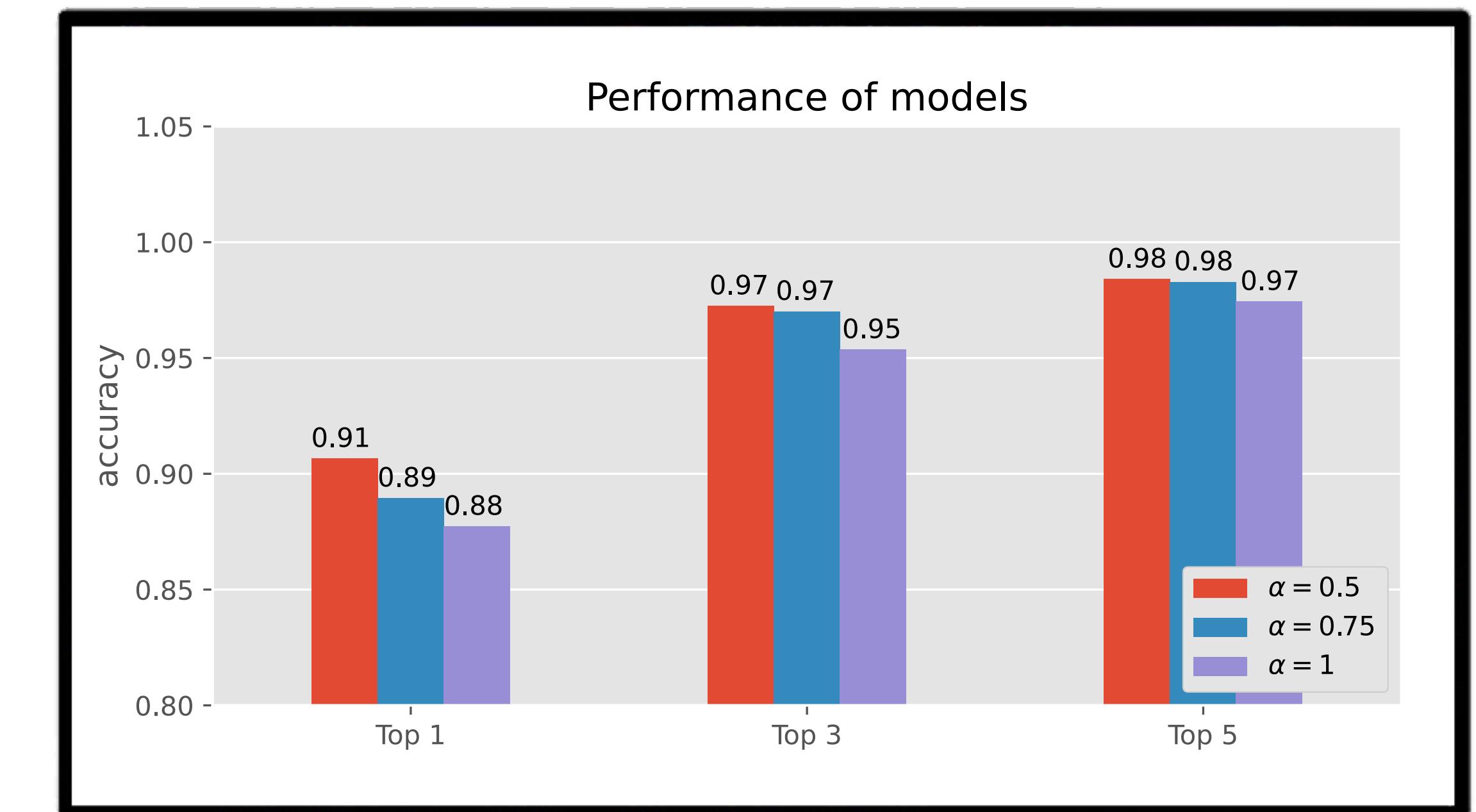
Models

## MobileNetV2 comparison

MobileNet allowed to handle network width through a **parameter**  $\alpha$ .

Parameter values tested:

- $\alpha = 0.5$
- $\alpha = 0.75$
- $\alpha = 1$

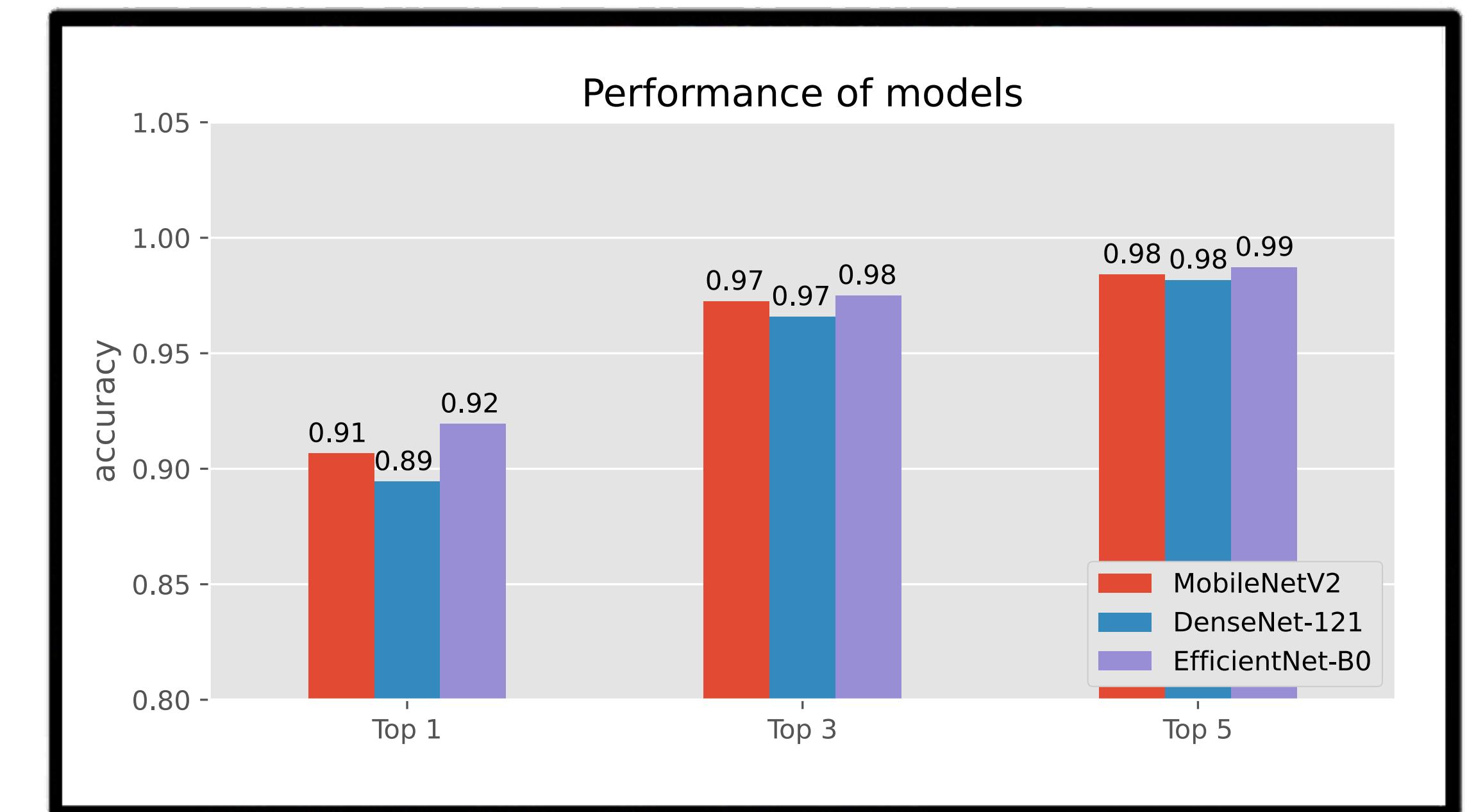


# Models

Models

## Accuracy comparisons

The **final comparison** brought good performances of the three model but in terms of accuracy EfficientNet was the best.



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- 
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  2. Dataset
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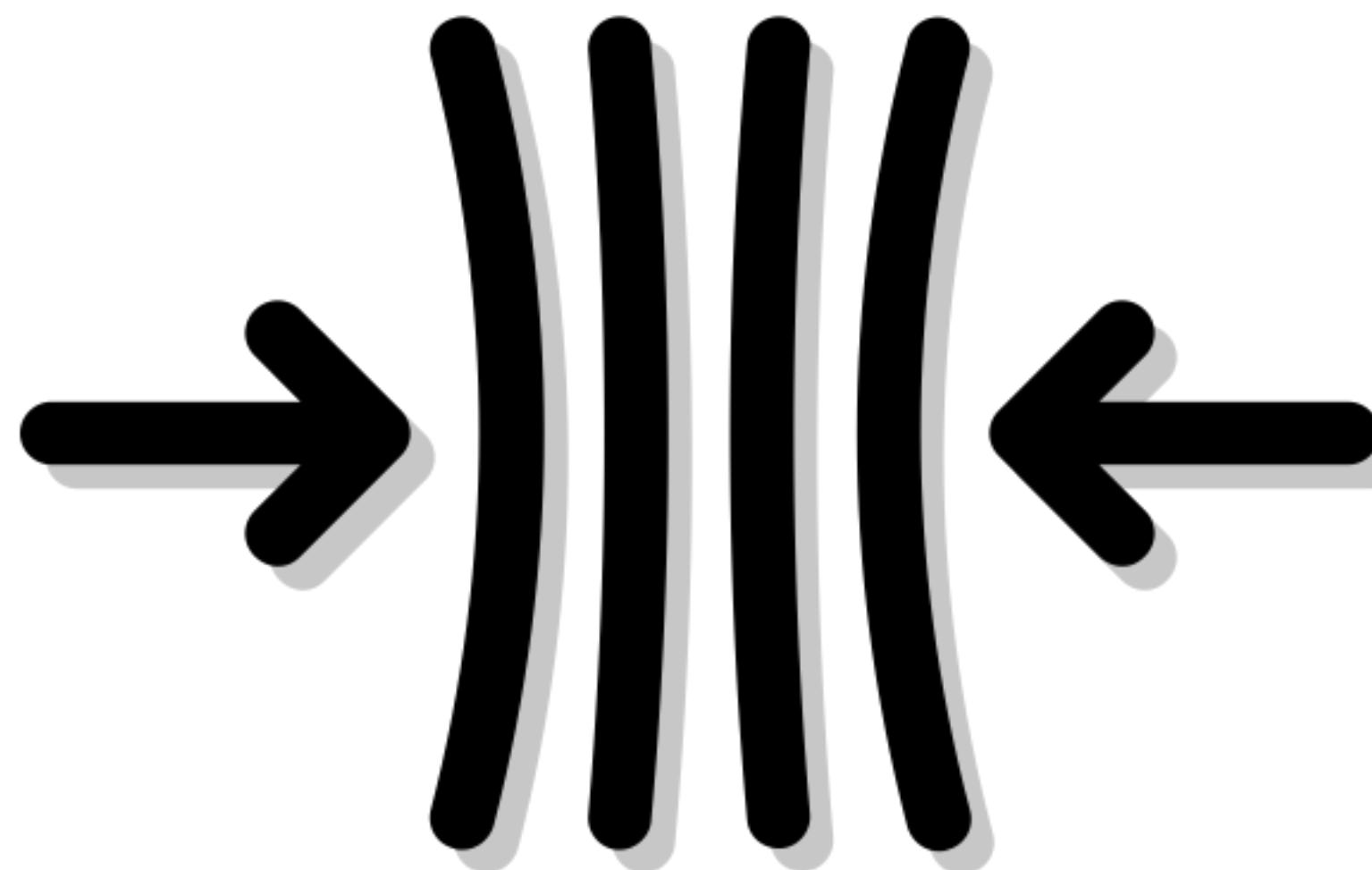
# Models compression

## Iterative pruning

- Increasing sparsity through iterations
- Using **Keras magnitude-based pruning**
- On **convolutional** (normal and pointwise)  
and **fully connected** layers



# Models compression



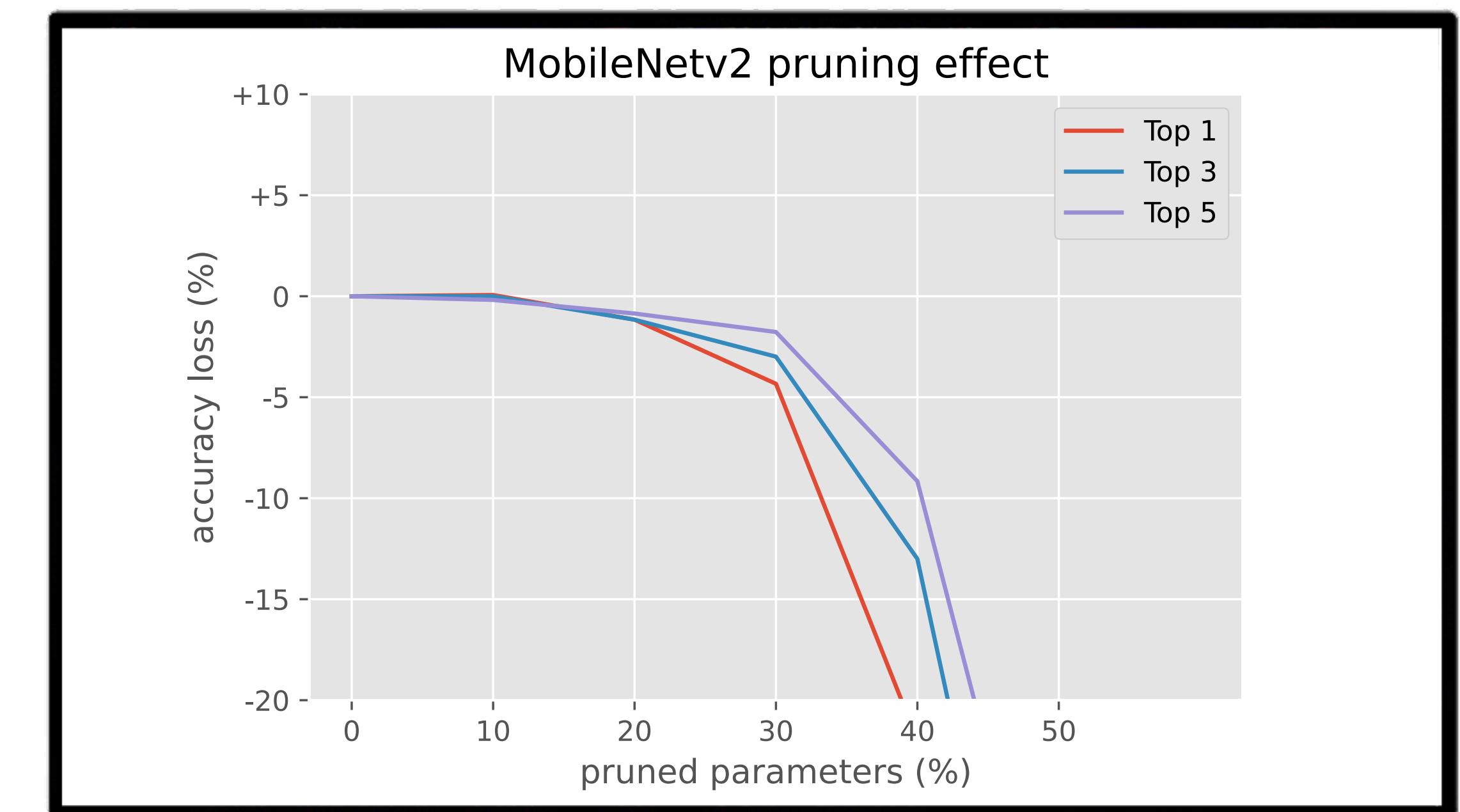
## Quantization

- Post training quantization using **TensorFlow Lite**
- **Dynamic range quantization** for mobile
- **Float16 quantization** for GPU

# Models compression

## MobileNetV2

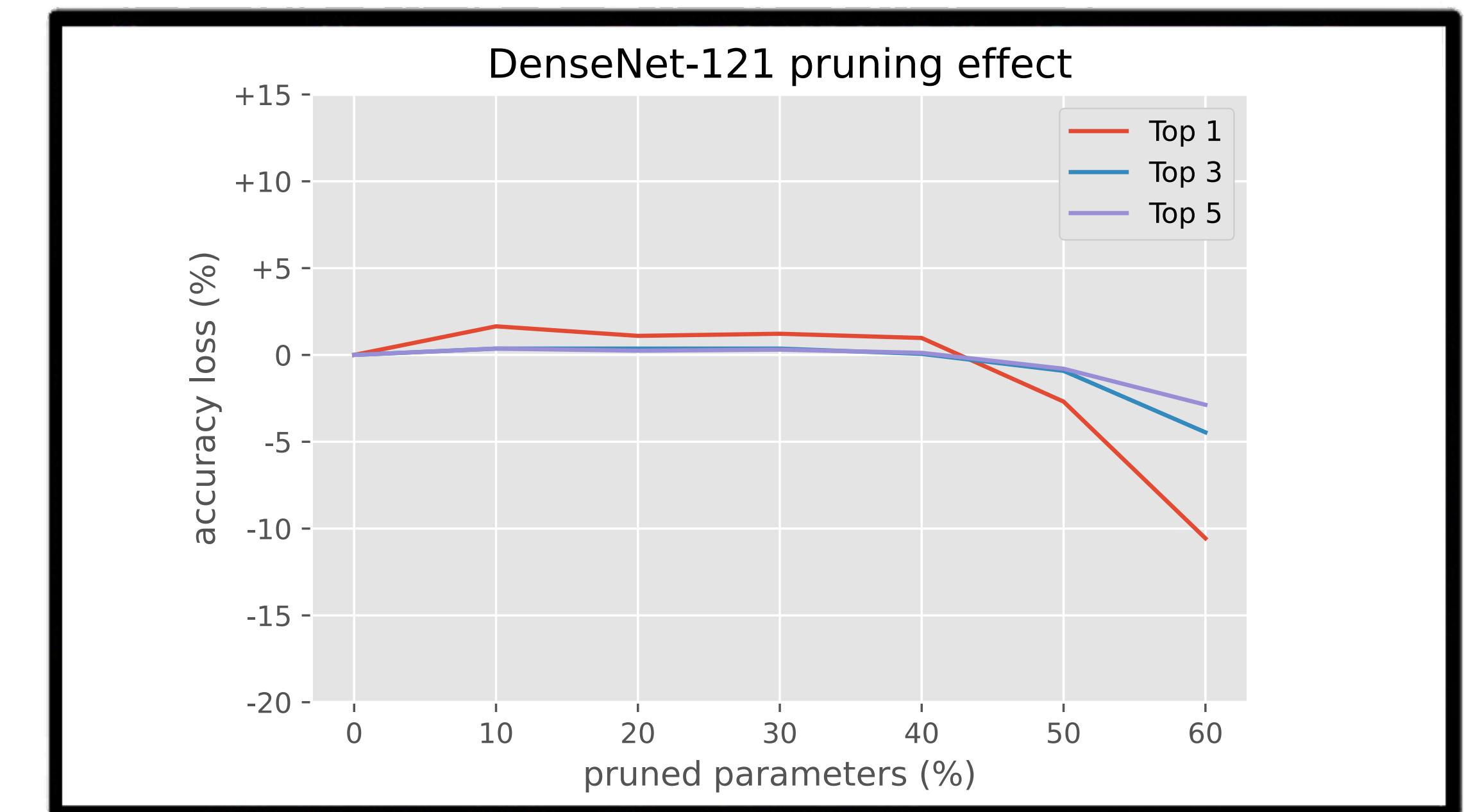
- **Sparsity:** 20%
- **Accuracy:** from 90.66% to 89.82%



# Models compression

## DenseNet

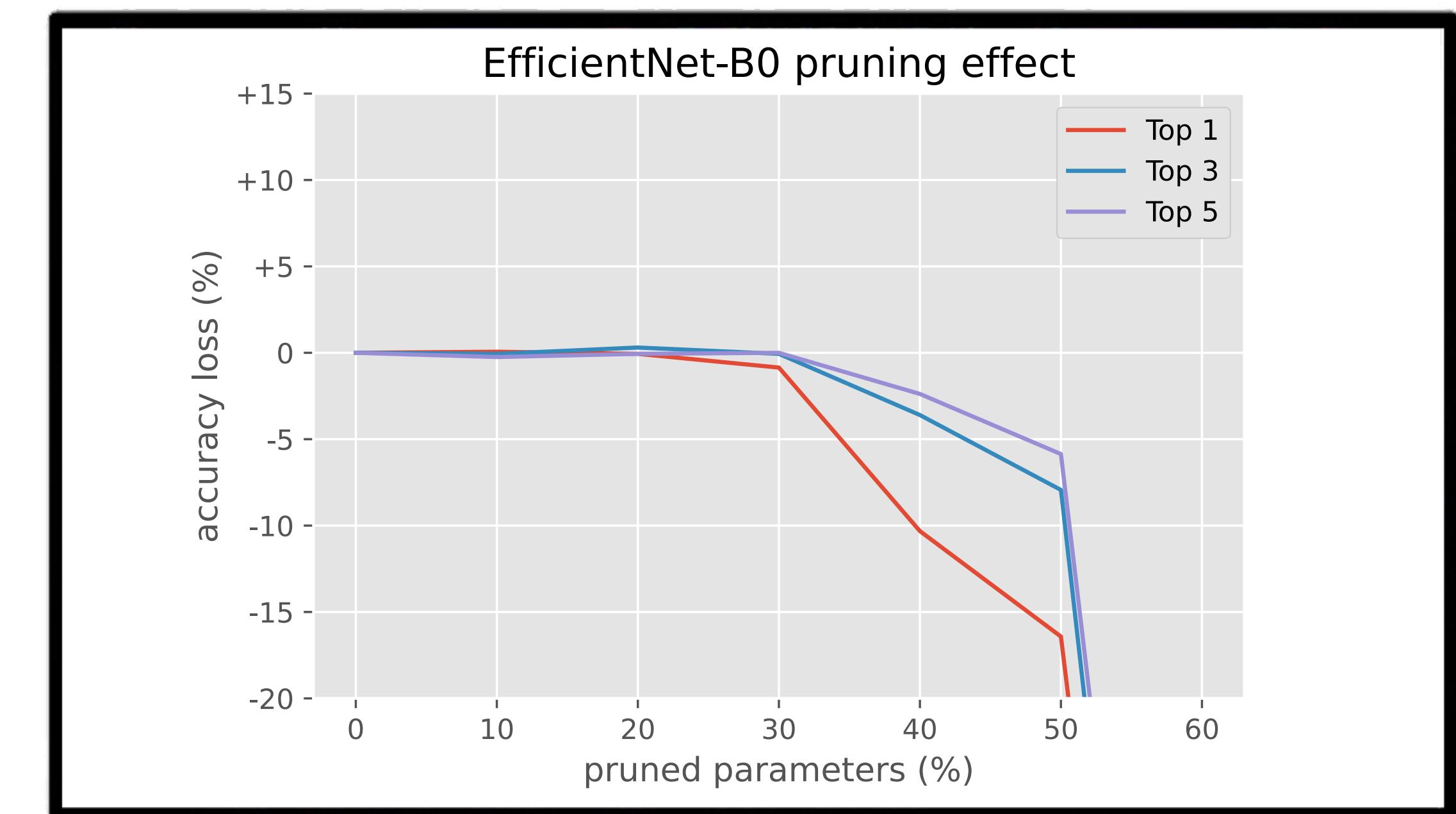
- **Sparsity:** 40%
- **Accuracy:** from 89.44% to 90.42%



# Models compression

## EfficientNet

- **Sparsity:** 30%
- **Accuracy:** from 91.94% to 91.09%



# Models compression

## Quantization

- **MobileNetV2**

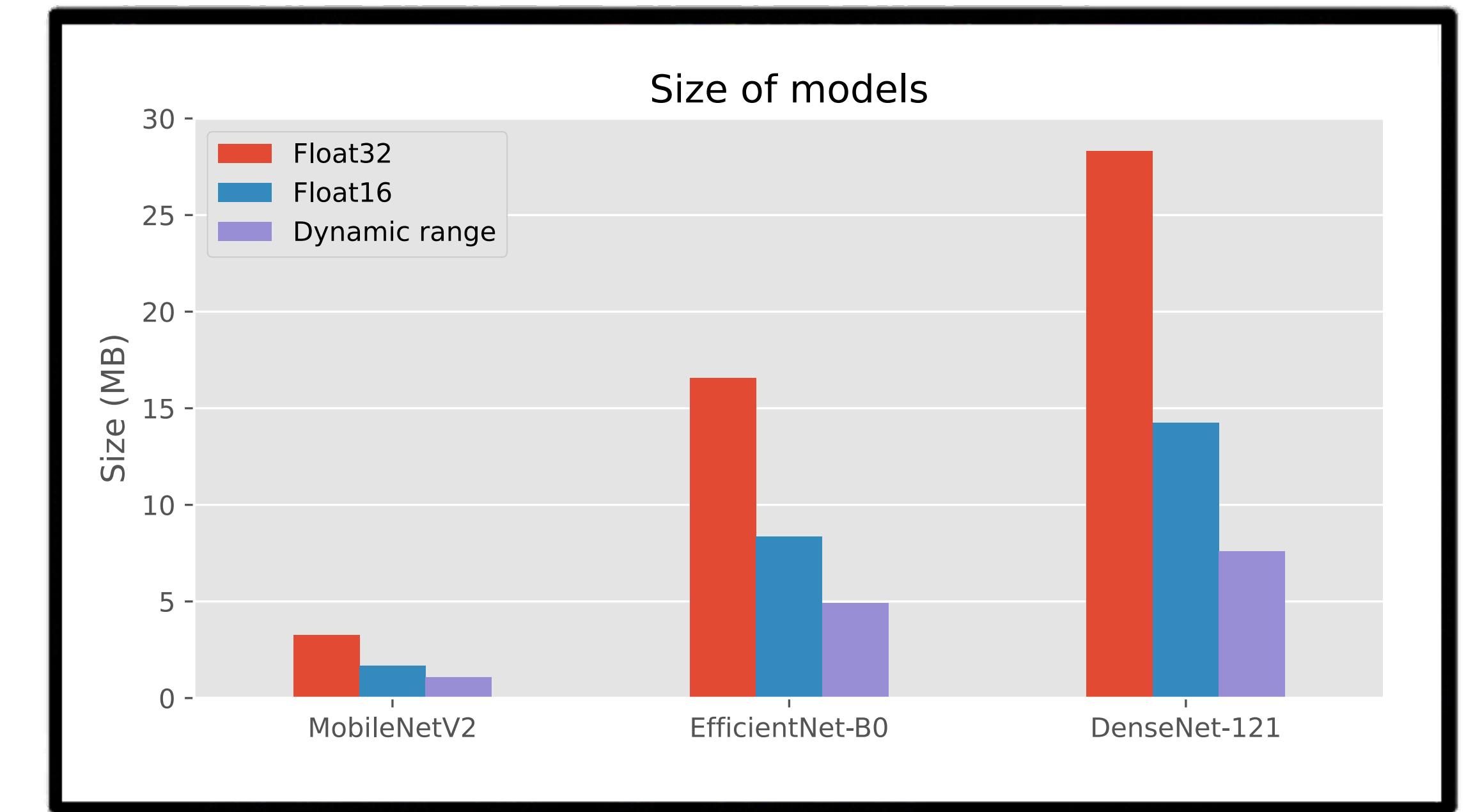
- **Size:** from 3.27 MB to 1.07 MB (x3.06)
- **Accuracy:** from 89.50% to 89.26%

- **EfficientNet**

- **Size:** from 16.56 MB to 4.92 MB (x3.37)
- **Accuracy:** from 91.09% to 91.33%

- **DenseNet**

- **Size:** from 28.31 MB to 7.60 MB (x3.72)
- **Accuracy:** from 90.42% to —



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- 
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  3. **Models**
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# Conclusions

## Results and future studies

- Model based on EfficientNet with 91.33% accuracy and size 4.92 MB
- Investigating impact of data augmentation on performance



# References

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**THANK YOU**