

# Neural Network Project - MobileNet v3

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# 1 Introduction

Nell'ultimo decennio la potenza di device portatili di piccole dimensioni, come gli smartphone, è cresciuta in modo esponenziale, quasi a raggiungere potenze di low-budget computer. Questo ha fatto sì che si studiasse la possibilità di utilizzo di reti neurali su questi devices.

Come sappiamo, utilizzare tecniche di machine learning è molto heavy load, per tale motivo è necessario fare delle assumptions prima di addentrarsi in questo modo. Allo stato attuale è impensabile effettuare il train su un singolo device mobile con così poca potenza wrt workstation e big datacenter utilizzate generalmente per il train delle reti. Anche se l'edge computing e la possibilità di utilizzare un'insieme di devices contemporaneamente anche per il train di reti neurali si fa sempre più insistente, in questo lavoro ci focalizziamo su un altro tipo di studio: nello specifico nell'utilizzo di lightweight reti neurali, appositamente ingegnerizzate, che vengono trainate a priori ma che possono essere utilizzate per fare inference proprio sui device mobili, come gli smartphone.

In questo senso, abbiamo deciso di implementare quella che è allo stato attuale la state of the art per questo tipo di reti e cioè MobileNetV3 [1]. Gli autori propongono due tipologie di reti, che vengono chiamate MobileNetV3 Small and Large. La prima si è un'evoluzione della rete MobileNetV2 [2], mentre la seconda si basa sul lavoro contenuto in MnasNet-A1 [3].

The goal of the reference paper is to develop the best possible mobile computer vision architectures optimizing the accuracy-latency trade off on mobile devices. To accomplish this they introduce (1) complementary search techniques, (2) new efficient versions of nonlinearities practical for the mobile setting, (3) new efficient network design, (4) a new efficient segmentation decoder.

In questo lavoro viene implementata la soluzione proposta in MobileNetV3 e applicata a due dataset differenti per image detection and classification: MNIST [4] and CIFAR10 [5].

# 2 Related works

Tale lavoro, come già detto, è un'evoluzione di MobileNetV2 alla ricerca di un modello quasi-ottimo per soluzioni con poca potenza computazionale. Per realizzare questa soluzione è ovviamente necessario raggiungere un punto di trade-off tra l'accuratezza del modello e la complessità computazionale in fase di inferenza (efficienza). Both novel handcrafted structures and algorithmic neural architecture search have played

important roles in advancing this field.

For example, as stated by the authors, in SqueezeNet [6] 1x1 convolutions with squeeze and expand modules are extensively used, primarily focusing on reducing the number of parameters. More recent works shifts the focus from reducing parameters to reducing the number of operations (MAdds) and the actual measured latency. MobileNetV1 [7] employs depthwise separable convolution to substantially improve computation efficiency; while MobileNetV2 [2] expands on this by introducing a resource-efficient block with inverted residuals and linear bottlenecks. More studies on the subject, like ShuffleNet [8], CondenseNet [9] and ShiftNet [10] were taken into account by the authors for the uses of group convolution at training phase and shift operation with point-wise convolutions in order to replace expensive spatial convolutions.

Another major study performed regards the automatization of the architecture design search, which can be done using Reinforcement Learning to search efficient architectures with interesting and very good accuracy. Recently, the authors in MnasNet [3] explored a block-level hierarchical search space allowing different layer structures at different resolution blocks of a network.

## 3 Solutions

All these above mentioned ideas and studies are taken into account by the authors and used, together with other innovative proposal, reaching state of the art network for mobile devices, as explained in this section.

### 3.1 MobileNetV3 Block

block

### 3.2 Network search

block

### 3.3 Nonlinearities

As a replacement for the ReLU function, the swish nonlinearity is taken into account. It can be defined as

$$swish(x) = x \cdot \sigma(x)$$

This nonlinearities improves the overall accuracy, however it's more expensive because of the sigmoid function, difficult to compute on mobile devices.

For this reason it's replaced with its piece-wise linear hard analog:

$$hswish(x) = x \frac{ReLU6(x + 3)}{6}$$

This hard version have no big differences in terms of accuracy. A comparison between them can be seen in figure 1

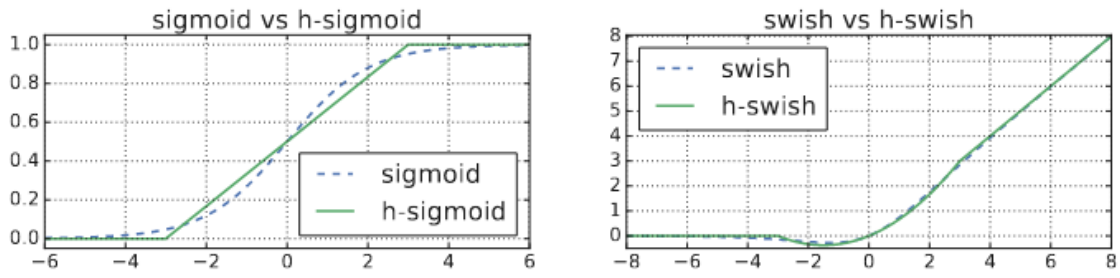


Figure 1: Comparison between Sigmoid and swish function with their hard cor-  
 rerspective

## 4 Implementation

The MobileNetV3 consists of two different design architectures, one used for high resources and another one for low resources, respectively Large and Small models. In this work both of them are implemented from scratch using pytorch and pytorch-lightning, framework used essentially to simplify multi-gpu training, using Distributed Data Parallel paradigm.

Initially the implementation was done using Jupyter Notebooks, however cause of a bug regarding multi-gpu training, the implementation was completed using classical python script files.

Both proposed model, small and large, were trained using the structure defined by the authors and replicated in the Figure 2.

Input	Operator	exp size	#out	SE	NL	s
$224^2 \times 3$	conv2d	-	16	-	HS	2
$112^2 \times 16$	bneck, 3x3	16	16	-	RE	1
$112^2 \times 16$	bneck, 3x3	64	24	-	RE	2
$56^2 \times 24$	bneck, 3x3	72	24	-	RE	1
$56^2 \times 24$	bneck, 5x5	72	40	✓	RE	2
$28^2 \times 40$	bneck, 5x5	120	40	✓	RE	1
$28^2 \times 40$	bneck, 5x5	120	40	✓	RE	1
$28^2 \times 40$	bneck, 3x3	240	80	-	HS	2
$14^2 \times 80$	bneck, 3x3	200	80	-	HS	1
$14^2 \times 80$	bneck, 3x3	184	80	-	HS	1
$14^2 \times 80$	bneck, 3x3	184	80	-	HS	1
$14^2 \times 80$	bneck, 3x3	480	112	✓	HS	1
$14^2 \times 112$	bneck, 3x3	672	112	✓	HS	1
$14^2 \times 112$	bneck, 5x5	672	160	✓	HS	2
$7^2 \times 160$	bneck, 5x5	960	160	✓	HS	1
$7^2 \times 160$	bneck, 5x5	960	160	✓	HS	1
$7^2 \times 160$	conv2d, 1x1	-	960	-	HS	1
$7^2 \times 960$	pool, 7x7	-	-	-	-	1
$1^2 \times 960$	conv2d 1x1, NBN	-	1280	-	HS	1
$1^2 \times 1280$	conv2d 1x1, NBN	-	k	-	-	1

(a) Large model

Input	Operator	exp size	#out	SE	NL	s
$224^2 \times 3$	conv2d, 3x3	-	16	-	HS	2
$112^2 \times 16$	bneck, 3x3	16	16	✓	RE	2
$56^2 \times 16$	bneck, 3x3	72	24	-	RE	2
$28^2 \times 24$	bneck, 3x3	88	24	-	RE	1
$28^2 \times 24$	bneck, 5x5	96	40	✓	HS	2
$14^2 \times 40$	bneck, 5x5	240	40	✓	HS	1
$14^2 \times 40$	bneck, 5x5	240	40	✓	HS	1
$14^2 \times 40$	bneck, 5x5	120	48	✓	HS	1
$14^2 \times 48$	bneck, 5x5	144	48	✓	HS	1
$14^2 \times 48$	bneck, 5x5	288	96	✓	HS	2
$7^2 \times 96$	bneck, 5x5	576	96	✓	HS	1
$7^2 \times 96$	bneck, 5x5	576	96	✓	HS	1
$7^2 \times 96$	conv2d, 1x1	-	576	✓	HS	1
$7^2 \times 576$	pool, 7x7	-	-	-	-	1
$1^2 \times 576$	conv2d 1x1, NBN	-	1024	-	HS	1
$1^2 \times 1024$	conv2d 1x1, NBN	-	k	-	-	1

(b) Small model

Figure 2: MobileNetV3 specifications for Large and Small model

These specifications are stored inside two different json files, loaded before training the neural network to create the model architecture on the fly. Every row of the table 2 is associated to an object of the json file, containing:

- the input and output size
- kernel size
- the stride size
- expansion dimension



- if the squeeze and excite must be used
- the type of non-linearity to be used (ReLU or hard-swish)

## 4.1 Adroid app

After the training all the models are transformed in order to use them in an android workspace. The workflow followed for this operation can be seen in figure 3, which consists in the scripting of the model with the *just in time* built-in pytorch compiler and the transformation of this to a model for pytorch lite.

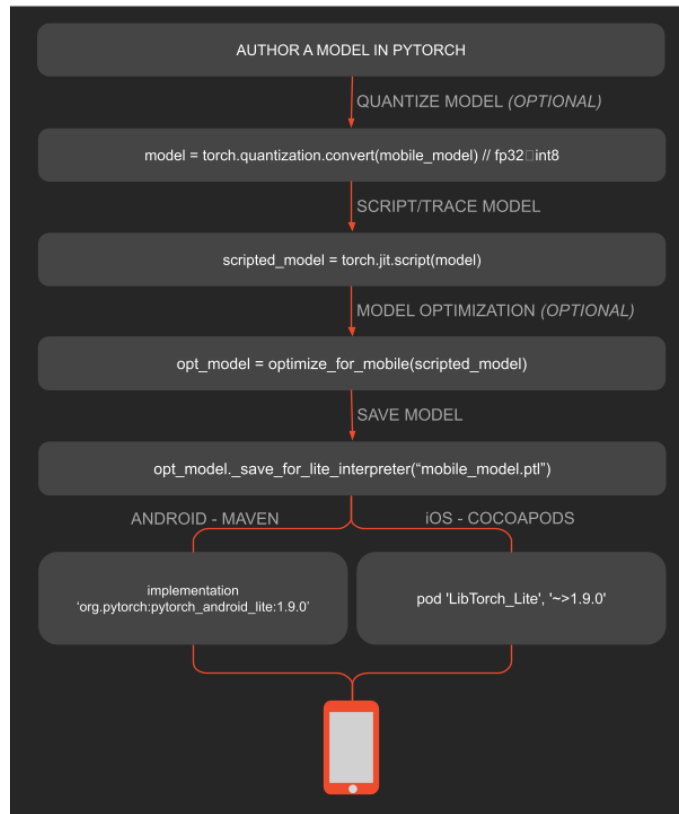


Figure 3: Mobile deployment workflow: <https://pytorch.org/mobile/home/>

After this workflow as output we have a model that is ready to use inside a Android or iOS app. To make a demo, we created a simple app in Android Studio using Kotlin, in order to test the mobile version of the trained models. The app is very simple, as shown in the figure 4. In the main view the image to

be predicted is shown, while on the bottom the prediction is set in a light grey box. There are two buttons, always on the bottom, one for Mnist and another one for Cifar10 image prediction. Both of them upload the needed model, put inside the asset folder, while a new image is randomly chosen inside the associated asset directory (`asset/MNIST` or `asset/Cifar10`).



Figure 4: Android demo app

Even if this is only a demo app, it's noticeable that, without using model quantization and suitable optimization, there is a significant drop in model accuracy, underlying moreover the improvements that can be done using model inference on mobile devices.

## 5 Experiments and results

The implementation of MobileNetV3 in this work is trained and test using two different datasets: **MNIST** and **Cifar10**.

Both of them are trained using normalization of the channels using Gaussian Normalization. Upsampling to a dimension of 224 width and 224 height is also needed for the images, considering the low quality of the networks.

All the datasets are splitted in training and validation set, in a classical way to evaluate the network on never seen images and trying to not occur in overfitting.

### 5.1 MNIST

The MNIST dataset consist in a collection of black and white (one channel) images of hand written digit.

The classification of the MNIST dataset is a very simple task for this kind of networks, for this reason only the small version of MobileNetV3 is trained on this dataset.

In this case a Gaussian Normalization with mean and standard deviation in 0.5 is firstly applied, with some data augmentation using the transforms built-in function of the torchvision framework: random crop and random horizontal flip is applied to training dataset.

The network is trained for 50 epochs.

As we can see from Figure 5 the accuracy during training reaches high values after only 10 epochs, while in Figure 6 we can notice a complementar pattern for the training loss.

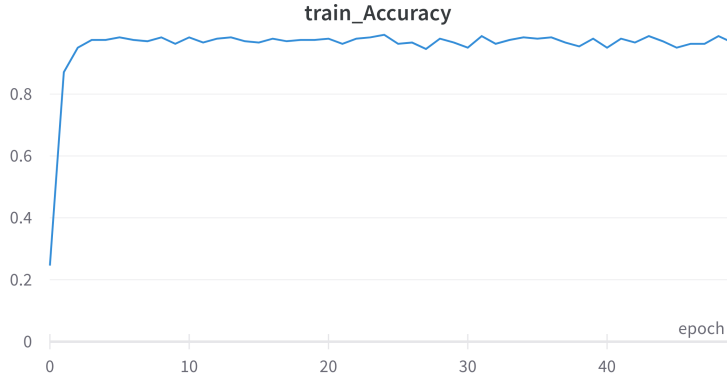


Figure 5: Mnist train accuracy

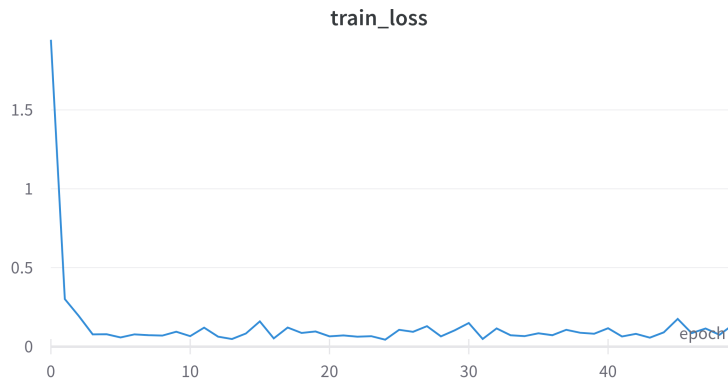


Figure 6: Mnist train loss

After training the test dataset is used for evaluation, in this case we notice an overall test accuracy very high, about 0.95%. The associated classification report with all the evaluation metrics is shown in Figure 7.

In the confusion matrix plotted in Figure 8 we can notice that the network has a high sensitivity with the number 1 while it struggles more with number 5, confused often with numbers 2 and 3.

Accuracy: 0.95

Micro Precision: 0.95  
 Micro Recall: 0.95  
 Micro F1-score: 0.95

Macro Precision: 0.95  
 Macro Recall: 0.95  
 Macro F1-score: 0.95

Weighted Precision: 0.95  
 Weighted Recall: 0.95  
 Weighted F1-score: 0.95

#### Classification Report

	precision	recall	f1-score	support
0 - zero	0.95	0.97	0.96	980
1 - one	0.99	0.99	0.99	1135
2 - two	0.93	0.92	0.93	1032
3 - three	0.95	0.94	0.94	1010
4 - four	0.98	0.97	0.97	982
5 - five	0.88	0.90	0.89	892
6 - six	0.96	0.95	0.95	958
7 - seven	0.97	0.97	0.97	1028
8 - eight	0.97	0.97	0.97	974
9 - nine	0.96	0.96	0.96	1009
accuracy			0.95	10000
macro avg	0.95	0.95	0.95	10000
weighted avg	0.95	0.95	0.95	10000

Figure 7: Mnist classification report

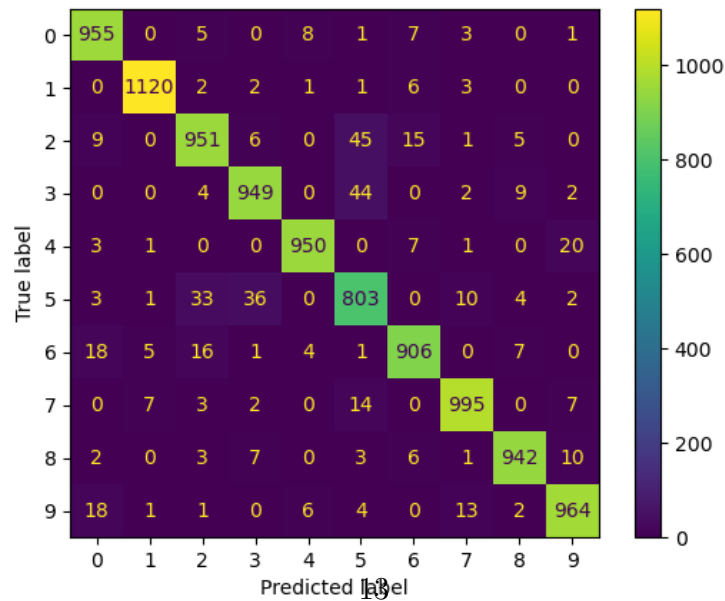


Figure 8: Mnist confusion matrix

## 5.2 Cifar10

The Cifar10 dataset consist in a collection of rgb (three channels) images belonging to 3 different categories.

This classification task is more complex than the MNIST one, for this reason in this work the train is done with both the networks architectures, Small and Large.

Also in this case a Gaussian Normalization is used with mean in  $[0.485, 0.456, 0.406]$  and standard deviation in  $[0.247, 0.243, 0.261]$  is firstly applied. Like before, some data augmentation is applied: random crop and random horizontal flip is applied to training dataset.

The network is trained for 25 epochs.

**Small** As we can see from Figure 9 the accuracy during training reaches not so good values, while in Figure 10 we can notice a complementar pattern for the training loss.

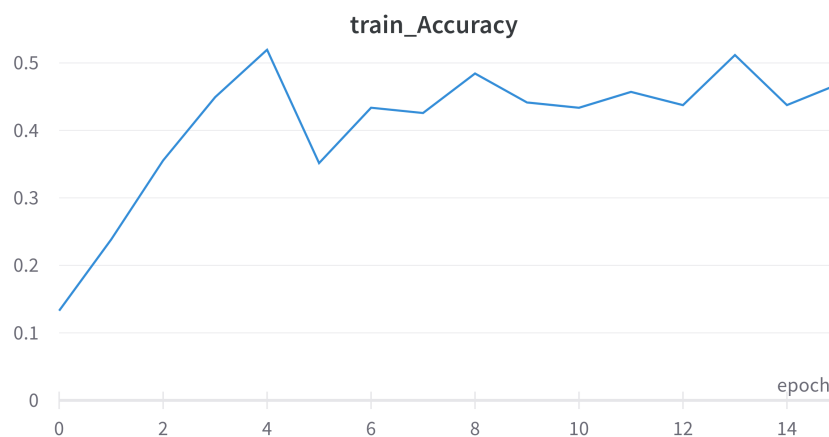


Figure 9: Cifar10 train accuracy using MobileNetV3 small and stride 2

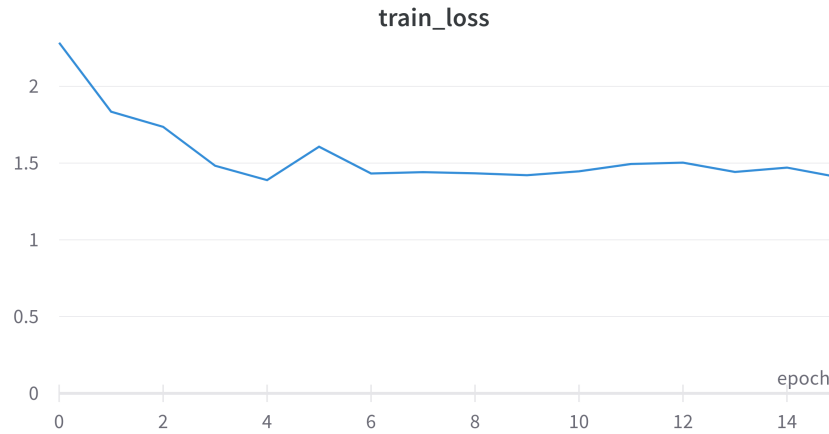


Figure 10: Cifar10 train loss using MobileNetV3 small and stride 2

This low training accuracy and loss is due to the datasets itself, it has very low image quality. An attempt to cut out this problem is done changing the stride of the first two convolutional layers.

In the architecture proposed by the authors, trained on the ImageNet dataset, the stride is set to two, loosing some informations in the convolution operation. For this type of dataset the stride is changed to one resulting in less information loss and better results.

In fact, as we can see from Figure 11 and 12 the loss and accuracy gets better during training with this small change.

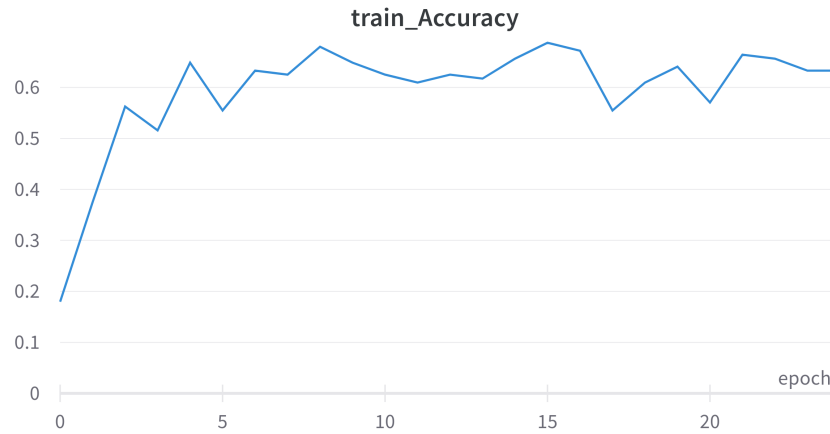


Figure 11: Cifar10 train accuracy using MobileNetV3 small and stride 1



Figure 12: Cifar10 train loss using MobileNetV3 small and stride 1

As before, after training the test dataset is used for evaluation. In this case we notice an overall test accuracy very high, about 0.59%. The associated classification report with all the evaluation metrics is shown in Figure 13.

In the confusion matrix plotted in Figure 14 we can notice that the network has low sensitivity with the class associated to label 2, 3, 4 associated respectively to cat, deer and dog images. The network, therefore, is often confused in the identification



of images belonging to these classes.

```
Accuracy: 0.59

Micro Precision: 0.59
Micro Recall: 0.59
Micro F1-score: 0.59

Macro Precision: 0.58
Macro Recall: 0.59
Macro F1-score: 0.58

Weighted Precision: 0.58
Weighted Recall: 0.59
Weighted F1-score: 0.58

Classification Report
```

	precision	recall	f1-score	support
airplane	0.63	0.61	0.62	1000
automobile	0.75	0.83	0.79	1000
bird	0.44	0.40	0.42	1000
cat	0.35	0.31	0.33	1000
deer	0.52	0.39	0.45	1000
dog	0.47	0.51	0.49	1000
frog	0.61	0.73	0.66	1000
horse	0.64	0.62	0.63	1000
ship	0.70	0.75	0.72	1000
truck	0.70	0.74	0.72	1000
accuracy			0.59	10000
macro avg	0.58	0.59	0.58	10000
weighted avg	0.58	0.59	0.58	10000

Figure 13: Cifar10 classification report using MobileNetV3 Small and stride 1

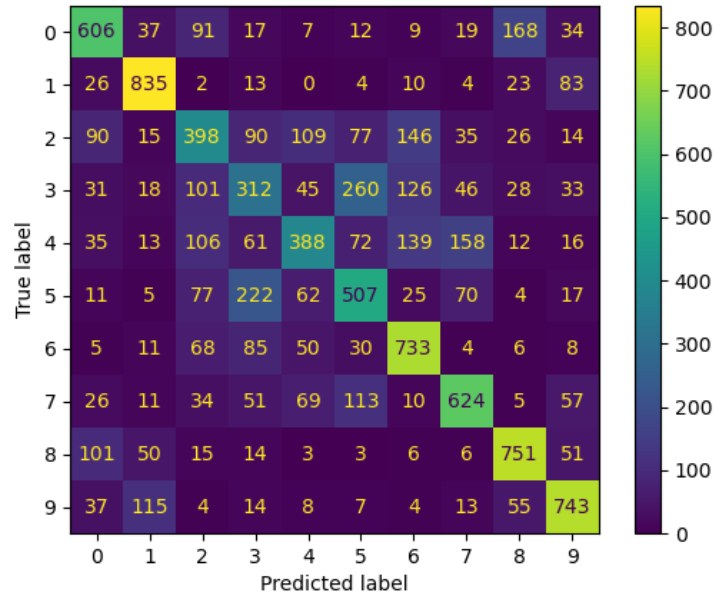


Figure 14: Cifar10 confusion matrix using MobileNetV3 Small and stride 1

**Large** Similarly to the Small version of MobileNetV3, the dataset is used to train MobileNet Large.  
This time

## 6 Conclusion

## References

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