

MobileFaceNets: Efficient CNNs for Accurate Real-time Face Verification on Mobile Devices

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Abstract—In this paper, we present a class of extremely efficient CNN models called MobileFaceNets, which use no more than 1 million parameters and specifically tailored for high-accuracy real-time face verification on mobile and embedded devices. We also make a simple analysis on the weakness of common mobile networks for face verification. The weakness has been well overcome by our specifically designed MobileFaceNets. Under the same experimental conditions, our MobileFaceNets achieve significantly superior accuracy as well as more than 2 times actual speedup over MobileNetV2. After trained by ArcFace loss on the refined MS-Celeb-1M from scratch, our single MobileFaceNet model of 4.0MB size achieves 99.55% face verification accuracy on LFW and 92.59% TAR (FAR1e-6) on MegaFace Challenge 1, which is even comparable to state-of-the-art big CNN models of hundreds MB size. The fastest one of our MobileFaceNets has an actual inference time of 18 milliseconds on a mobile phone. Our experiments on LFW, AgeDB, and MegaFace show that our MobileFaceNets achieve significantly improved efficiency compared with the state-of-the-art lightweight and mobile CNNs for face verification.

Index Terms—Mobile network, face verification, face recognition, convolutional neural network, deep learning.

I. INTRODUCTION

FACE verification is an important identity authentication technology used in more and more mobile and embedded applications such as device unlock, application login, mobile payment and so on. Some mobile applications equipped with face verification technology, for example, smartphone unlock, need to run offline. To achieve user-friendliness with limited computation resources, the face verification models deployed locally on mobile devices are expected to be not only accurate but also small and fast. However, modern high-accuracy face verification models are built upon deep and big convolutional neural networks (CNNs) which are supervised by novel loss functions during training stage. The big CNN models requiring high computational resources are not suitable for many mobile and embedded applications. Several highly efficient neural network architectures, for example, MobileNetV1 ([1]), ShuffleNet ([2]), and MobileNetV2 ([3]), have been proposed for common visual recognition tasks rather than face

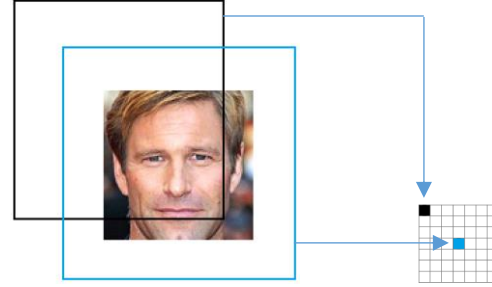


Fig. 1. The receptive field in CNN face verification model. The Left is an aligned face image of resolution 112×112 as an input of a CNN face verification model and the right is a channel of the last 7×7 feature map (denoted as FMap-end) outputted by this model. The region of the black rectangle is the receptive field of the top left corner unit of FMap-end and the region of the blue rectangle is the receptive field of the center unit.

verification in recent years. It is a straight-forward way to use these common CNNs unchanged for face verification, which only achieves very inferior accuracy (see Table II) compared with state-of-the-art results according to our experiments.

In this paper, we present a class of extremely efficient CNN models called MobileFaceNets, which use no more than 1 million parameters and specifically tailored for high-accuracy real-time face verification on mobile and embedded devices. We also make a simple analysis on common mobile networks' weakness for face verification. The weakness has been well overcome by our specifically designed MobileFaceNets. Under the same experimental conditions, our MobileFaceNets achieve significantly superior accuracy as well as more than 2 times actual speedup over MobileNetV2. After trained on the refined MS-Celeb-1M [4] with ArcFace ([5]) loss from scratch, our single MobileFaceNet model of 4.0MB size achieves 99.55% face verification accuracy (see Table III) on LFW ([6]) and 92.59% TAR@FAR 10^{-6} (see Table IV) on MegaFace Challenge 1 ([7]), which is even comparable to state-of-the-art big CNN models of hundreds MB size. Note that many existing techniques such as pruning, low-bit quantization, and knowledge distillation are able to improve MobileFaceNets' efficiency additionally, but these are not included in the scope of this paper.

The major contributions of this paper are summarized as follows: (1) After the last (non-global) convolutional layer of a face feature embedding CNN, we use a global depthwise

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convolution layer rather than a global average pooling layer or a fully connected layer to output a discriminative feature vector. The advantage of this choice is also analyzed in both theory and experiment. (2) We carefully design a class of face feature embedding CNNs, namely MobileFaceNets, with extreme efficiency for face verification on mobile and embedded devices. (3) Our experiments on LFW, AgeDB ([8]), and MegaFace show that our MobileFaceNets achieve significantly improved efficiency compared with the state-of-the-art lightweight and mobile CNNs for face verification.

II. RELATE WORKS

Tuning deep neural architectures to strike an optimal balance between accuracy and performance has been an area of active research for the last several years ([3]). For common visual recognition tasks, many efficient architectures have been proposed recently ([1, 2, 3, 9]). Some efficient architectures can be trained from scratch. For example, SqueezeNet ([9]) uses a bottleneck approach to design a very small network and achieves AlexNet-level ([10]) accuracy on ImageNet ([11, 12]) with 50x fewer parameters (i.e., 1.25 million). MobileNetV1 ([1]) uses depthwise separable convolutions to build lightweight deep neural networks, one of which, i.e., MobileNet-160 (0.5x), achieves 4% better accuracy on ImageNet than SqueezeNet at about the same size. ShuffleNet ([2]) utilizes pointwise group convolution and channel shuffle operation to reduce computation cost and achieve higher efficiency than MobileNetV1. MobileNetV2 ([3]) architecture is based on an inverted residual structure with linear bottleneck and improves the state of the art performance of mobile models on multiple tasks and benchmarks. The mobile NASNet [13] model, which is an architectural search result with reinforcement learning, has much more complex structure and much more actual inference time on mobile devices than MobileNetV1, ShuffleNet, and MobileNetV2. However, these lightweight basic architectures are not so accurate for face verification when trained from scratch (see Table II).

Accurate lightweight architectures specifically designed for face verification are rarely researched. [14] presents a light CNN framework to learn a compact embedding on the large-scale face data, in which the Light CNN-29 model achieves 99.33% face verification accuracy on LFW with 12.6 million parameters. Compared with MobileNetV1, Light CNN-29 is not lightweight for mobile and embedded platform. Light CNN-4 and Light CNN-9 are much less accurate than Light CNN-29. [15] proposes ShiftFaceNet based on ShiftNet-C model with 0.78 million parameters, which only achieves 96.0% face verification accuracy on LFW. In [5], an improved version of MobileNetV1, namely LMobileNetE, achieves comparable face verification accuracy to state-of-the-art big models. But LMobileNetE is actually a big model of 112MB model size, rather than a lightweight model. All above models are trained from scratch.

Another approach for obtaining lightweight face verification models is compressing pretrained networks by knowledge distillation ([16]). In [17], a compact student network (denoted as MobileID) trained by distilling knowledge from the teacher

network DeepID2+ [33] achieves 97.32% face verification accuracy on LFW with 4.0MB model size. In [1], several small MobileNetV1 models for face verification are trained by distilling knowledge from the FaceNet ([18]) model and only face verification accuracy on the authors' private test dataset are reported. Regardless of the small student models' accuracy on public test datasets, our MobileFaceNets achieve comparable accuracy to the strong teacher model FaceNet on LFW (see Table III) and MegaFace (see Table IV).

III. APPROACH

In this section, we will describe our approach towards extremely efficient CNN models for accurate real-time face verification on mobile devices, which overcome the weakness of common mobile networks for face verification. To make our results totally reproducible, we use ArcFace loss to train all face verification models on public datasets, following the experimental settings in [5].

A. The Weakness of Common Mobile Networks for Face Verification

There is a global average pooling layer in most recent state-of-the-art mobile networks proposed for common visual recognition tasks, for example, MobileNetV1, ShuffleNet, and MobileNetV2. For face verification and recognition, some researchers ([14], [5], etc.) have observed that CNNs with global average pooling layers are less accurate than those without global average pooling. However, no theoretical analysis for this phenomenon has been given. Here we make a simple analysis on this phenomenon in the theory of receptive field ([19]).

A typical deep face verification pipeline includes preprocessing face images, extracting face features by a trained deep model, and matching two faces by their features' similarity or distance, as shown in Fig. 1. Following the preprocessing method in [5, 20, 21, 22], we use MTCNN [23] to detect faces and five facial landmarks in images. Then we align the faces by similarity transformation according to the five landmarks. The aligned face images are of size 112×112 , and each pixel in RGB images is normalized by subtracting 127.5 then divided by 128. Without loss of generality, we use MobileNetV2 as the face feature embedding CNN in the following discussion. To preserve higher feature map resolution, we use the setting of stride = 1 in the first convolutional layer instead of stride = 2. So, before the global average pooling layer, the output feature map of the last convolutional layer, denoted as FMap-end for convenience, is of spatial resolution 7×7 . Although the theoretical receptive fields of the corner units and the central units of FM-end are of the same size, they are in different positions of the input image. The receptive fields' center of FMap-end's corner units is in the corner of the input image and the receptive fields' center of FM-end's central units are in the center of the input image, as shown in Fig. 1. According to [24], pixels at the center of a receptive field have a much larger impact on an output and the distribution of impact within a receptive field on the output is nearly a Gaussian distribution. The effective receptive field ([24]) sizes of FMap-

end’s corner units are much smaller than the ones of FMap-end’s central units. When the input image is an aligned face, a corner unit of FMap-end carries less information of the face than a central unit. Therefore, different units of FMap-end are of different importance for extracting a face feature vector.

In MobileNetV2, the flattened FMap-end is unsuitable to be directly used as a face feature vector since it is of a too high dimension 62720. It is a natural choice to use the output of the global average pooling (denoted as GAPool) layer as a face feature vector, which achieves inferior verification accuracy in many researchers’ experiments ([14, 5]) as well as ours (see Table II). The global average pooling layer treats all units of FMap-end with equal importance, which is unreasonable according to the above analysis. Another popular choice is to replace the global average pooling layer with a fully connected layer to project FMap-end to a compact face feature vector, which adds large number of parameters to the whole model. Even when the face feature vector is of a low dimension 128, the fully connected layer after FMap-end will bring additional 8 million parameters to MobileNetV2. We do not consider this choice since small model size is one of our pursuits.

B. Global Depthwise Convolution

To treat different units of FMap-end with different importance, we replace the global average pooling layer with a global depthwise convolution layer. A global depthwise convolution (denoted as GDConv) layer is a depthwise convolution (c.f. [25, 1]) layer with kernel size equaling the input size, pad = 0, and stride = 1. The output for global depthwise convolution layer is computed as:

$$G_m = \sum_{i,j} K_{i,j,m} \cdot F_{i,j,m} \quad (1)$$

where F is the input feature map of size $W \times H \times M$, K is the depthwise convolution kernel of size $W \times H \times M$, G is the output of size $1 \times 1 \times M$, the m_{th} channel in G has only one element G_m , (i, j) denotes the spatial position in F and K and m denotes the channel index.

Global depthwise convolution has a computational cost of:

$$W \cdot H \cdot M \quad (2)$$

When used after FMap-end in MobileNetV2 for face feature embedding, the global depthwise convolution layer of kernel size $7 \times 7 \times 1280$ outputs a 1280-dimensional face feature vector with a computational cost of 62720 MAdds (i.e., the number of operations measured by multiply-adds, c.f. [3]) and 62720 parameters. Let MobileNetV2-GDConv denote MobileNetV2 with global depthwise convolution layer. When both MobileNetV2 and MobileNetV2-GDConv are trained on CIASIA-Webface ([26]) for face verification by ArcFace loss, the latter achieves significantly better accuracy on LFW and AgeDB (see TABLE II). Global depthwise convolution layer is an efficient structure for our design of MobileFaceNets.

C. MobileFaceNet Architectures

Now we describe our MobileFaceNet architectures in detail.

TABLE I
MOBILEFACENET ARCHITECTURE FOR FEATURE EMBEDDING

Input	Operator	t	c	n	s
$112^2 \times 3$	conv3x3	-	64	1	2
$56^2 \times 64$	depthwise conv3x3	-	64	1	1
$56^2 \times 64$	bottleneck	2	64	5	2
$28^2 \times 64$	bottleneck	4	128	1	2
$14^2 \times 128$	bottleneck	2	128	6	1
$14^2 \times 128$	bottleneck	4	128	1	2
$7^2 \times 128$	bottleneck	2	128	2	1
$7^2 \times 128$	conv1x1	-	512	1	1
$7^2 \times 512$	linear GDConv7x7	-	512	1	1
$1^2 \times 512$	linear conv1x1	-	128	1	1

We use almost the same notations as MobileNetV2 [3]. Each line describes a sequence of operators, repeated n times. All layers in the same sequence have the same number c of output channels. The first layer of each sequence has a stride s and all others use stride 1. All spatial convolutions in the bottlenecks use 3×3 kernels. The expansion factor t is always applied to the input size. GDConv7x7 denotes the global depthwise convolution of 7×7 kernels.

The residual bottlenecks proposed in MobileNetV2 ([3]) are used as our main building blocks. For convenience, we use the same conceptions as those in MobileNetV2 [3]. The detailed structure of our primary MobileFaceNet architecture is shown in Table I. Particularly, expansion factors for bottlenecks in our architecture are much smaller than those in MobileNetV2. We use PReLU ([27]) as the non-linearity, which is slightly better for face verification than using ReLU (see table II). In addition, we use a fast downsampling strategy at the beginning of our network, an early dimension-reduction strategy at the last several convolutional layers, and a linear 1×1 convolution layer following a linear global depthwise convolution layer as the feature output layer. Batch normalization ([28]) is utilized during training and batch normalization folding (c.f. Section 3.2 of [29]) is applied before deploying.

Our primary MobileFaceNet network has a computational cost of 130 million MAdds and uses 0.99 million parameters. We further tailor our primary architecture as follows. To reduce computational cost, we change input resolution from 112×112 to 112×96 or 96×96 . To reduce the number of parameters, we remove the linear 1×1 convolution layer after the linear global depthwise convolution layer from MobileFaceNet, the resulting network of which is called MobileFaceNet-M. From MobileFaceNet-M, removing the 1×1 convolution layer before the linear global depthwise convolution layer results the smallest network called MobileFaceNet-S. These MobileFaceNet networks’ effectiveness is demonstrated by the experiments in the next section.

IV. EXPERIMENTS

In this section, we will first describe the training settings of our MobileFaceNet models and our baseline models. Then we will compare the performance of our trained face verification models with some previous published face verification models, including several state-of-the-art big models.

A. Training settings and accuracy comparison on LFW and AgeDB

We use MobileNetV1, ShuffleNet, and MobileNetV2 (stride

TABLE II
PERFORMANCE COMPARISON AMONG MOBILE MODELS TRAINED ON
CASIA-WEBFACE

Network	LFW Acc.	AgeDB Acc.	Params	MAdds	Speed (CPU)
MobileNetV1	98.63%	88.95%	3.2M	574M	60ms
ShuffleNet (1x, g = 3)	98.70%	89.27%	1.1M	139M	27ms
MobileNetV2	98.58%	88.81%	2.1M	299M	49ms
MobileNetV2-GDConv	98.88%	90.67%	2.1M	299M	50ms
MobileFaceNet	99.28%	93.05%	0.99M	130M	24ms
MobileFaceNet (112 × 96)	99.18%	92.96%	0.99M	112M	21ms
MobileFaceNet (96 × 96)	99.08%	92.63%	0.99M	96M	18ms
MobileFaceNet-M	99.18%	92.67%	0.92M	129M	24ms
MobileFaceNet-S	99.00%	92.48%	0.84M	126M	23ms
MobileFaceNet (ReLU)	99.15%	92.83%	0.98M	130M	23ms
MobileFaceNet (expansion factor×2)	99.10%	92.81%	1.1M	140M	27ms

In the last column, we report actual inference time in milliseconds (ms) on the CPU of mobile device (using NCNN [30] inference framework). The platform is based on a Qualcomm Snapdragon 820 CPU of Xiaomi 5 phone.

= 1 for the first convolutional layers of them) as our baseline models. All MobileFaceNet models and baseline models are trained on CASIA-Webface dataset from scratch by ArcFace loss, for a fair performance comparison among them. We set the weight decay parameter to be $4e-5$, except the weight decay parameter of the last layers after the global operator (GDConv or GAPool) being $4e-4$. We use SGD with momentum 0.9 to optimize models and the batch size is 512. The learning rate begins with 0.1 and is divided by 10 at the 32K, 48K and 56K iterations. The training is finished at 60K iterations. Then, the

TABLE III
PERFORMANCE COMPARISON WITH PREVIOUS PUBLISHED FACE
VERIFICATION MODELS ON LFW AND AGEDB

Method	Training Data	#Net	Model Size	LFW Acc.	AgeDB Acc.
Deep Face [31]	4M	3	-	97.35%	-
DeepFR [32]	2.6M	1	0.5GB	98.95%	-
DeepID2+ [33]	0.3M	25	-	99.47%	-
Center Face [34]	0.7M	1	105MB	99.28%	-
DCFL [35]	4.7M	1	-	99.55%	-
SphereFace [20]	0.49M	1	-	99.47%	-
CosFace [22]	5M	1	-	99.73%	-
ArcFace [5]	-	-	-	-	-
(LResNet100E-IR)	3.8M	1	250MB	99.83%	98.08%
FaceNet [18]	200M	1	30MB	99.63%	-
ArcFace [5]	3.8M	1	112MB	99.50%	96.06%
(LMobileNetE)	-	-	-	-	-
Light CNN-29 [14]	4M	1	50MB	99.33%	-
MobileID [17]	-	1	4.0MB	97.32%	-
ShiftFaceNet [15]	-	1	3.1MB	96.00%	-
MobileFaceNet	3.8M	1	4.0MB	99.55%	96.07%
MobileFaceNet (112 × 96)	3.8M	1	4.0MB	99.53%	95.85%
MobileFaceNet (96 × 96)	3.8M	1	4.0MB	99.52%	95.63%

face verification accuracy on LFW and AgeDB is compared in Table II.

As shown in Table II, compared with the baseline models of common mobile networks, our MobileFaceNets achieve significantly better accuracy with fewer parameters and faster inference speed. Our primary MobileFaceNet achieves the best accuracy and MobileFaceNet with a lower input resolution of 96×96 has the fastest inference speed.

To pursue ultimate performance, MobileFaceNet, MobileFaceNet (112 × 96), and MobileFaceNet (96 × 96) are further trained by ArcFace loss on the cleaned training set of MS-Celeb-1M database [5] with 3.8M images from 85K subjects. The accuracy of our primary MobileFaceNet is boosted to 99.55% and 96.07% on LFW and AgeDB, respectively. The three trained models' accuracy on LFW and AgeDB is compared with previous published face verification models in Table III.

B. Evaluation on MegaFace Challenge1

In this paper, we use the Facescrub ([36]) dataset as the probe set to evaluate the performance of our primary MobileFaceNet on Megaface Challenge 1. Table IV summarizes the results of our models trained on two protocols of MegaFace where the training dataset is regarded as small if it has less than 0.5 million images, large otherwise.

TABLE IV
FACE IDENTIFICATION AND VERIFICATION EVALUATION ON
MEGAFACE CHALLENGE1

Method	Protocol	Rank 1 @ 10^6	VR @ FAR 10^{-6}
SIAT MMLAB [34]	small	65.23	76.72
DeepSense-Small	small	70.98	82.85
SphereFace-Small [20]	small	75.76	90.04
Beijing FaceAll V2	small	76.66	77.60
CosFace (3-patch) [22]	small	79.54	92.22
MobileFaceNet	small	83.40	88.08
MobileFaceNet	large	90.39	92.59
Google-FaceNet v8 [18]	large	70.49	86.47
SIATMMLAB Tencent Vision	large	74.20	87.27
DeepSense V2	large	81.29	95.99
Vocord-deepVo V3	large	91.76	94.96
CosFace (3-patch) [22]	large	84.26	97.96
iBUG_DeepInsight (ArcFace [5])	large	98.06	98.48

"Rank 1" refers to rank-1 face identification accuracy and "VR" refers to face verification TAR (True Accepted Rate) under 10^{-6} FAR (False Accepted Rate). Our MobileFaceNets are evaluated on the refined version of MegaFace dataset (c.f. [5]).

Our primary MobileFaceNet shows comparable accuracy for the identification and verification tasks on both the protocols.

V. CONCLUSION

We proposed a class of face feature embedding CNNs, namely MobileFaceNets, with extreme efficiency for real-time face verification on mobile and embedded devices. Our experiments show that MobileFaceNets achieve significantly improved efficiency compared with the state-of-the-art lightweight and mobile CNNs for face verification .

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