Towards Real-Time Action Recognition on Mobile Devices Using Deep Models

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Abstract

Action recognition is a vital task in computer vision, and many methods are developed to push it to the limit. However, current action recognition models have huge computational costs, which cannot be deployed to real-world tasks on mobile devices. In this paper, we first illustrate the setting of real-time action recognition, which is different from current action recognition inference settings. Under the new inference setting, we investigate state-of-the-art action recognition models on the Kinetics dataset empirically. Our results show that designing efficient real-time action recognition models is different from designing efficient ImageNet models, especially in weight initialization. We show that pretrained weights on ImageNet improve the accuracy under the real-time action recognition setting. Finally, we use the hand gesture recognition task as a case study to evaluate our compact real-time action recognition models in real-world applications on mobile phones. Results show that our action recognition models, being 6x faster and with similar accuracy as state-of-the-art, can roughly meet the real-time requirements on mobile devices. To our best knowledge, this is the first paper that deploys current deep learning action recognition models on mobile devices.

1. Introduction

Video-based action recognition, which is a vital task in computer vision, has drawn enormous attention from the community [26, 33, 13, 15]. Since the remarkable success of deep learning, researchers have proposed various deep models for action recognition. These models need enormous computational resources and are mostly applied on GPU equipped servers.

However, due to the rapid growth of mobile applications, there are increasing demands for conducting action recognition tasks on mobile devices. Some researches have been done on performing single image recognition on portable devices directly [20, 31], and some other researches try to collect sensor’s data to conduct action recognition, which does not use the camera sensor. However, temporal dependency plays a vital role in these tasks, and it is insufficient to only conduct single image and sensor data based action recognition. Due to the large video file size, it is not applicable to transfer them to a cloud server with GPUs for processing. Hence, it is essential to perform action recognition tasks on mobile devices directly.

In action recognition, many methods try to explain and capture the temporal dependencies between frames and push the limit of current state-of-the-art models. 3D convolutional models are proposed to capture the dense temporal dependencies in the time domain [24, 25, 27, 4, 10]. Besides 3D models, some other models are proposed to capture the long-term temporal dependencies in videos [28, 32]. However, all these deep learning methods need enormous computational resources (hundreds of BFLOPs and millions of parameters).

Many architectures have been developed to conduct image recognition tasks on mobile platforms [20, 23]. However, little attention has been paid on developing efficient computational action recognition models, especially in a resource constrained environment like mobile devices. Current state-of-the-art action recognition models are too heavy to run on mobile devices for real-world applications. Hence, currently mobile devices still use non-deep learning methods to conduct action recognition tasks, whose accuracy are lower than the state-of-the-art deep learning methods.

Besides the architecture part, the inference setting of performing action recognition on mobile devices should be different from current inference setting of many action recognition models. State-of-the-art action recognition models will perform heavy data augmentations from input videos when testing, e.g., sample 10 or more clips from the original videos and 10 crop image augmentation, then average the predictions among all these clips. However, heavy data augmentation will consume huge pre-processing time and cannot meet the low latency requirement of real-time action recognition. Hence, heavy data augmentation is not preferred on mobile devices.

All these factors encourage us to explore the inference
setting of action recognition on mobile devices. We re-
evaluate current state-of-the-art models under this new in-
ference setting, and achieve state-of-the-art performance
under the real-time constraint. Based on these new results,
we have some suggestions for future model design.

Our contributions are listed as follows:

- We explore the setting of real-time action recognition
tasks on devices with limited resources like mobile
phones, and perform an empirical study of state-of-the-
art action recognition models on the Kinetics dataset un-
der the real-time action recognition setting.
- With the help of some extra modules, we achieve per-
formance comparable to state-of-the-art models with 6x
fewer FLOPs and running time on the Kinetics dataset.
- We conduct a case study on the Jester gesture recogni-
tion dataset in mobile environments, which can lead to
efficient action recognition models in real-world tasks.
To our best knowledge, we are the first to introduce deep
learning action recognition models onto mobile devices
for real-time processing.

For efficient action recognition model design, our results
show that designing efficient real-time action recognition
models is different from designing image recognition mod-
els. In detail, we have the following findings:

- In the real-time action recognition setting, 2D based
models with temporal segments (TSN) are superior to
3D conv and other models considering both FLOPs and
accuracy.
- In the real-time action recognition setting, models with
joint training on ImageNet and Kinetics perform better
than training only on Kinetics. Moreover, the accuracy
on Kinetics is directly correlated with accuracy on Im-
geNet, which is different from previous conclusions.
- For compact models, overfitting is a key factor that hin-
ders performance, which is also different from Image-
Net conclusions.
- Branch architectures like Inception are suitable for the
real-time action recognition tasks, but it will also cost a
lot of mobile CPU latency, even with the same FLOPs.

2. Related Works

In this section, we will give a brief introduction to current
deep learning models and action recognition models.

2.1. Efficient Deep Learning

Efficient deep learning models have drawn a lot of atten-
tion in the computer vision society. Early network designs
such as VGGNet [22] and ResNet [13] are proven to be re-
dundant, and pruning methods are proposed to prune these
models [19][30]. Other researchers focus on directly design-
ring new efficient modules and structures, e.g., MobileNet
series [20] and ShuffleNet [31].

Besides these hand-crafted neural architectures,
NAS (Neural Architecture Search), which focuses on
developing methods to generate efficient neural network
architectures automatically, become popular these days.
The pioneering work [35] uses reinforcement learning
algorithms to train a Recurrent Neural Network (RNN)
controller that generates coded architectures. Some works
try to accelerate the whole search process with regular-
ization and pruning. NASNet [36] searches architectures
on CIFAR-10 and transfer the searched architectures to
the large-scale ImageNet. PNASNet [17] factorizes the
search space and accelerates the search process, achieving
comparable results with NASNet. MnasNet [23] takes
real-world device latency into the searching constraint.

All these efficient models are designed for image recogni-
tion, and some works transfer the image recognition
model to other tasks like object detection and semantic seg-
mentation [20]. However, little effort has been paid on de-
veloping efficient models in action recognition tasks, which
encourages us to explore this new problem setting.

2.2. Action Recognition

Compared to the image recognition task, action recogni-
tion is much harder because there exist time dependencies
in videos. Before the era of deep learning, various hand-
crafted features are proposed [26]. Motion vectors (optical
flows) are also proved to be useful [18]. After the success
of deep learning, researchers start to use deep learning in
action recognition tasks.

Two-Stream ConvNet [21] is a popular method in the
field of action recognition, which uses both RGB and optical
flow modality. Some improvements are proposed then
to achieve better results [9]. However, methods in this two
stream fashion pay no attention to the time axes and need
extra modalities.

Another popular trend is to expand spatial (2D) CNN
into spatial-temporal (3D) CNN. However, 3D CNNs have
more parameters than 2D CNNs, and they consume huge
resources in the training and testing process. Meanwhile,
since most datasets in action recognition are small (about
10k videos), 3D CNNs cause serious overfitting problems.
In 2017, the Kinetics dataset [2], which has about 300k
videos, is proposed to solve the dataset problem in action
recognition. Since the publishing of Kinetics, various 3D
models are proposed to improve the performance [5][7]. [2]
first proposes I3D network, which inflates 2D convolution
kernels into 3D convolution kernels. [29] shows that 3D
convolution near the classifier is helpful for action recogni-
tion. [4] uses group convolution to enlarge the capacity
of 3D CNN models. However, these models can only take
short clips due to memory limits and lack attention in long-
term dependencies.

Again, little attention has been paid on applying current
Figure 1. Overall inference framework of two action recognition settings. The key differences between these two settings are the data augmentation and size of the models.

action recognition models on real-world tasks. Some efforts have been paid on online video understanding [34, 16]. However, both are applied on GPU devices, without trying to apply it on mobile devices.

3. A Realistic Setting

The key difference between current inference setting and real-time action recognition setting is the running time. The goal of current state-of-the-art inference setting is achieving high accuracy. However, real-time action recognition needs to consider the inference time constraint.

To illustrate the real-time action recognition better, we list the environment constraint below (cf. Fig. 1):

- Heavy data augmentation is not possible: Data augmentation is not preferred especially in mobile environments due to the long processing time.
- Small model size and FLOPs: Mobile devices have much fewer computation and storage resources than desktop CPUs and GPUs. Since we need to input multiple frames into the models, we need models with fewer parameters and FLOPs.
- Extra modality is not preferred: We need low preprocessing time. Hence, we can not add extra modalities like optical flow and RGB difference.

Based on these constraints, we propose the following setting for real-time action recognition:

“Given an input video or a stream of input frames, we directly sample frames and do not perform any data augmentations. Then, these sampled frames are fed into the model, and the predictions are obtained through its output.”

This setting is different from most inference protocols of current action recognition models. Current inference protocols mostly use heavy data augmentations like 10 crop and 10 sampled clips from original videos and they often use these results to compare with other methods. However, these results are unsuitable in this real-time problem setting. Some 3D models provide results such as clip@1, and these results use the same inference protocol as our real-time action recognition protocol. We will directly cite these results in our paper. However, for other methods, they do not report results in this new setting. We need to re-evaluate the performance of state-of-the-art models.

4. Experimental Configuration

In this section, we will give detailed experimental setups.

4.1. Base Model Preparation

For empirically studying the effect of different modules and architectures, we prepare these models:

- Compressed VGG models (ThiNet-Tiny): Various techniques are developed for compressing CNNs. Among these models, ThiNet achieves state-of-the-art (better than AlexNet) performance with only 1.32M parameters [19].
- MobileNet series (MobileNet V1 and MobileNet V2): The MobileNet series of models are created to conduct deep learning tasks on mobile devices. MobileNetV1 uses depthwise separable convolution to reduce computation costs [20]. MobileNetV2 adds inverted residual blocks and residual connections to the MobileNet and improves the performance [20]. These two models achieve good results on ImageNet. For further comparison, we add an extra widen MobileNetV2 model called MobileNetV2-1.4, which has about 2x FLOPs than Mo-
Figure 2. Architectures of exactly one building cell of the three NAS searched models. Please note that in this figure, \texttt{avg} and \texttt{max} represent average and maximum pooling, \texttt{sep} represents depthwise convolution operation.

MobileNetV2 and 2.7\% performance gain on ImageNet.

- NASNet-A-mobile: After the pioneering work on NAS, some improvements are made to transfer the learned network structure from CIFAR-10 to large-scale datasets like ImageNet \cite{36}. NASNet-A-mobile, which achieves 74.0\% accuracy on ImageNet with only 5.3M parameters and 564M FLOPs, is also a good backbone network for action recognition.

- PNASNet-5-mobile: Compared to NASNet \cite{36}, PNASNet uses progressive search strategies to reduce search costs for NASNet with comparable costs \cite{17}. The mobile series of PNASNet, PNASNet-5-mobile, achieves comparable results with NASNet.

- MnasNet: After NASNet, MnasNet \cite{36} uses reinforcement learning to take real CPU latency on mobile phones into consideration and achieves comparable results with NASNet-A-mobile with less real latency on mobile devices.

For the first three manually designed networks, their building blocks are rather simple. They are mostly composed of simple convolution layers (including traditional, depthwise and separable convolution). For NAS searched models, basic blocks of these networks are shown in Fig. 2. From these figures, we can see that NAS models are more complex than manually designed models, except for MnasNet.

4.2. 2D or 3D CNN models?

Long-term dependency is another critical factor for action recognition. Some previous methods use LSTM to handle long-term dependencies \cite{6}. However, these methods also have overfitting problems.

Temporal segment network (TSN) \cite{28} shows that random sampling between large intervals can also capture the long-term dependencies in a video. \cite{32} proposes a relational reasoning module to capture dependencies better. In this section, we will give a brief recapitulation to TSN.

The TSN method is composed of three parts: A random sparse sampling part, a spatial ConvNet part, and an aggregation part. Given a video \( V \), TSN will divide \( V \) into \( k \) segments: \( \{Seg_1, \ldots, Seg_k\} \). Then precisely one frame will be sampled from each segment. These sampled images will be fed into a spatial CNN to get independent prediction scores for each frame. Finally, these scores are fused to get the final prediction score for the whole video. In TSN, the author chooses random sampling techniques for training TSN-based models and medium sampling for inference. For aggregating function, the author chooses the average function, i.e., all predictions are averaged together to get the final prediction.

For base method choice and comparison, there is a fundamental question: Should we choose 3D conv-based models, or do we need to choose methods based on 2D models?

We conducted experiments on 2D and 3D CNN models. For all models with TSN, we add a dropout layer with 0.8 dropout ratio, following the suggestions in \cite{28}. According to Table 1 and Fig. 3, we can easily see that: In the setting of real-time action recognition, 3D models are inferior to 2D based models. With 11.1B FLOPs, the state-of-the-art MFNet \cite{4} only achieves 65.0\% accuracy on Kinetics. However, NASNet-A-Mobile with TSN achieves 64.2\% accuracy with only 4.48B FLOPs, which is about two times less than MFNet. For other 3D models, the FLOPs is mostly over 100G and is not suitable for running on mobile devices. Furthermore, 2D models with TSN performs much better than single 2D models. From Fig. 3 we can see that 2D models with TSN are in the up left corner. According to the observations, we decide to use 2D models with TSN in our subsequent experiments.

4.3. Experimental Setup

We use PyTorch for our deep learning framework and the PyTorch implementation of TSN code\footnote{https://github.com/yjxiong/tsn-pytorch}. We use a GPU server equipped with eight M40 GPUs, two Intel E5-2650 v4 CPUs and 256GB memory support for training and testing our models. All our models are trained using single pre-
Table 1. Performance of state-of-the-art models (number of parameters, FLOPs and accuracy) of current 2D and 3D models re-evaluated under the real-time action recognition setting on the Kinetics dataset. The second column is the number of input frames and the third to fifth column represent the number of parameters, FLOPs and accuracy on the Kinetics validation dataset. Please note that all models only take 1 clip from the RGB modality of origin video and all results with our TSN use models initialized with the weights pretrained from ImageNet. Some results are drawn from previous papers [16, 3, 11, 34].

| Model                  | Frames | Params   | FLOPs   | Acc   |
|------------------------|--------|----------|---------|-------|
| C2D [27]               | 32     | 24.3M    | 26.3B   | 62.4% |
| BN-Inception+TSN [28]  | 8      | 11.3M    | 16.3B   | 67.0% |
| ResNet-50+TSN [28]     | 8      | 25.6M    | 33.9B   | 66.8% |
| MnasNet+TSN [23]       | 8      | 5.1M     | 2.6B    | 61.9% |
| NASNet-A-Mobile+TSN [36]| 8     | 4.2M     | 4.5B    | 64.2% |
| PNASNet-5-Mobile+TSN   | 8      | 5.1M     | 4.7B    | 63.0% |
| C3D [27]               | 32     | 35.0M    | 164.8B  | 64.7% |
| MFNet [4]              | 16     | 8.0M     | 11.1B   | 65.0% |
| StNet [11]             | 75     | 33.2M    | 189.3B  | 69.9% |
| ResNet26-A^2 [3]       | 16     | 7.7M     | 10.1B   | 53.0% |
| ECOLite\(_{4F}\) [34]  | 4      | 37.5M    | 11.6B   | 57.9% |
| ECOLite\(_{16F}\) [34] | 16     | 37.5M    | 11.6B   | 64.4% |
| ECO\(_{4F}\) [34]      | 4      | 47.5M    | 16.1B   | 66.2% |

For better evaluating our models, we choose the Kinetics dataset to evaluate our models. Kinetics is a large-scale high-quality dataset of YouTube videos, which include a diverse range of human-focused actions [2]. Videos in Kinetics are clipped from Youtube videos, while some other datasets (Chardes, Something-Something) are collected from the Amazon Mechanical Turk (AMT). The Kinetics dataset is highly related to daily actions, which is similar to the tasks in mobile action recognition scenes.

We evaluate our models on the trimmed version. In this paper, we use Kinetics-400. Kinetics-400 consists of approximately 300,000 video clips and covers 400 human action classes with at least 400 video clips for each action class. For validation, each class has 50 video clips. We remove some unavailable videos in Kinetics-400. There are about 240k videos in the training set and we report the accuracy on the validation dataset.

Hyperparameters are set the same for all these experiments. The learning rate is 0.01 for first 45 epochs, and decay 0.1 every 15 epochs. The weight decay is 0.0005 and the batch size is 128. We clip all the gradients when the gradients are larger than 20. Unless specified, all model do not have the last dropout layer, i.e., the dropout ratio is set to 0 for all models.
For testing, we first sample 8 RGB frames from each action video. Different from standard TSN protocol, we do not perform 10 crop data augmentation among the data input due to the constraint we have mentioned before. Finally, 8 images are fed into the TSN models to get individual scores for each input. Then 8 scores are averaged to get the final score.

5. Results and Analysis

In this section, we will provide detailed experimental results and findings.

5.1. General results

First, we conduct experiments over all base models. Please note that all our base models in this section use pre-trained weights on ImageNet.

The training curve of all these models are in Fig. 4. According to Table 2 and Fig. 4, we can easily find that:

• It is interesting that MobileNetV1 has better accuracy than MobileNetV2 on the Kinetics dataset. This observation suggests that some optimized structures on ImageNet like inverse bottleneck may not be suitable for the task of action recognition. This phenomenon shows that designing efficient real-time action recognition models is different from designing image recognition models.

• Although the FLOPs of NASNet-A-Mobile, PNASNet-5-Mobile and MobileNetV2-1.4 are roughly the same, their mobile CPU latency time are totally different. MobileNetV2-1.4 has the least CPU latency while the NASNet-A-Mobile has 2x CPU time on mobile devices. This phenomenon may explained by the fact that MobileNetV2-1.4 only uses simple forward block, while PNASNet-5-Mobile and NASNet-A-Mobile use complex searched branch blocks according to Fig. 2. However, these complex branch blocks improve the accuracy. For example, NASNet-A-mobile achieves the best performance among all these models, and it has the most complex basic building blocks.

• MnasNet has the least FLOPs and mobile CPU latency among all these models while having a comparable accuracy. It is a suitable model for further detailed experiments and for deployment on mobile devices.

5.2. Do We Really Need ImageNet?

Some previous researches such as the SlowFast network [8] [12] show that in the field of object detection and action recognition, pretrained models on ImageNet is not an essential part. In this section, we will discuss the relationship between ImageNet pretrained models and Kinetics accuracy. Several models are prepared for evaluating the effectiveness of ImageNet.

For models with weights pretrained on ImageNet, we use the same hyperparameter settings as in Sec 4.3. For models trained from scratch, we use longer training epochs to ensure a fair comparison on Kinetics. The learning rate is 0.01 for first 90 epochs, and reduced to 10% every 30 epochs. As [8] suggests, we use a linear warmup strategy for first 5 epochs. According to results in Table 3, we can have the following observations. In the setting of real-time action recognition, ImageNet pretraining improves 2-3% accuracy on almost all our base models. This conclusion is different from that in [8]. This may be explained by the fact that TSN models use global average pooling to simply capture the relationship between frames while SlowFast uses 3D conv to capture the temporal dependencies explicitly. Hence, it is easy for our models to get overfit. ImageNet pretrained models provide a better start point and accelerate the convergence of the training process.

Furthermore, we are interested in the relationship between the accuracy on ImageNet and the accuracy on Kinetics, i.e., does a higher performance on ImageNet directly correlates with a higher Kinetics accuracy?

We perform an ablation study on PNASNet and MnasNet. For pretrained models, we prepare models at different accuracy level, i.e., models at different training epochs on ImageNet for initial weights of PNASNet and MnasNet. As shown in Table 4 we can see that in the setting of real-time action recognition, ImageNet performance is directly related to Kinetics performance. This phenomenon is also different from previous conclusion [8]. It may indicate that pretrained models on ImageNet is essential for real-time action recognition, and proves that the linear warmup technique is not sufficient for current models. Moreover, for NAS on real-time action recognition tasks, it is vital to consider the ImageNet factor.

5.3. Overfitting Matters

In all our previous models, we set dropout to 0 in our models. Previous researches on ImageNet shows that shallow models do not tend to overfit, i.e., for shallow models, they are easy to underfit. We want to explore this problem in the real-time action recognition setting. Hence, we choose MnasNet as our baseline model and evaluate two kinds of strategies. One is adding dropout before the final classification layer, and the dropout ratio is set to 0.8. The other strategy is partial BN, which fixes all batch normalization layer except the first one. Both strategies are introduced by [28]. As illustrated in Table 5, we can have the following observation: Different from ImageNet, models on Kinetics are easy to get overfit, even though the MnasNet model is compact. Dropout and fix BN are both effective for migrating the overfitting problem.
Figure 4. Training and testing accuracy curves on Kinetics for various models of TSN under the problem setting of real-time action recognition. Different color represents different base models. For each model, the solid line represents training accuracy and the dotted line represents testing accuracy. This figure is best viewed in color.

Table 2. Number of parameters, FLOPs, mobile CPU latency and accuracy of current compact models on ImageNet and the Kinetics dataset for compact models. The second column represents the number of parameters and the third to seventh column represent FLOPs, accuracy on ImageNet 2012 validation set, single image latency on HUAWEI Mate 10, FLOPs of TSN model and accuracy of the Kinetics validation dataset. For FLOPs calculation, we treat multiply and add operation as a single operation. The last two rows are for reference only.

| Model          | Params     | FLOPs    | ImageNet acc | Image Latency | TSN FLOPs | Kinetics acc |
|----------------|------------|----------|--------------|---------------|-----------|--------------|
| ThiNet-Tiny    | 1.32M      | 1.12B    | 57.4%        | 256.03ms      | 4.64B     | 54.6%        |
| MobileNetV1    | 4.2M       | 0.57B    | 70.6%        | 106.47ms      | 4.56B     | 59.0%        |
| MobileNetV2    | 3.4M       | 0.30B    | 72.0%        | 89.79ms       | 2.40B     | 54.0%        |
| MobileNetV2-1.4| 6.9M       | 0.59B    | 74.7%        | 144.86ms      | 4.72B     | 58.7%        |
| NASNet-A-Mobile| 5.3M       | 0.57B    | 74.0%        | 320.76ms      | 4.48B     | 61.9%        |
| PNASNet-5-Mobile| 5.1M      | 0.59B    | 74.2%        | 289.58ms      | 4.72B     | 61.7%        |
| MnasNet        | 4.2M       | 0.32B    | 74.2%        | 78.12ms       | 2.56B     | 60.7%        |
| BN-Inception   | 11.3M      | 2.04B    | 74.8%        | 299.44ms      | 16.32B    | 67.0%        |
| ResNet-50      | 25.6M      | 3.86B    | 75.3%        | 512.70ms      | 33.88B    | 66.8%        |

5.4. Extra Modules

Some researchers propose small modules for improving the performance on both 2D ImageNet and action recognition models. In this section, we choose MnasNet as our baseline model, and use the temporal shift module (TSM) \cite{13} and the squeeze and excitation (SE) module \cite{14} as extra modules.

The temporal shift module shifts part of the channels along the temporal dimension, which facilitates information exchange among neighboring frames \cite{13} with zero FLOPs cost and negligible time cost. For the SE module, it adaptively recalibrates channel-wise feature responses by explicitly modeling interdependencies between channels \cite{14}.

The training hyperparameters are set the same as in Sec 4.1. For TSM, we follow the official guide in \cite{13}. For SE modules, we add them in every block of MnasNet, and we add 10 TSM and SE modules in total.

As Table 6 shows, different modules can cooperate together to improve the accuracy on the Kinetics dataset. With the help of these extra modules, MnasNet with TSN can achieve state-of-the-art accuracy with about 6x FLOPs and running times savings, which indicates the effectiveness of our models.
Table 3. Results of different pretrained models on the Kinetics dataset. The second column represents whether the model is pretrained on ImageNet and the third column represents accuracy on the Kinetics validation dataset.

| Model          | Pretrained | Kinetics acc |
|----------------|------------|--------------|
| ThiNet-Tiny    | -          | 52.5%        |
| MnasNet        | ImageNet   | 57.0%        |
| PNASNet-5-Mobile | -       | 57.0%        |
| ResNet-50      | ImageNet   | 63.0%        |
| ResNet-50      | -          | 66.8%        |

Table 4. Results of different pretrained models on the Kinetics dataset. The second column represents the accuracy of pretrained models on ImageNet and the third column represents accuracy on the Kinetics validation dataset. Please note that all our models only takes 1 clip from the RGB modality of origin video.

| Model         | ImageNet acc | Kinetics acc |
|---------------|--------------|--------------|
| MnasNet       | 67.5%        | 60.3%        |
| MnasNet + dropout | 74.2%    | 60.7%        |
| PNASNet-5-Mobile | 68.8%    | 60.6%        |
| PNASNet-5-Mobile | 74.2%    | 61.7%        |

Table 5. Results of different regularization techniques on the Kinetics dataset. The second column represents pretrained datasets and the third column represents accuracy on the Kinetics validation dataset.

| Model          | Kinetics acc |
|----------------|--------------|
| MnasNet        | 60.7%        |
| MnasNet + dropout | 61.9%    |
| MnasNet + fix BN | 62.2%    |

Table 6. Results of different extra models on the Kinetics dataset. The second column represents added extra modalities and the third column represents accuracy on Kinetics validation dataset.

| Model          | Extra module | Kinetics acc |
|----------------|--------------|--------------|
| MnasNet        | TSM          | 64.6%        |
| MnasNet        | SE           | 62.7%        |
| MnasNet TSM + SE + dropout | 66.5%    |

Table 7. Results of different models on the 20BN Jester dataset. The second column represents accuracy on the Jester validation dataset. The third column represents the real CPU latency on HUAWEI MATE 10 when taking the whole 8 sampled frames as input. The fourth column represents the real CPU latency on HUAWEI MATE 10 when the frames are sequentially fed into the action recognition model. For all latencies, we feed the image into action recognition 100 times and report the average result.

| Model          | Acc | Batch latency | Sequential latency |
|----------------|-----|---------------|---------------------|
| MnasNet        | 80.9% | 533.19ms | 90.24ms             |
| MnasNet + TSM  | 93.6% | 588.70ms | -                   |
| MnasNet + SE   | 80.5% | 558.19ms | 105.09ms            |
| MnasNet + TSM + SE | 93.7% | 570.47ms | -                   |
| ResNet-50 [16] | 81.0% | 3151.57ms | 512.70ms            |
| ResNet-50 + TSM [16] | 94.4% | 3243.11ms | -                   |

5.5. Real-World Applications: A Live Demo

In this section, we will provide a real-world case study of real-time action recognition on mobile devices. We choose gesture recognition to evaluate our model on real-world scenes. The Jester dataset is a large collection of densely-labeled video clips that show humans performing pre-defined hand gestures in front of a laptop camera or webcam [1]. It allows training models to recognize human hand gestures. The dataset has a total number of 148,092 videos and we use the training set with 118,562 for training, and 14,787 in the validation set to evaluate our model.

We use the MnasNet models pretrained from Kinetics and fine-tune it on the target Jester dataset. The fine-tuning is conducted for 25 epochs with initial learning rate 0.001 and decayed by a factor of 0.1 every 10 epochs.

Beyond the simple measurement, we put the model into a live demo on mobile devices with a HUAWEI Mate 10 phone. This application directly captures video frames from cameras and perform action recognition locally, which is an online video understanding scenario. Since TSN process each frame individually, we can cache prediction results of previous frames. Hence, in this section, we will discuss two kinds of inputs: whole sampled clips and sequential input images. Since TSM will shift the feature along the temporal dimension, so it can only be applied in whole video inputs.

Based on the results in Table 7 and Table 2, we can see that our models perform roughly the same as ResNet-50 with only 20% of its latency and 10% of its FLOPs. With sequential image inputs, our model can achieve results with about 10FPS on HUAWEI MATE 10, which roughly meets the real-time requirements. To our best knowledge, this is the first paper which applies current deep learning action recognition models into real-world mobile devices and achieves comparable results with state-of-the-art models.

6. Conclusion

In this paper, we explored the inference setting of real-time action recognition. Based on this new inference setting, we empirically evaluated current state-of-the-art models. Some suggestions were found through empirical ablation studies including pretrained weights, overfitting issues and extra modules. We achieved state-of-the-art accuracy with 6x FLOPs and inference time saving with the help of extra modules. Finally, a case study on gesture recognition proves that our compact model can be applied in real-time action recognition scenarios on mobile devices. For future work, we will try to design more efficient and effective models in real-time action recognition.
References

[1] The 20BN-Jester Dataset V1. https://20bn.com/datasets/jester

[2] J. Carreira and A. Zisserman. Quo vadis, action recognition? a new model and the Kinetics dataset. In CVPR, pages 4724–4733, 2017.

[3] Y. Chen, Y. Kalantidis, J. Li, S. Yan, and J. Feng. A 2-Net: Double attention networks. In NIPS, pages 350–359, 2018.

[4] Y. Chen, Y. Kalantidis, J. Li, S. Yan, and J. Feng. Multi-fiber networks for video recognition. In ECCV, volume 11205 of LNCS, pages 364–380, 2018.

[5] A. Diba, M. Fayyaz, V. Sharma, M. M. Arzani, R. Yousefzadeh, J. Gall, and L. Van Gool. Spatio-temporal channel correlation networks for action classification. In ECCV, volume 11208 of LNCS, pages 299–315, 2018.

[6] J. Donahue, L. Anne Hendricks, S. Guadarrama, M. Rohrbach, S. Venugopalan, K. Saenko, and T. Darrell. Long-term recurrent convolutional networks for visual recognition and description. In CVPR, pages 2625–2634, 2015.

[7] Y. Du, C. Yuan, B. Li, L. Zhao, Y. Li, and W. Hu. Interaction-aware spatio-temporal pyramid attention networks for action classification. In ECCV, volume 11220 of LNCS, pages 388–404, 2018.

[8] C. Feichtenhofer, H. Fan, J. Malik, and K. He. SlowFast networks for video recognition. arXiv preprint arXiv:1812.03982, 2018.

[9] C. Feichtenhofer, A. Pinz, and A. Zisserman. Convolutional two-stream network fusion for video action recognition. In CVPR, pages 1933–1941, 2016.

[10] K. Hara, H. Kataoka, and Y. Satoh. Can spatiotemporal 3D CNNs retrace the history of 2D CNNs and ImageNet? In CVPR, pages 6546–6555, 2018.

[11] D. He, Z. Zhou, C. Gan, F. Li, X. Liu, Y. Li, L. Wang, and S. Wen. StNet: Local and global spatial-temporal modeling for action recognition. In AAAI, pages 1–8, 2019.

[12] K. He, R. Girshick, and P. Dollár. Rethinking ImageNet pre-training. arXiv preprint arXiv:1811.08883, 2018.

[13] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In CVPR, pages 770–778, 2016.

[14] J. Hu, L. Shen, and G. Sun. Squeeze-and-Excitation networks. In CVPR, pages 7132–7141, 2018.

[15] Y. Li, Y. Li, and N. Vasconcelos. RESOUND: Towards action recognition without representation bias. In ECCV, volume 11210 of LNCS, pages 520–538, 2018.

[16] J. Lin, C. Gan, and S. Han. Temporal shift module for efficient video understanding. arXiv preprint arXiv:1811.08383, 2018.

[17] C. Liu, B. Zoph, M. Neumann, J. Shlens, W. Hua, L.-J. Li, L. Fei-Fei, A. Yuille, J. Huang, and K. Murphy. Progressive neural architecture search. In ECCV, volume 11205 of LNCS, pages 19–34, 2018.

[18] B. D. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. In IJCAI, pages 674–679, 1981.

[19] J.-H. Luo, H. Zhang, H.-Y. Zhou, C.-W. Xie, J. Wu, and W. Lin. ThinNet: Pruning CNN filters for a thinner net. IEEE TPAMI, page in press, 2018.

[20] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen. MobileNetV2: Inverted residuals and linear bottlenecks. In CVPR, pages 4510–4520, 2018.

[21] K. Simonyan and A. Zisserman. Two-stream convolutional networks for action recognition in videos. In NIPS, pages 568–576, 2014.

[22] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In ICLR, pages 1–14, 2015.

[23] M. Tan, B. Chen, R. Pang, V. Vasudevan, and Q. V. Le. MnasNet: Platform-aware neural architecture search for mobile. arXiv preprint arXiv:1807.11626, 2018.

[24] D. Tran, L. Bourdev, R. Fergus, L. Torresani, and M. Paluri. Learning spatiotemporal features with 3D convolutional networks. In CVPR, pages 4489–4497, 2015.

[25] D. Tran, J. Ray, Z. Shou, S.-F. Chang, and M. Paluri. ConvNet architecture search for spatiotemporal feature learning. arXiv preprint arXiv:1708.05038, 2017.

[26] H. Wang and C. Schmid. Action recognition with improved trajectories. In ICCV, pages 3551–3558, 2013.

[27] L. Wang, W. Li, W. Li, and L. Van Gool. Appearance-and-relation networks for video classification. In CVPR, pages 1430–1439, 2018.

[28] L. Wang, Y. Xiong, Z. Wang, Y. Qiao, D. Lin, X. Tang, and L. Van Gool. Temporal segment networks: Towards good practices for deep action recognition. In ECCV, volume 11205 of LNCS, pages 20–36, 2016.

[29] S. Xie, C. Sun, J. Huang, Z. Tu, and K. Murphy. Rethinking spatiotemporal feature learning: Speed-accuracy trade-offs in video classification. In ECCV, volume 11219 of LNCS, pages 305–321, 2018.

[30] L. Xue, W. Li, J. Sun, and K. Murphy. Learning spatiotemporal features with 3D convolutional networks. In CVPR, pages 9194–9203, 2018.

[31] X. Zhang, X. Zhou, M. Lin, and J. Sun. ShuffleNet: An extremely efficient convolutional neural network for mobile devices. In CVPR, pages 6848–6856, 2018.

[32] B. Zhou, A. Andonian, A. Oliva, and A. Torralba. Temporal relational reasoning in videos. In ECCV, volume 11205 of LNCS, pages 831–846, 2018.

[33] C. Zhu and W. Sheng. Wearable sensor-based hand gesture and daily activity recognition for robot-assisted living. IEEE TSMC, 41(3):569–573, 2011.

[34] M. Zolfaghari, K. Singh, and T. Brox. ECO: Efficient convolutional network for online video understanding. In ECCV, volume 11206 of LNCS, pages 713–730, 2018.

[35] B. Zoph and Q. V. Le. Neural architecture search with reinforcement learning. In ICLR, pages 1–14, 2017.

[36] B. Zoph, V. Vasudevan, J. Shlens, and Q. V. Le. Learning transferable architectures for scalable image recognition. In CVPR, pages 8697–8710, 2018.