Advanced Machine Learning

Final Project Presentation — MobileViTs for Sign Language Recognition

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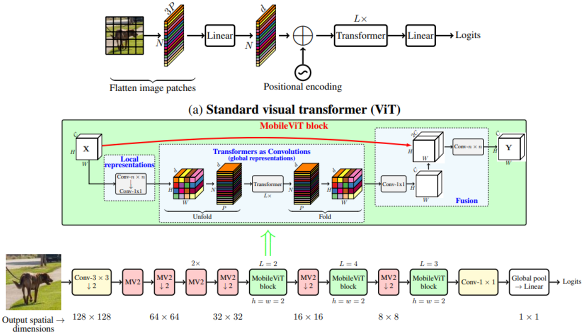
Task and Motivation

Task: Continuous Sign Language Recognition (CSLR). A sequence-to-sequence problem, where the input is a video and the output is a phrase in natural language.

Dataset: RWTH-PHOENIX-Weather 2014T. Around $\approx$ 4 thousand videos, 25 frames per second, 210×260 pixels.

MobileViTs

MobileViTs[2] are a lightweight version of Vision Transformers (ViTs) that are designed to run on mobile devices.



(b) **MobileViT**. Here, Conv-$n \times n$ in the MobileViT block represents a standard $n \times n$ convolution and MV2 refers to MobileNetv2 block. Blocks that perform down-sampling are marked with $\downarrow 2$.

Figure: MobileViT architecture.

Our novel MobileViT architecture

We adapt the MobileViT architecture to CSLR by performing spatio-temporal aggregation across multiple frames. This comes at no additional cost in terms of parameters, while allowing full exploitation of the temporal dimension.

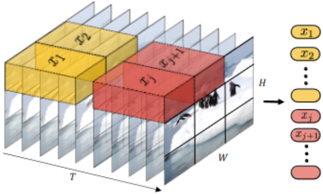


Figure: When the temporal dimension is processed in patches, the volume is called a tubelet.

First approach: Encoder-only MobileViT

To ensure a minimal amount of parameters, we first tried to train an encoder-only MobileViT. We use CTC loss to perform per-frame prediction of tokens from the encoder output, fusing repeated tokens.

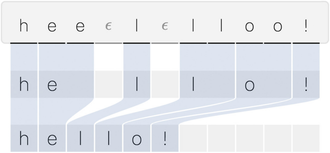


Figure: Output of a CTC loss trained model. repeated tokens separated by a blank token are fused.

Second approach: Encoder-decoder MobileViT

To compare ourselves with a more classical approach, we also trained an encoder-decoder MobileViT. We attach a decoder head to the encoder output, and train the model with classic CE loss and teacher forcing.
This massively increases the number of parameters w.r.t. the encoder-only model, but it simplifies the training process.

Encoder-only MobileViT: Results

The encoder-only model gets trapped in a local minimum (predicting 0-length sequences) and does not recover. Repeated experiments with different configurations did not yield better results.

Figure: Validation loss for the encoder-only MobileViT.

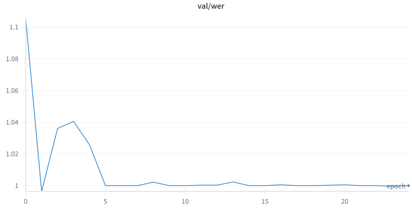


Figure: Validation Word Error Rate for the encoder-only MobileViT, stuck at 1.0.

Encoder Decoder MobileViT: Results

The encoder-decoder approach shows a smoother convergence and a lower WER w.r.t. the encoder-only model.

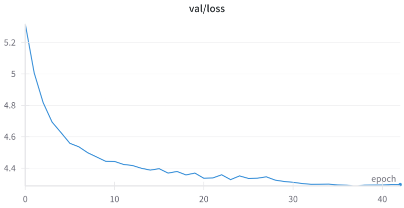


Figure: Validation loss for the encoder-decoder MobileViT.

Figure: Validation Word Error Rate for the encoder-decoder MobileViT.

Quantitative results

Model	Parameters (M)	WER
Encoder-only XXS MobileViT (ours)	6.09	1.00
Encoder-decoder XXS MobileViT (ours)	7.80	0.79
SlowFastSign[1]	52.90	0.18
LCSA[3]	16.17	0.21

Table: Parameters (in millions) and validation Word-Error-Rate (WER) for the models.

Conclusions

CSLR is a challenging task that requires massive computational resources. Even while employing models that are specifically designed for mobile devices, we still struggle to achieve sufficient capacity to match state-of-the-art models.
For both the encoder-only and encoder-decoder models, limited experiments with increasing parameter size showed improvements in terms of WER. Showing that scaling the model up might be beneficial.

Thank you for your attention!

Questions?

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