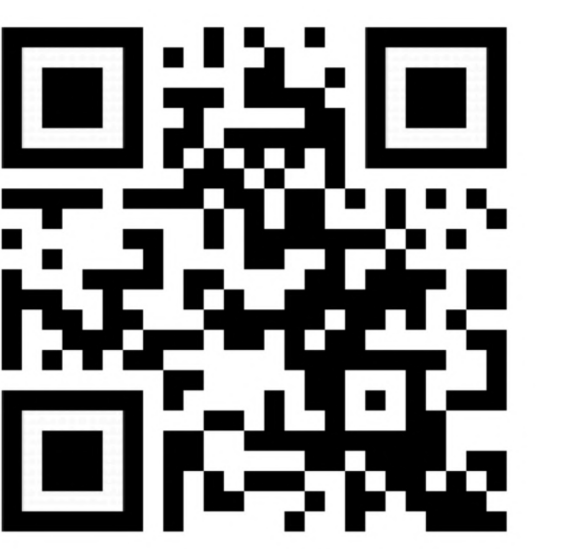




# FastDepth: Fast Monocular Depth Estimation on Embedded Systems

Massachusetts Institute of Technology, USA

Diana Wofk\*, Fangchang Ma\*, Tien-Ju Yang, Sertac Karaman, Vivienne Sze



Project  
Webpage

## 1. Motivation

Real-time low-power depth sensing is critical for successful navigation of small robotic vehicles.

Existing Work:

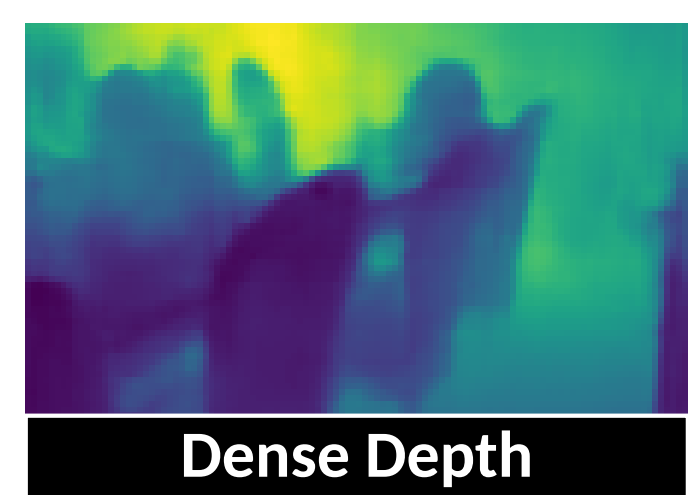
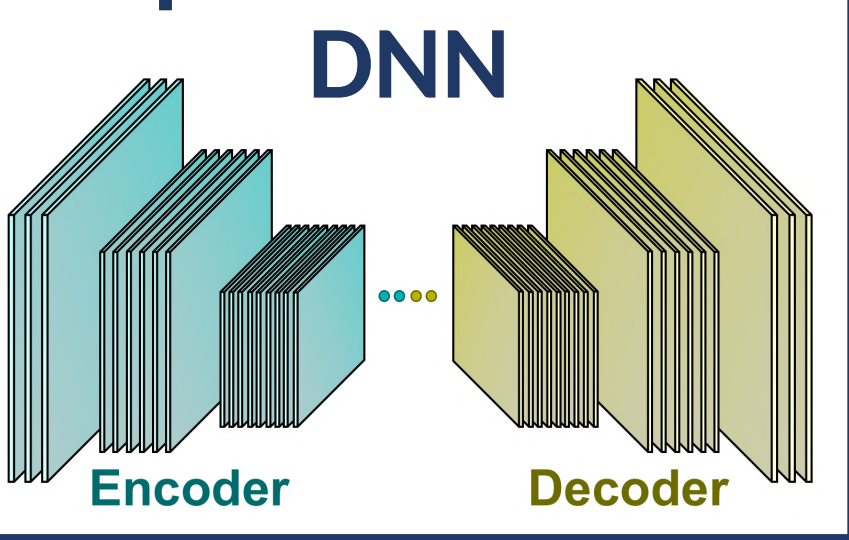
- ✓ High Accuracy
- ✗ High Complexity
- ✗ High Latency
- ✗ High Energy Cost

Our Work:

- ✓ High Accuracy
- ✓ Low Complexity
- ✓ Low Latency
- ✓ Low Energy Cost

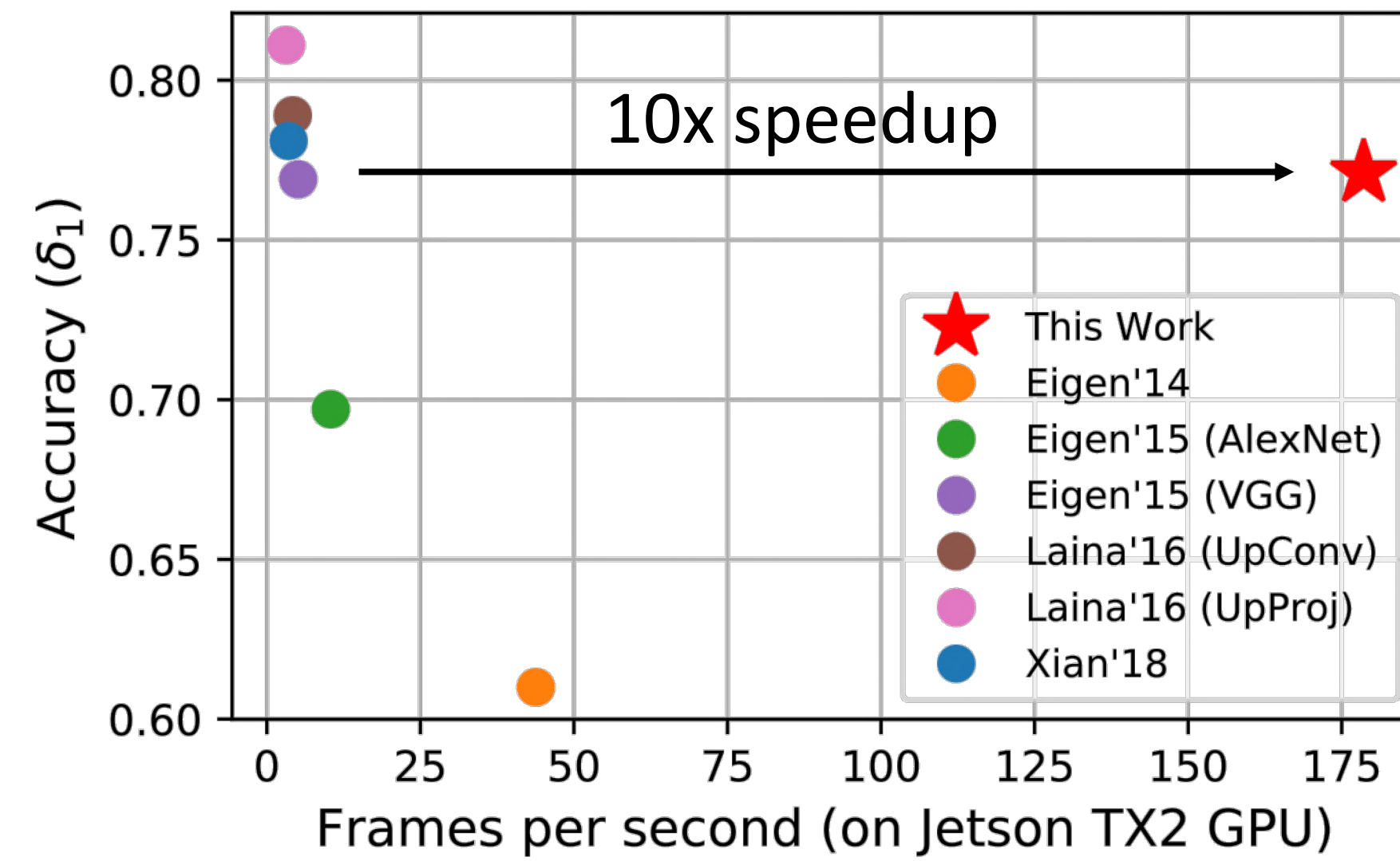


Depth Estimation DNN



farther closer

## 2. Contribution



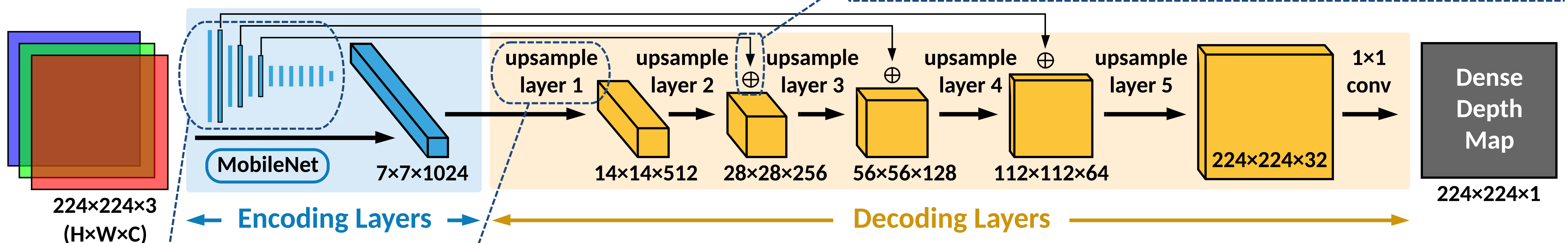
Our work is *an order of magnitude faster* than prior work, with *near state-of-the-art accuracy* on the NYU Depth v2 dataset.

Model Metrics		Jetson	Runtime	Power
# weights [ $10^6$ ]	1.34	TX2 GPU	5.6 ms (178 fps)	12.2 W (3.4 W idle)
# MACs [ $10^9$ ]	0.37			
Accuracy ( $\delta_1$ [%])	77.1	TX2 CPU	37 ms (27 fps)	10.5 W (3.4 W idle)
RMSE [cm]	60.4			

## 3. Methodology

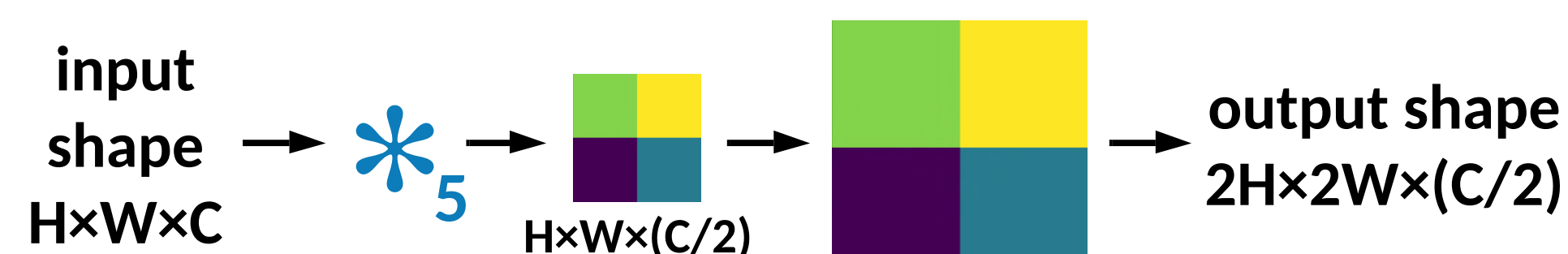
► We use a *lightweight encoder-decoder architecture*:

*Additive skip connections* result in improved accuracy.



Our encoder is based on a *computationally-simple and efficient image classification network*.

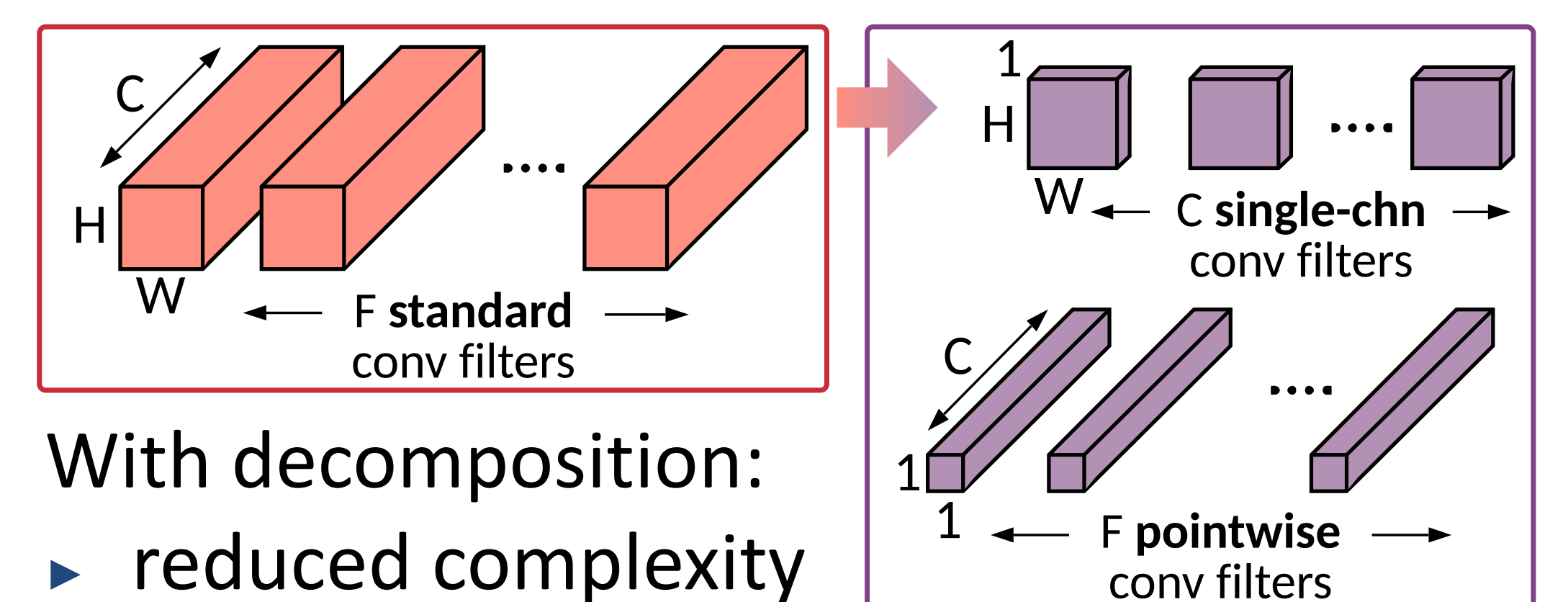
Each upsample layer performs *5x5 depthwise separable convolution* with *nearest-neighbors interpolation*.



- We perform *hardware-specific compilation* (TVM) to lower inference runtime on the target embedded platform.
- We apply *resource-aware network adaptation* (NetAdapt) to automatically simplify our model to further lower runtime.

### Depthwise Separable Convolution

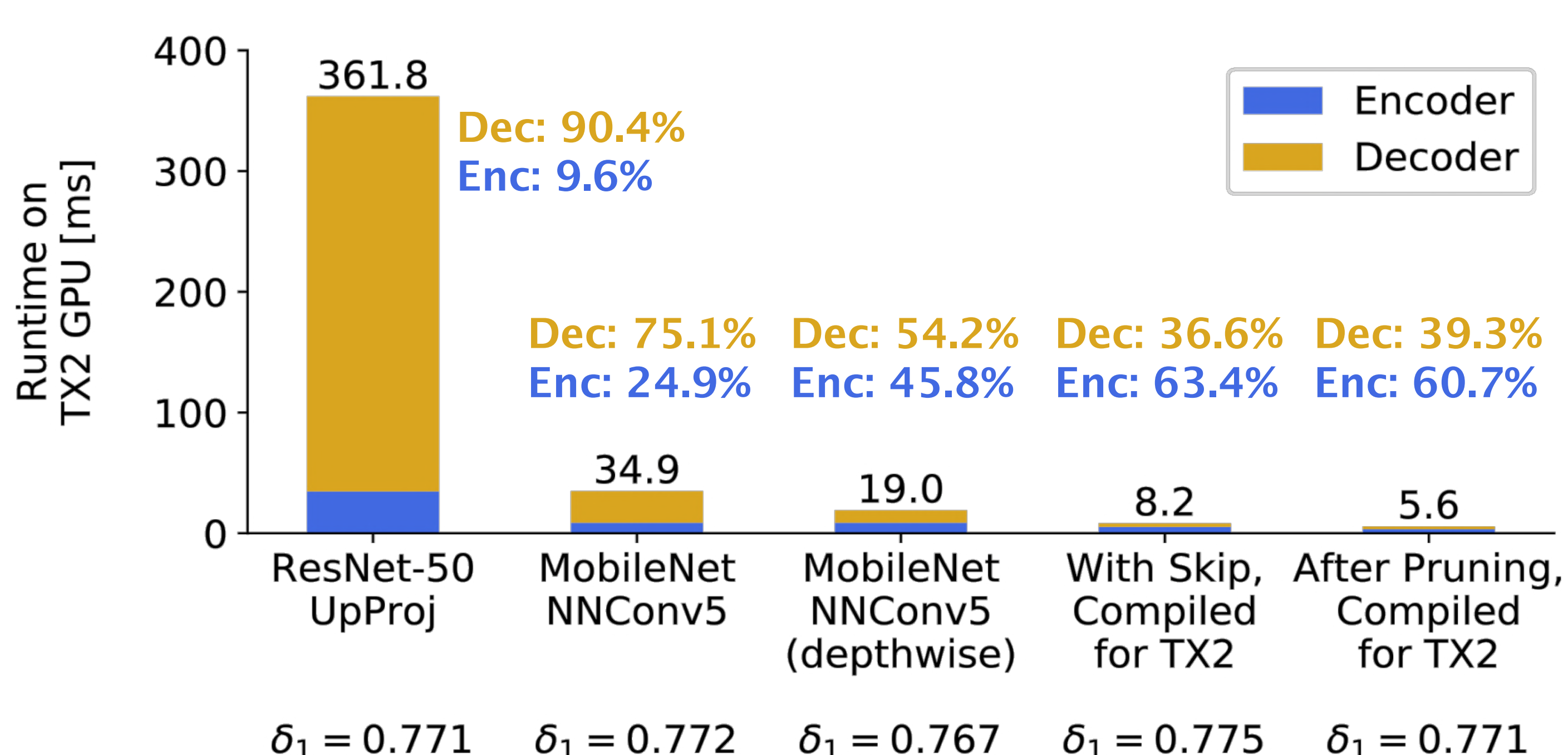
Used in both the encoder and decoder.



- With decomposition:
- reduced complexity
  - reduced runtime

## 4. Experiments

Runtime reduction achieved with our methodology:



## 5. Visualization & Phone Demo

Visualized results on NYU Depth v2:

Live Demo:

