CNNs for real-time object detection on mobiles

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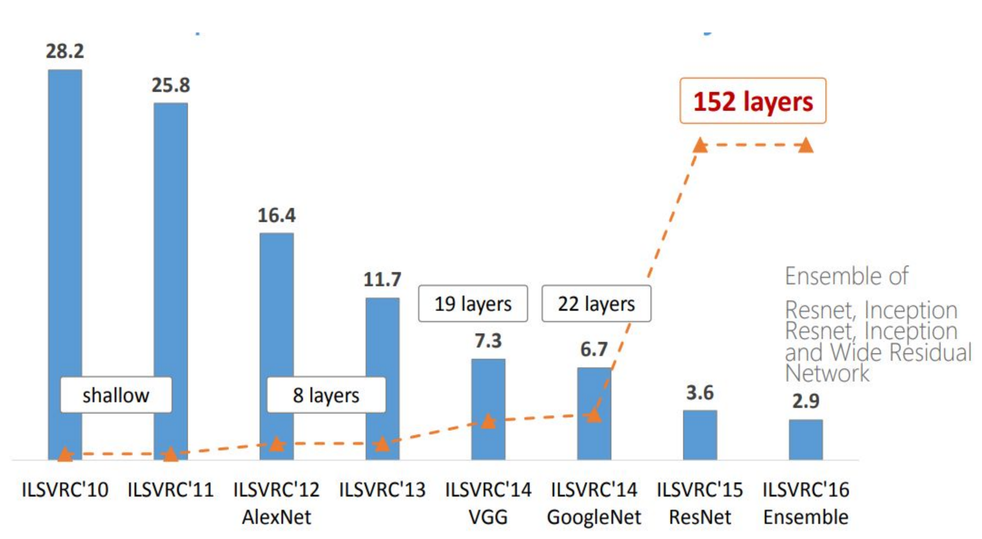
Introduction



ImageNet Classification Top-5 error (%)

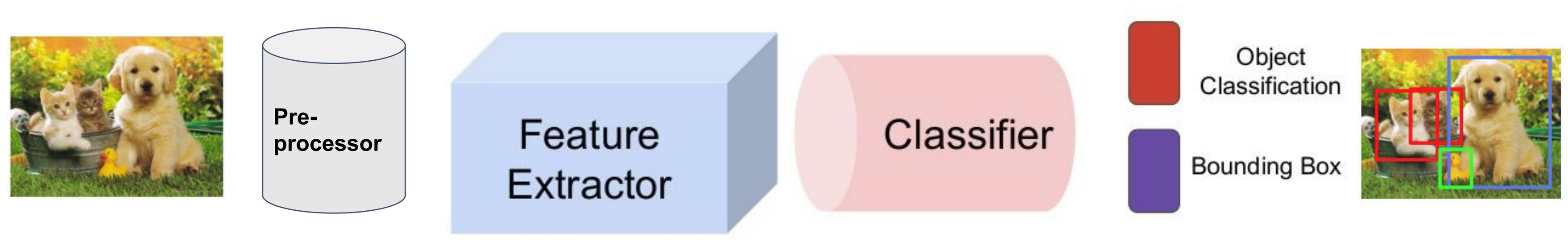
Strategies to make CNNs more efficient

- Shallow networks
- Compressing pre-trained networks
- Designing compact layers
- Quantizing parameters
- Network binarization

Model: Leeco Le 2
Chipset: Snapdragon 652
CPU: 4 x 1.8 GHz Cortex- A72 +
4 x 1.4 GHz Cortex-A53
GPU: Adreno 510
Memory: 3 GB RAM
Storage: 32 GB
OS: Android 6

Classification | **Classification + Localization** | **Object Detection**

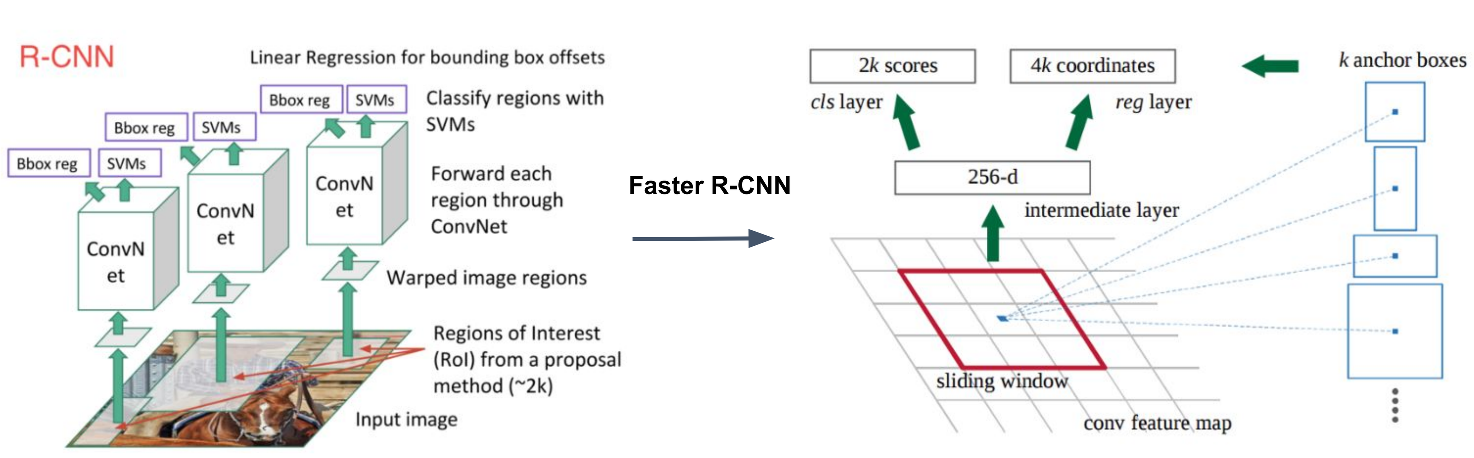
Object Detection Pipeline

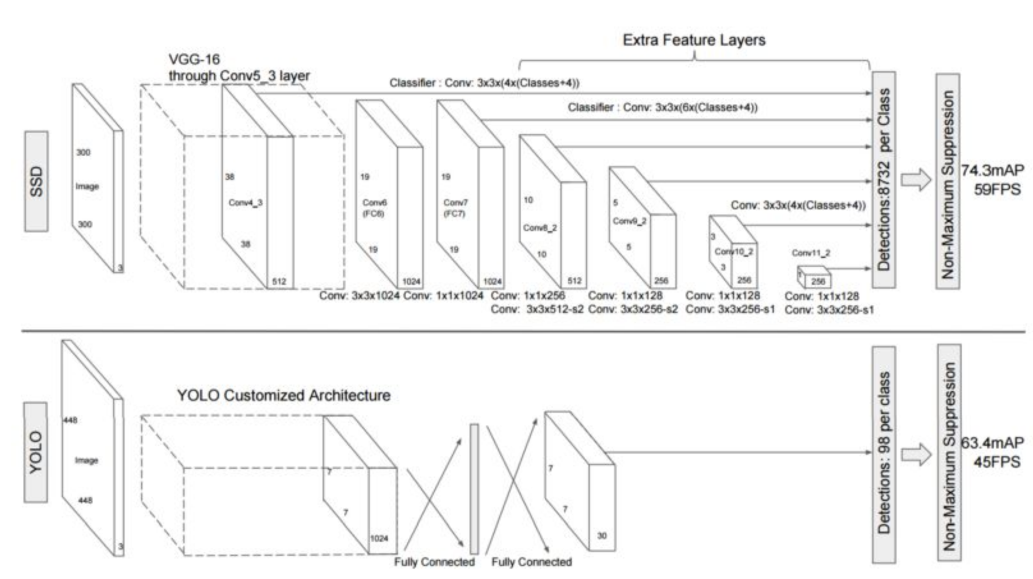


- **Image-resizing**
- **Image pixel normalization**
- **Data - Augmentation**
  - **flip**
  - **Random rotations**

- **VGG**
- **Inception**
- **Resnet**
- **Inception Resnet**
- **Googlenet**
- **MobileNet**

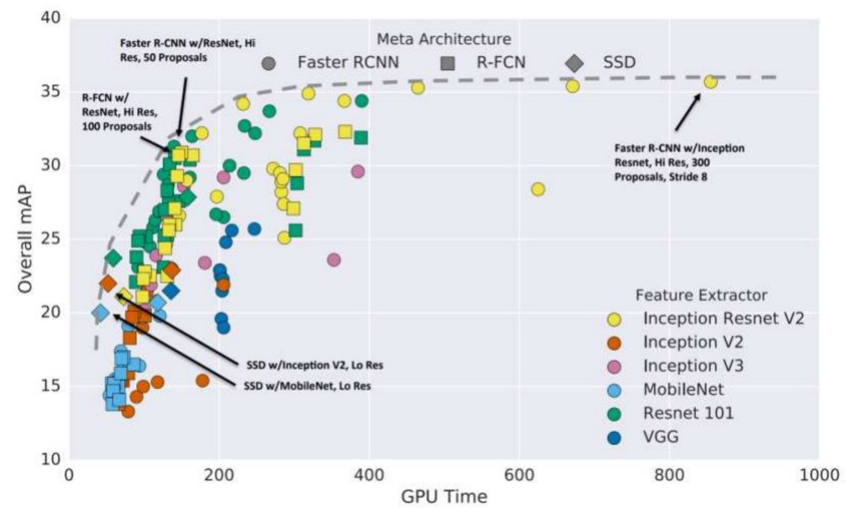
- **Single Shot Detector (SSD and YOLO)**
- **Faster R-CNN**
- **R-FCN**

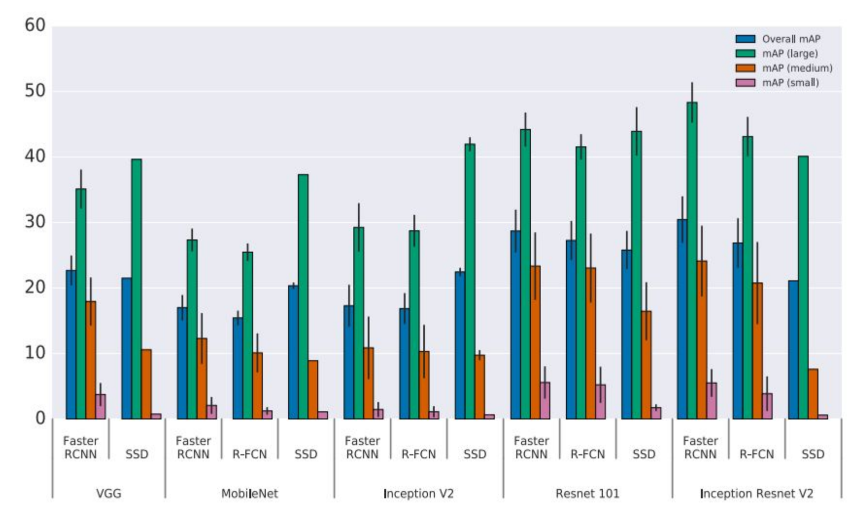




Evaluation Metrics and Test

- **Mean Average Precision (mAP)**
  - thresholding based on intersection of union score
  - average over all class predictions
  - higher the better
- **Inference time:** Preprocessing + prediction time per image
- **Memory usage:** Model's gpu/cpu usage while prediction





Transfer Learning and Implementation

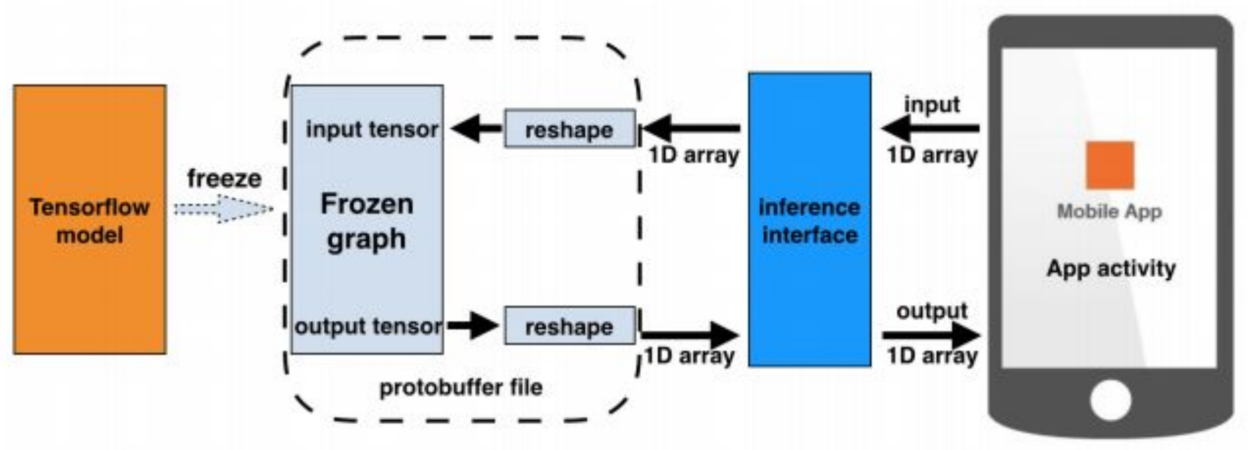
"Don't Be A Hero"
- Andrej Karpathy

Dataset

- 7481 labelled images
- 1240 x 375 pixels
- 11 classes

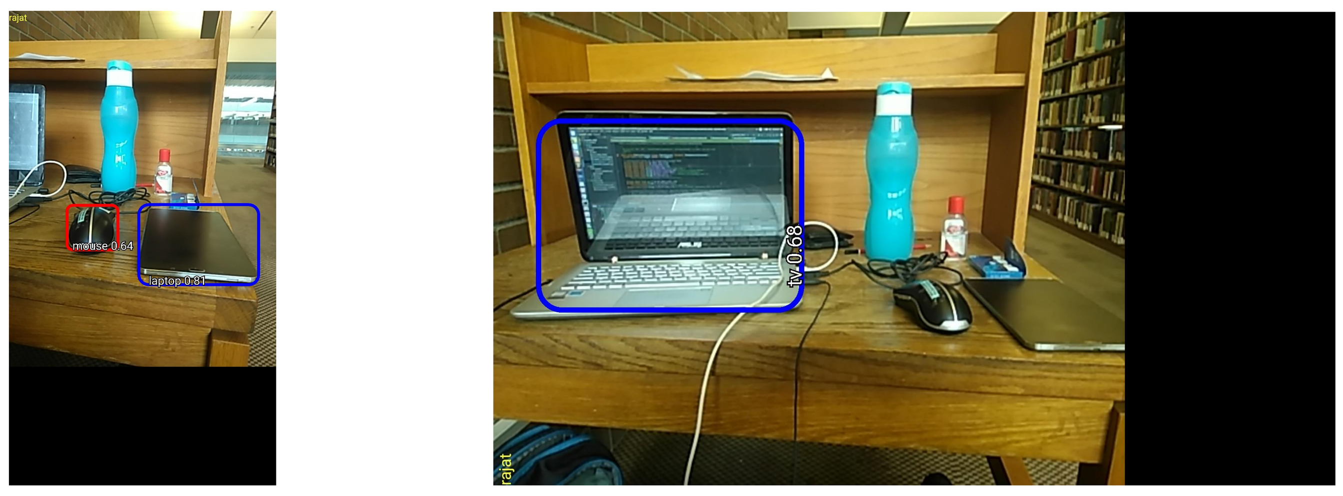
Transfer Learning	**Models**
• Finetune existing pre-trained models • Freeze the base extractor and train the classifier • Train a linear classifier at the final layer	• Mobilenet-SSD • Tiny-yolo • Incepted-SSD • Inception-Faster R-CNN

Android App Architecture

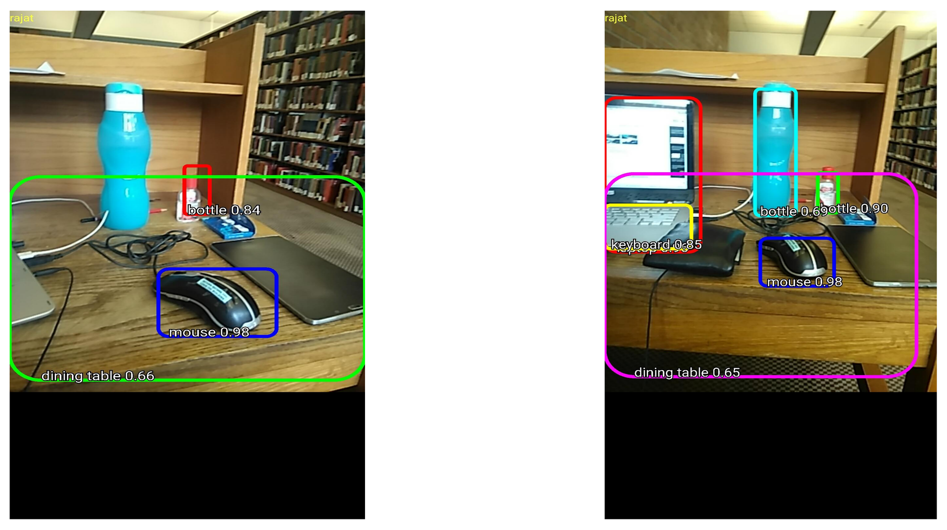


Results and Discussions

- **Mobilenet based SSD trained on COCO dataset**



- **Inception based R-CNN trained on COCO dataset**



Work in Progress

1. Benchmarking the models on the mobile device
2. Fine-tuning MobileNet-SSD on the Kitti dataset

References

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9. CSE/EE 576 Lecture Slides
10. CS231n Lecture Slides