

Towards Efficient On-Board Deployment of DNNs on Intelligent Autonomous Systems

Alexandros Kouris, Stylianos I. Venieris, **Christos-Savvas Bouganis**

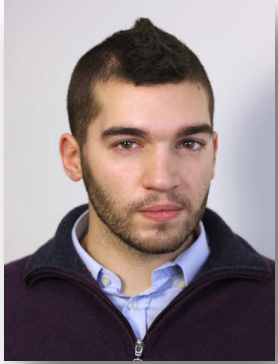
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ISVLSI, 17 July 2019

Intelligent Digital Systems Lab
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Who we are



Stylianos I. Venieris
Machine Learning
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Alexandros Kouris
Machine Learning,
Robotics



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Computer Vision, SLAM



Aditya Rajagopal
HW for Machine Learning



Mario Lopes Ferreira
Research Assistant



Christos-Savvas Bouganis
Lab Director
Reader at
Imperial College London



Manolis Vasileiadis
Computer Vision



Mudhar Bin Rabieah
Machine Learning



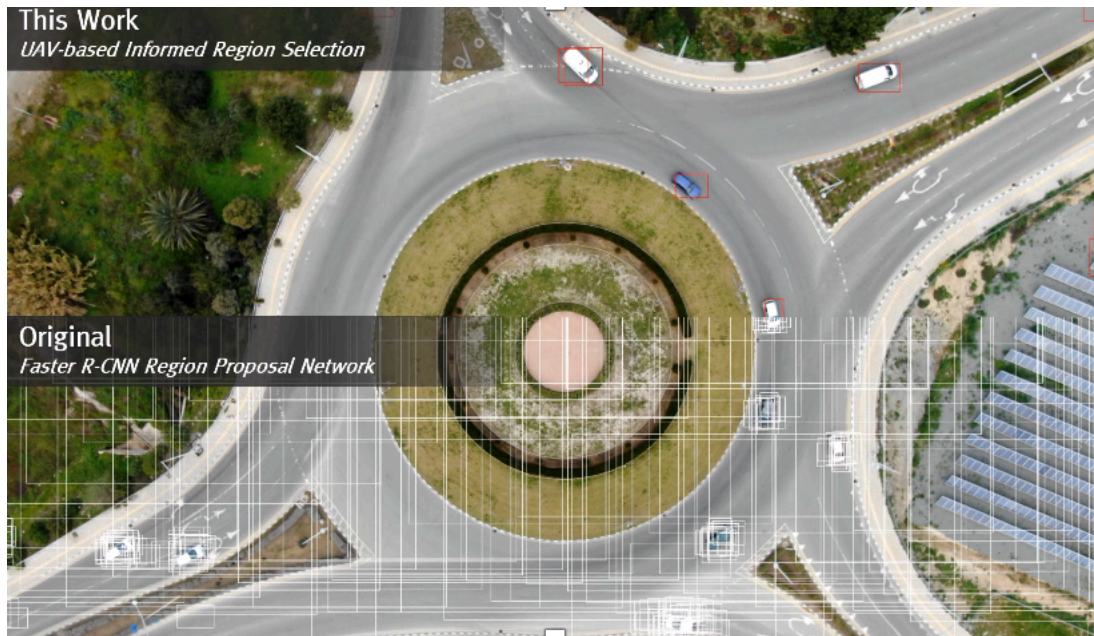
Nur Ahmadi
Brain-Machine Interface



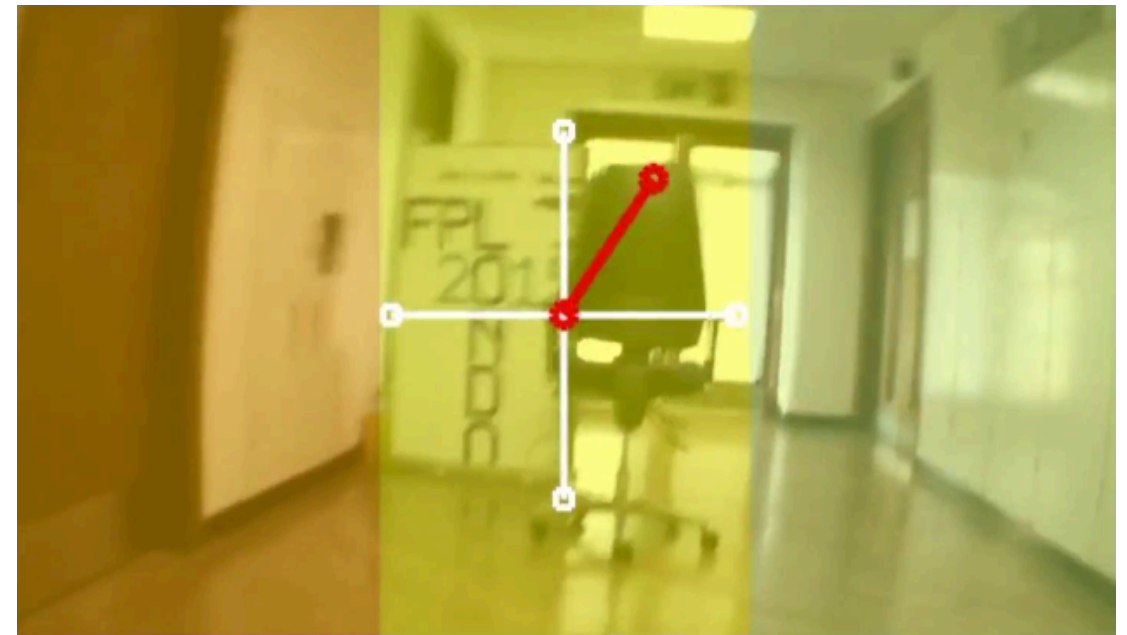
Diederik Vink
Machine Learning

Examples of Intelligent and Autonomous Systems

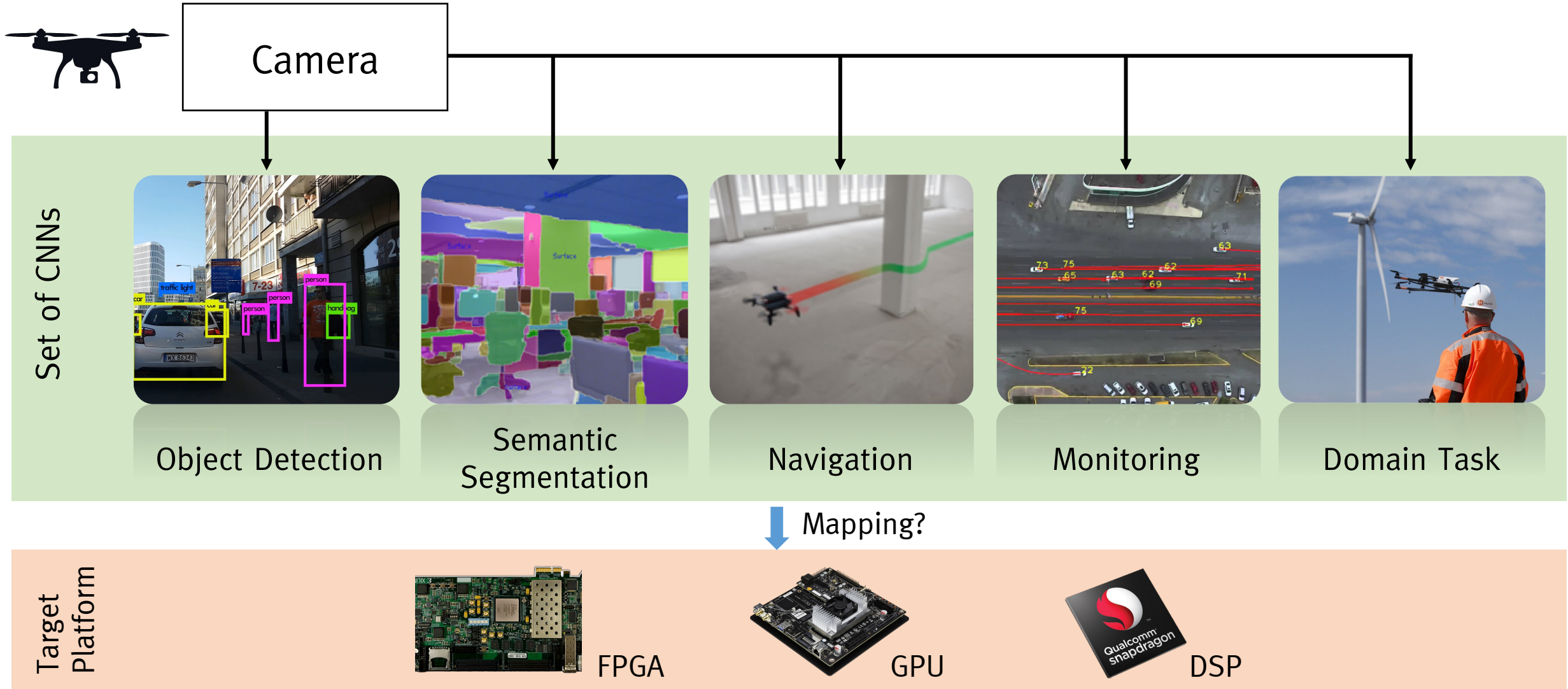
Traffic Detection



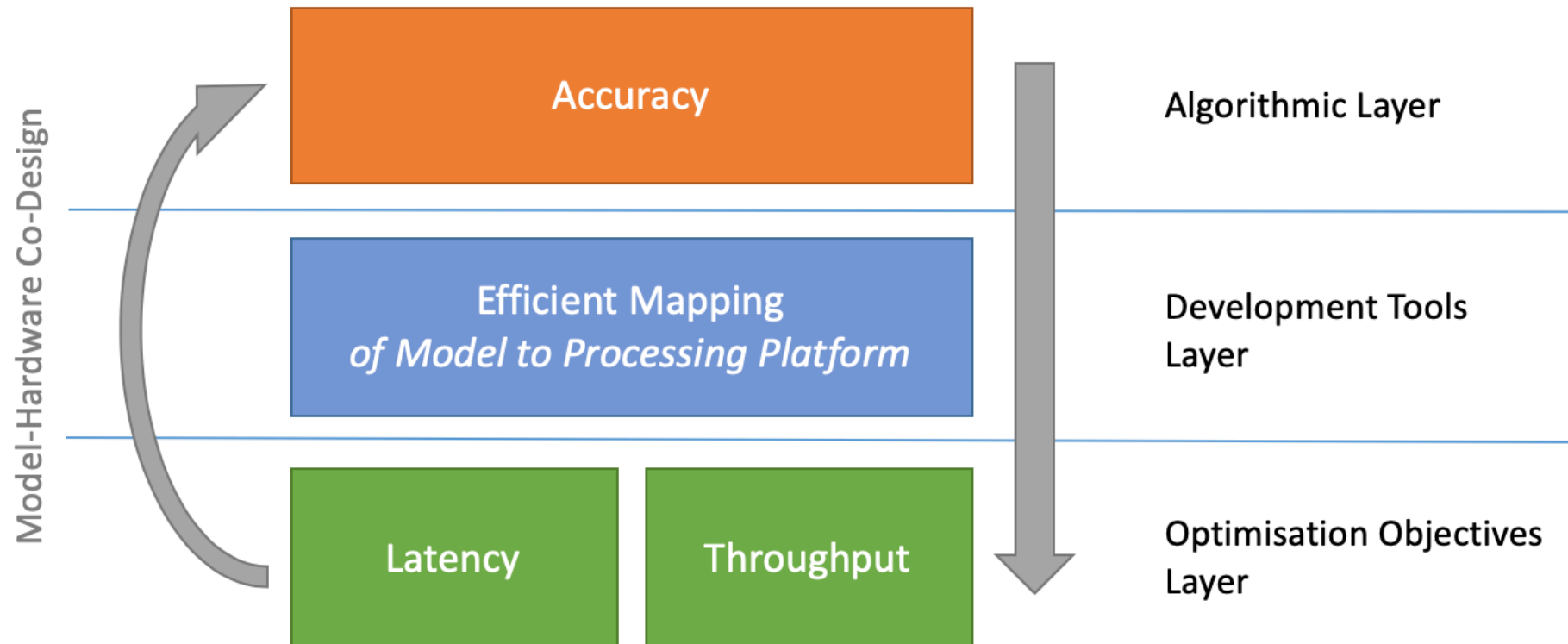
Autonomous Navigation

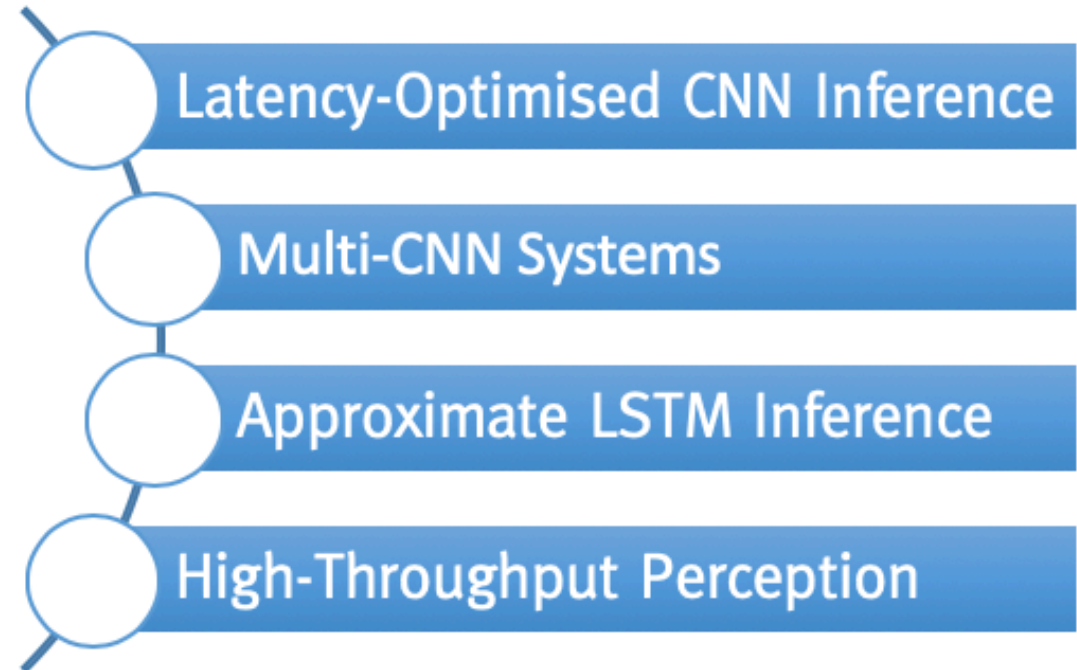


DNNs on Intelligent Autonomous Systems

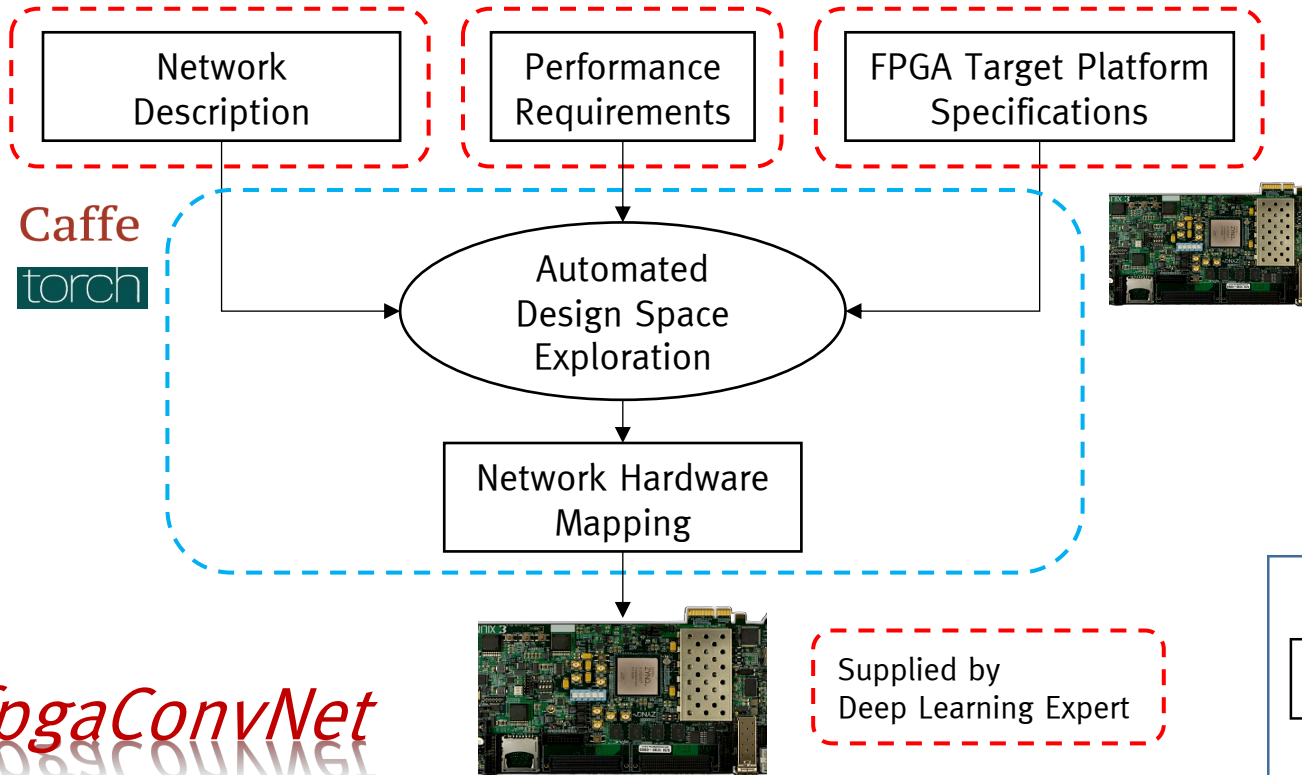


Our Approach – Intelligent Autonomous System Development Stack





Latency-Optimised CNN Inference

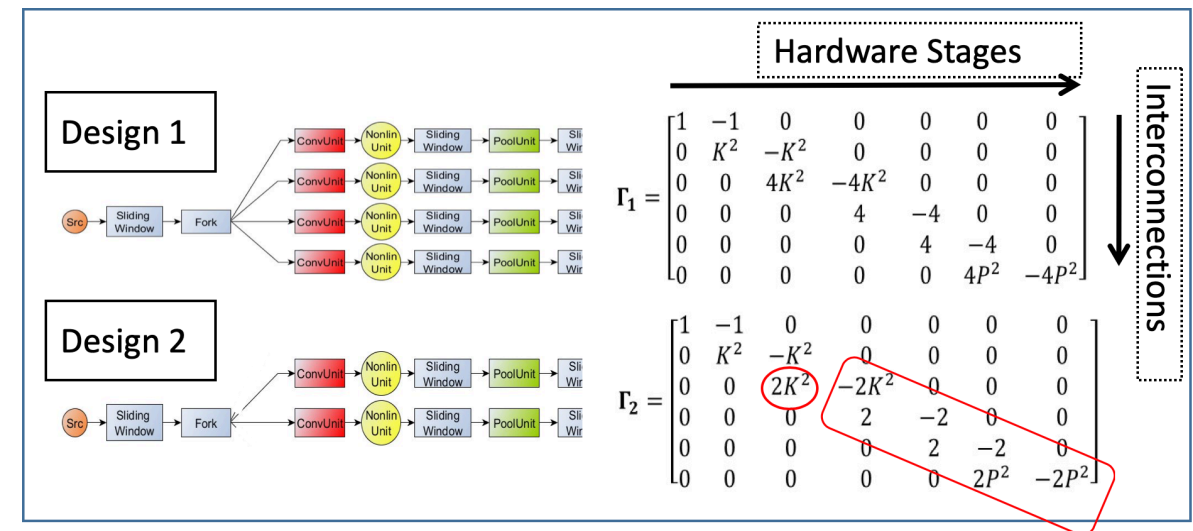


Challenges:

- High-dimensional design space
- Diverse application-level needs
- Utilise the FPGA resources
- Design automation

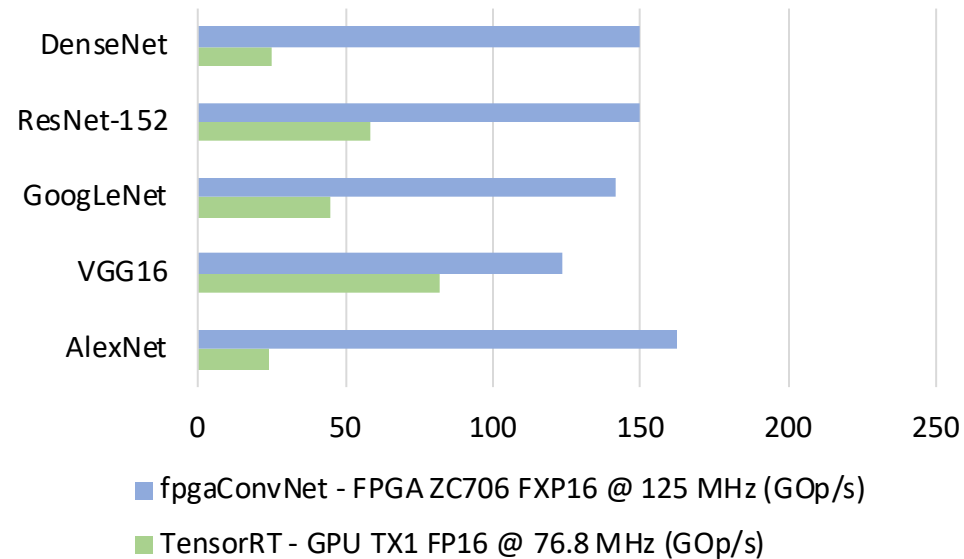
Synchronous Dataflow Modelling

- Capture hardware mappings as matrices
- Transformations as *algebraic operations*
- Analytical *performance model*
- Cast design space exploration as a mathematical optimisation problem

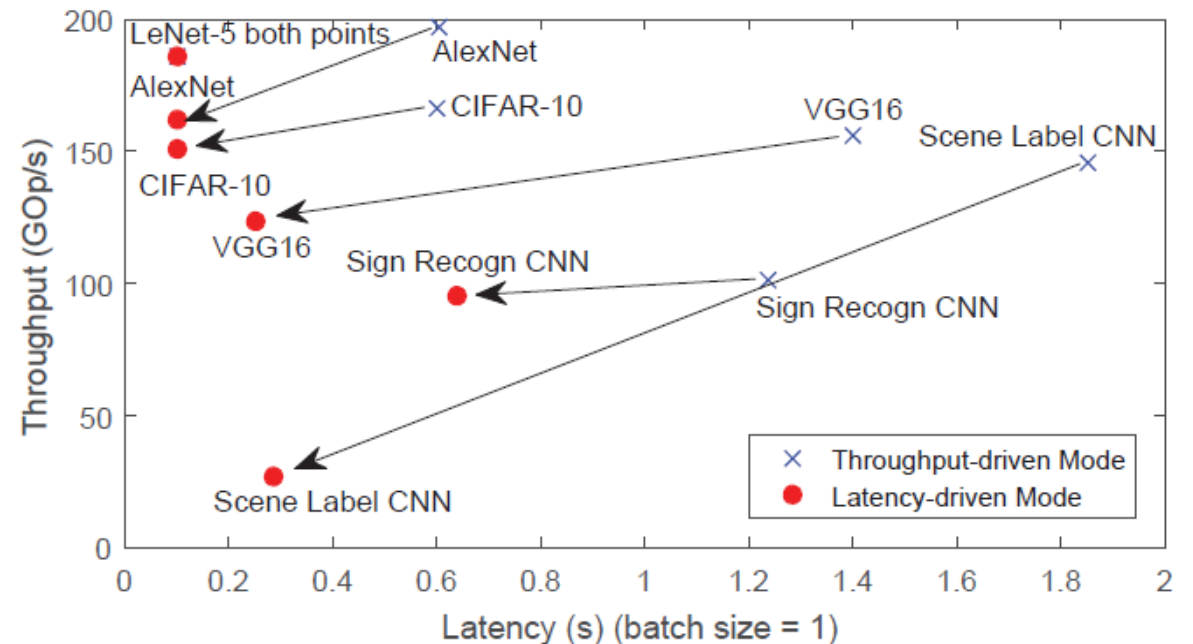


Latency-Optimised CNN Inference

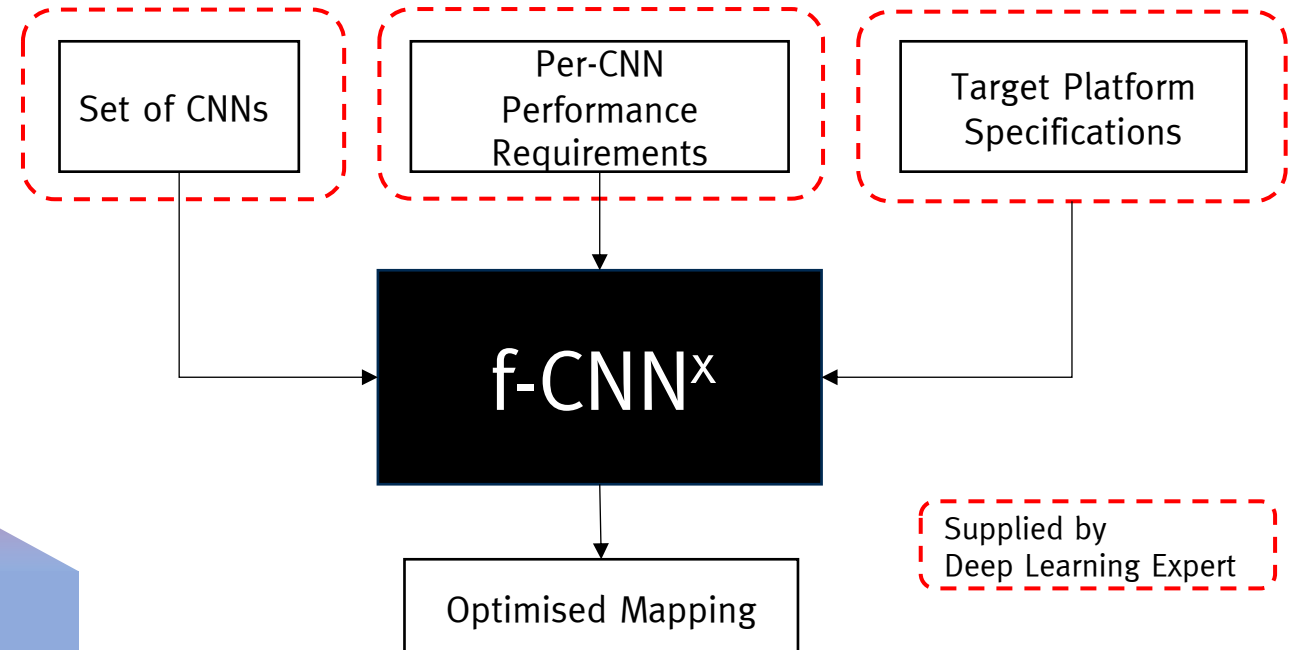
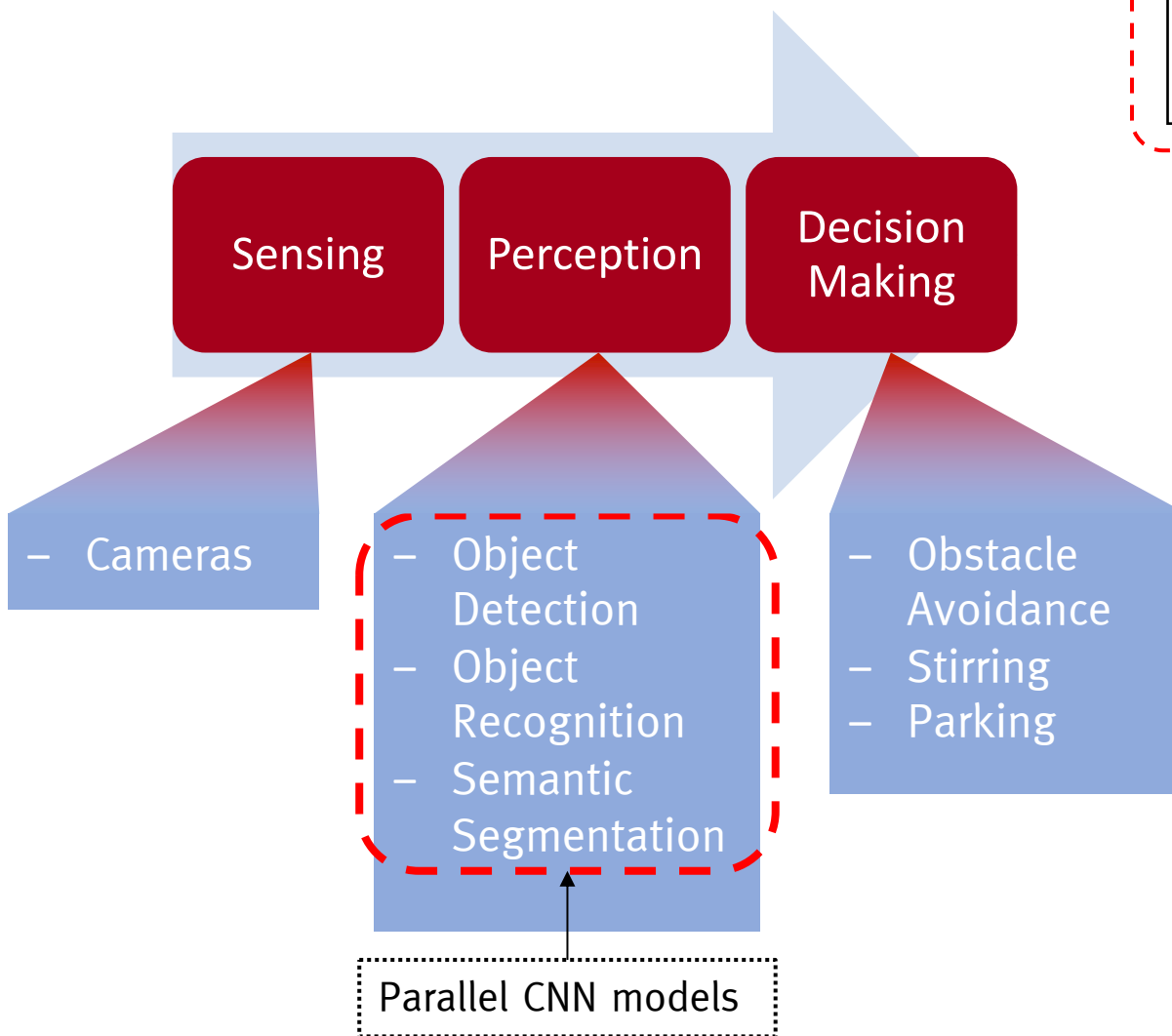
fpgaConvNet vs Embedded GPU (GOp/s)
for the same absolute power constraints (5W)



- Latency-driven scenario → batch size of 1
- Up to 6.65× speedup with an average of 3.95× (3.43× geo. mean)



Multi-CNN Autonomous Systems



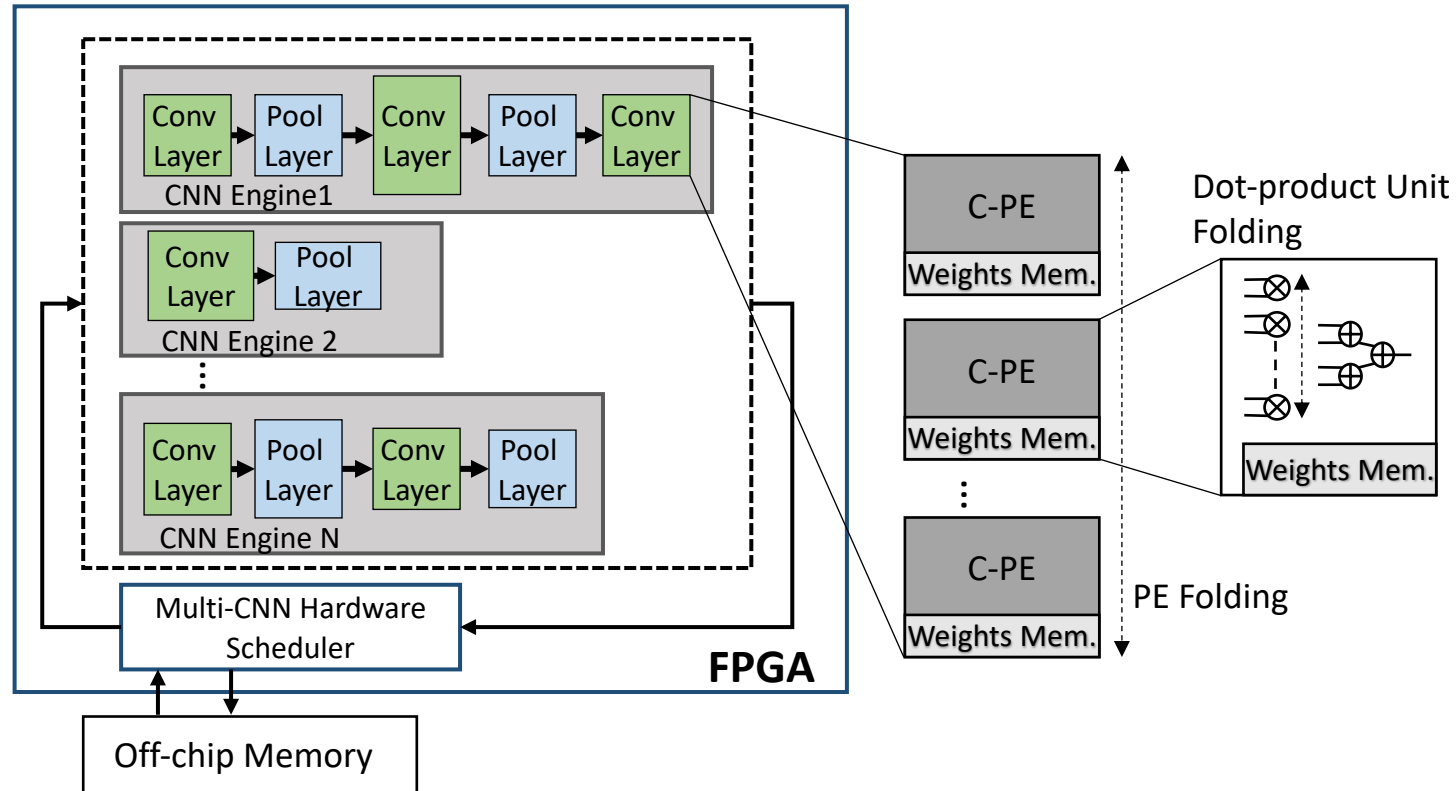
Challenges:

- Resource allocation among CNNs
- Design automation

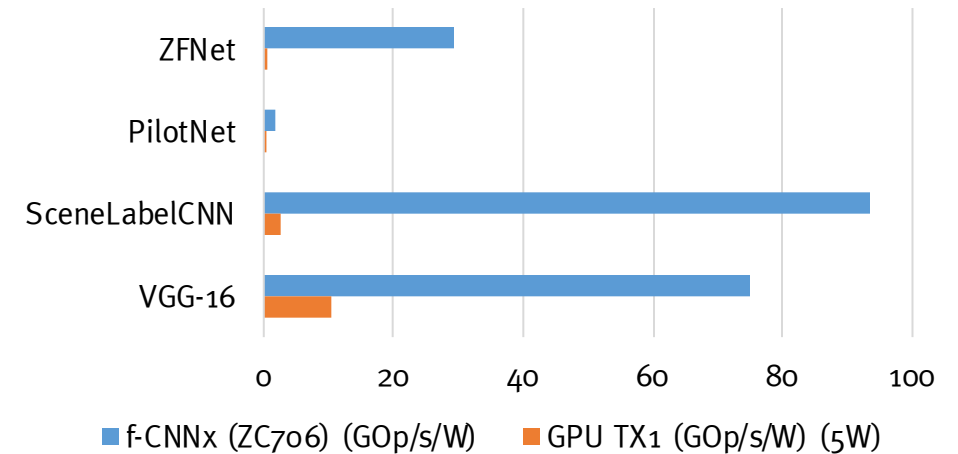
Why?

- Models with different performance constraints
- Competing for the same pool of resources
- High-dimensional design space

Multi-CNN Autonomous Systems

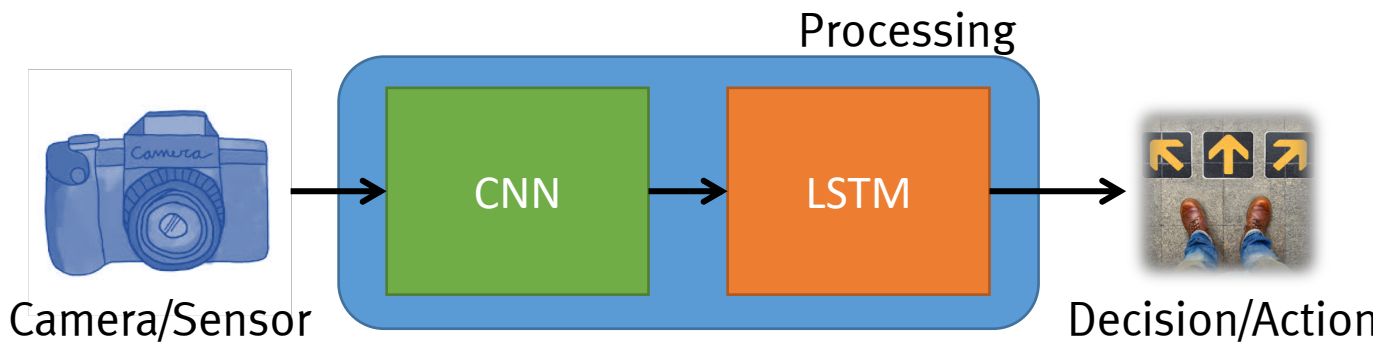
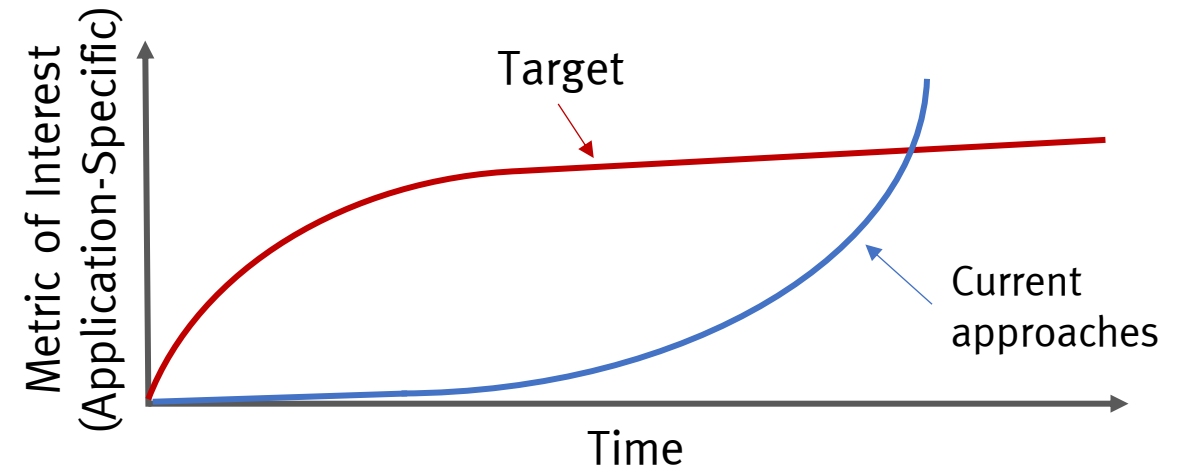


Performance-per-Watt: f-CNNx vs. TX1 at 5W



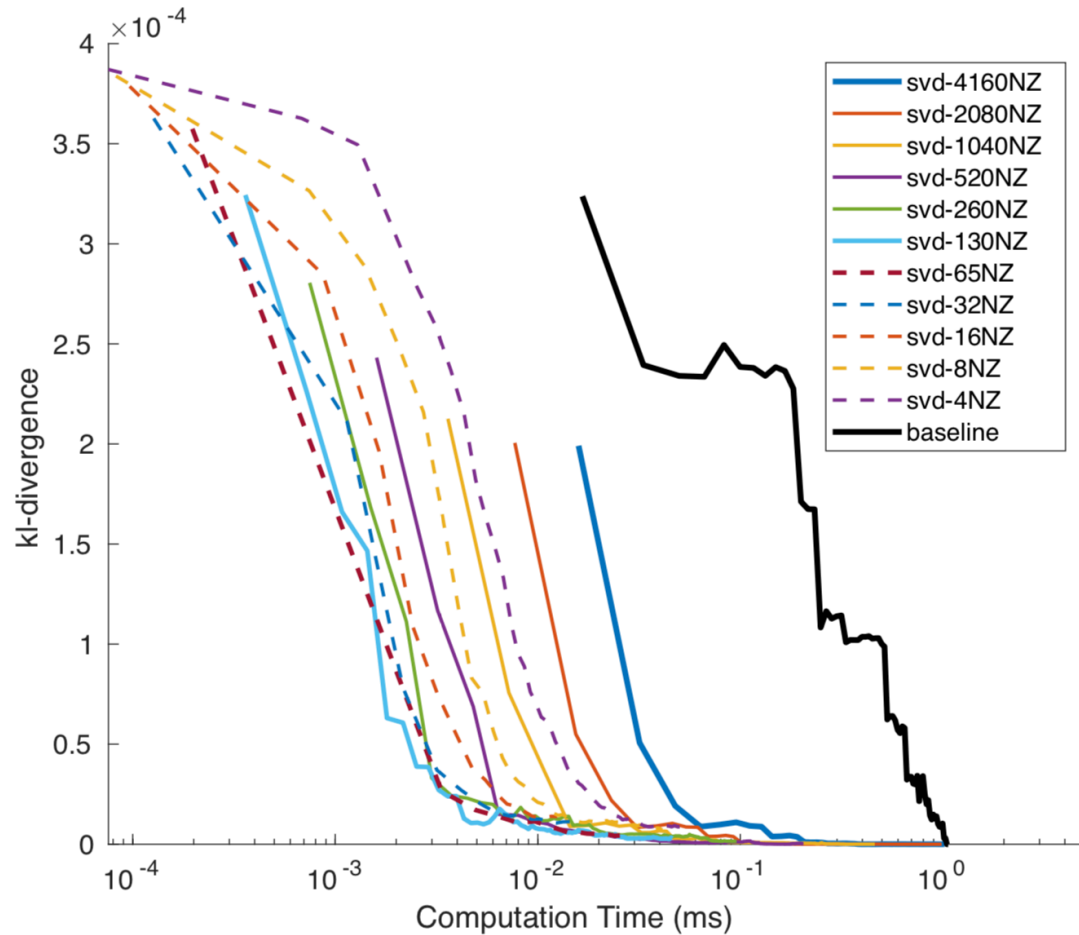
- Latency-driven scenario → batch size of 1
- Up to 19.09× speedup with an average of 6.85× (geo. mean)

Time-constrained Approximate LSTM Inference

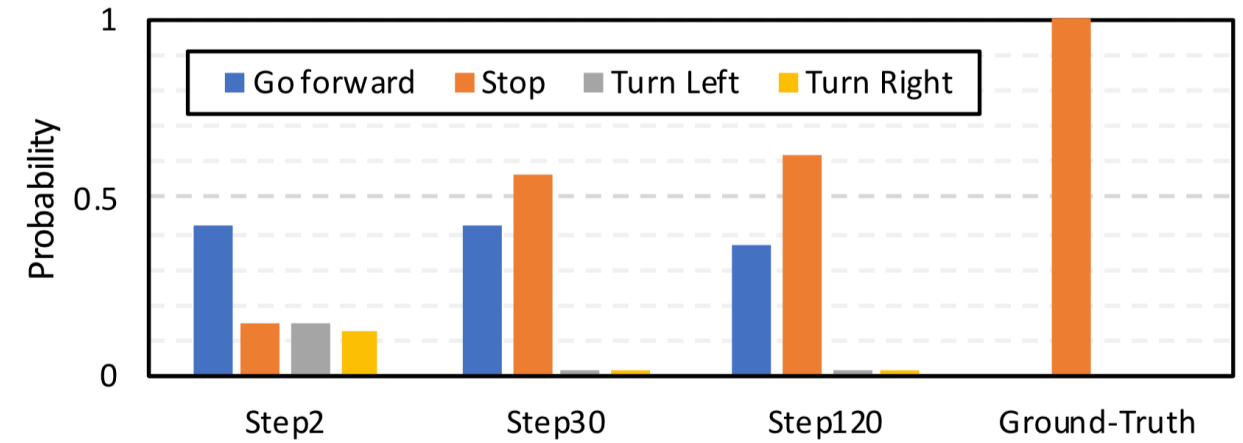


- Approximate LSTMs
 - Iterative refinement using:
 - SVD-based low-rank approximation
 - Sparsification (structured pruning)
- Co-optimize given a user-defined time budget
- Custom parametrisable architecture

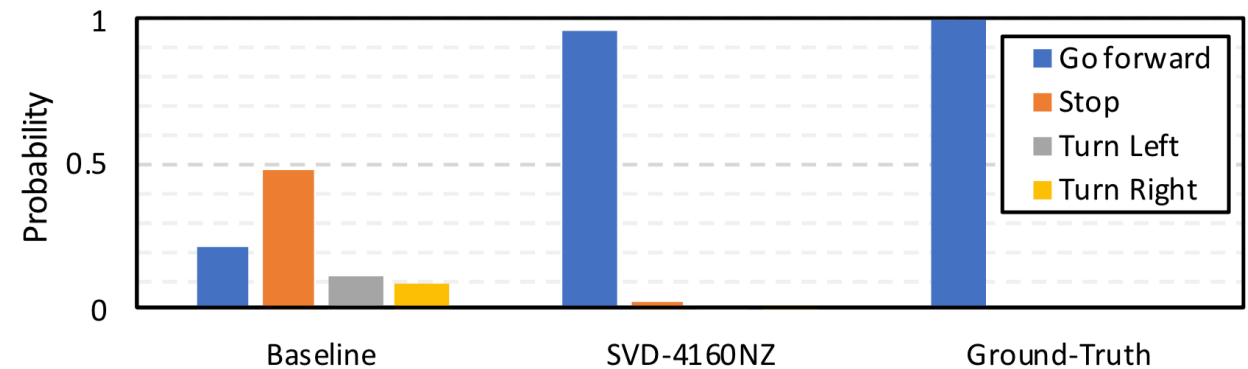
Time-constraint Approximate LSTM Inference



Progressive Inference:



Time-Constraints Inference:



Privacy-aware High-Throughput Inference

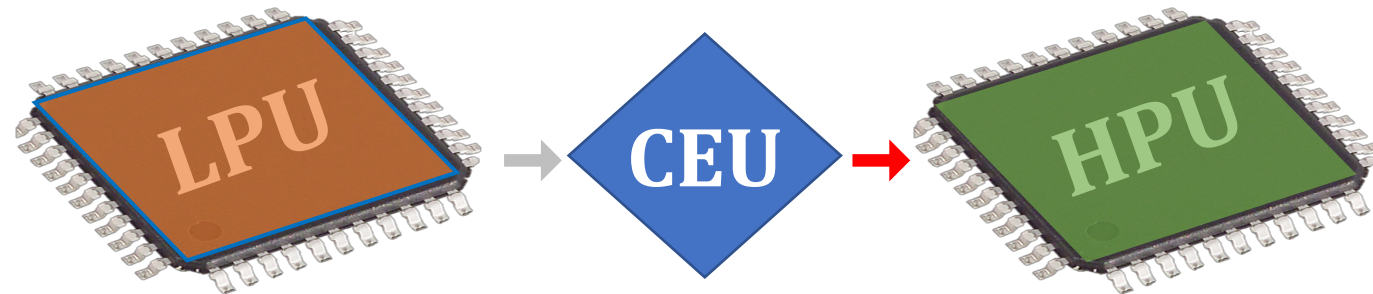
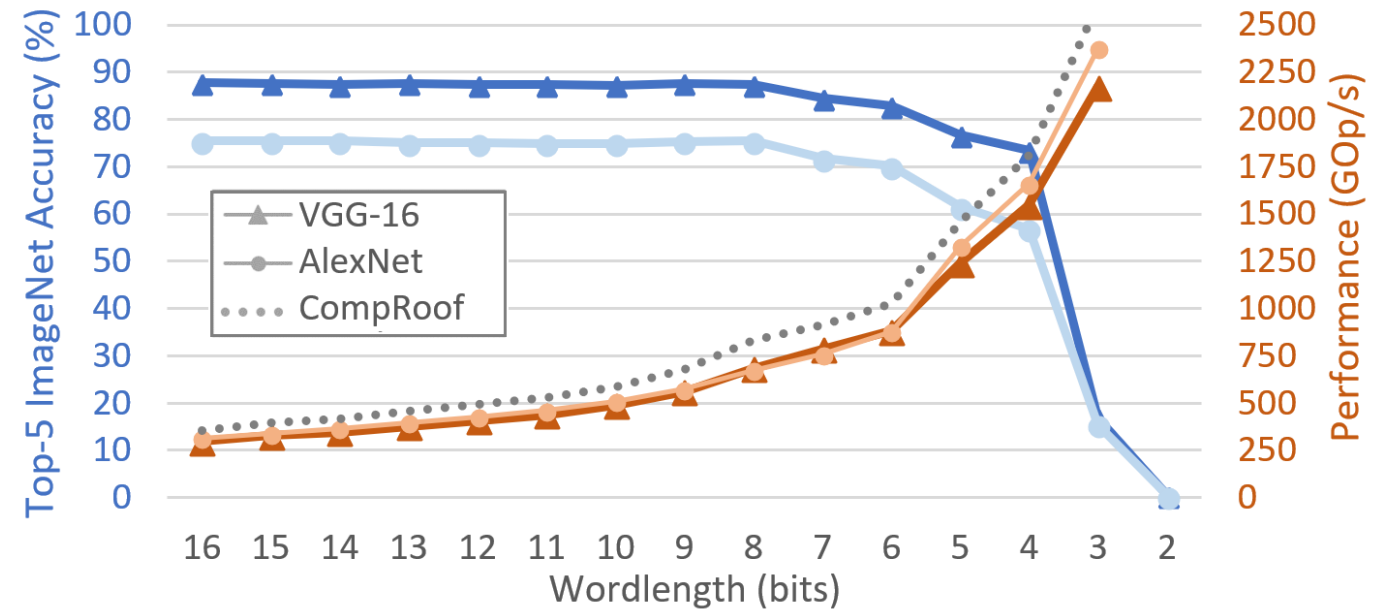
Aim: Design an optimised HW system (performance and accuracy)

Given:

- A High-Level CNN Description (i.e. Caffe)
- A target FPGA platform
- ~~Training Data~~ *privacy, availability*
- *Testing Data*
- Target metric (top1/top-5 accuracy, ...)

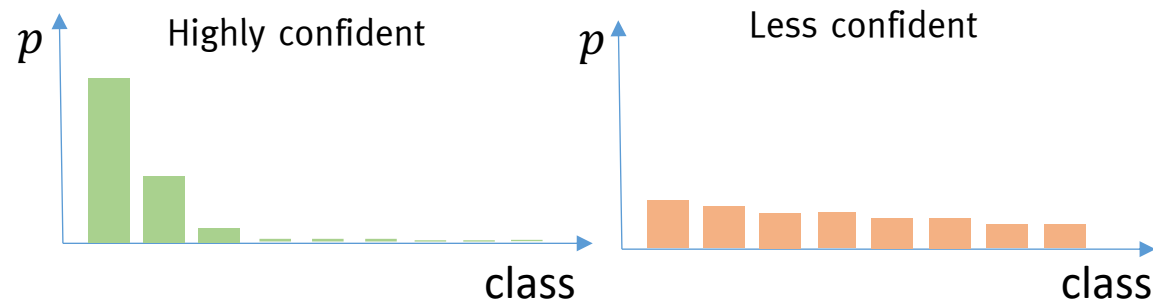
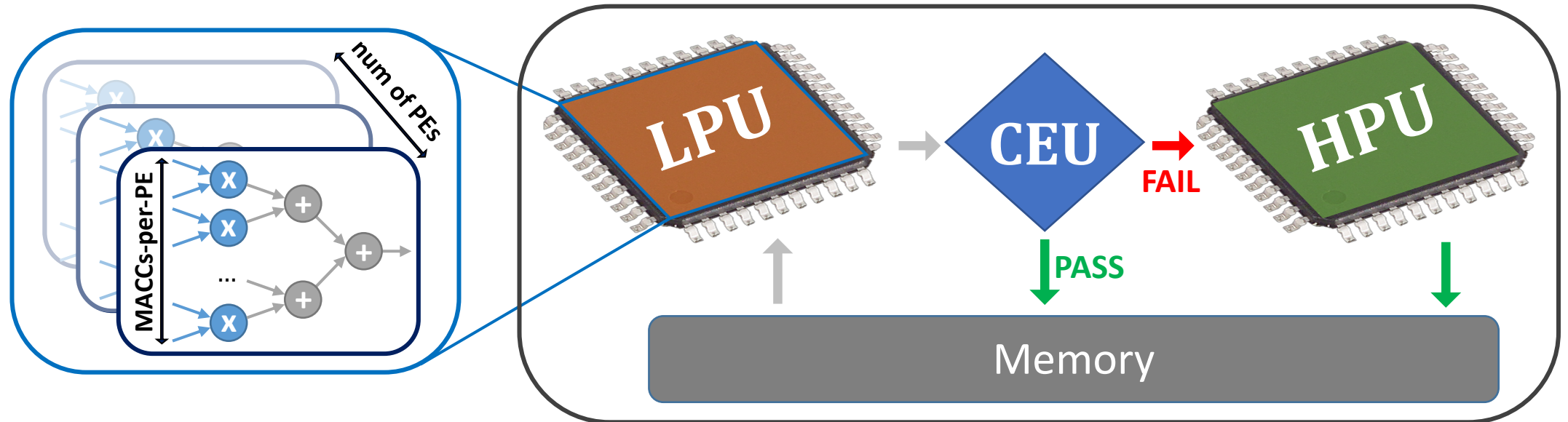
CascadeCNN:

- Exposes the application-level *error tolerance* to the Design Space Exploration
- Develops *highly parametrised search spaces* for: *quantisation & architectural configuration*
- Does not require access to the *training data*



Privacy-aware High-Throughput Inference

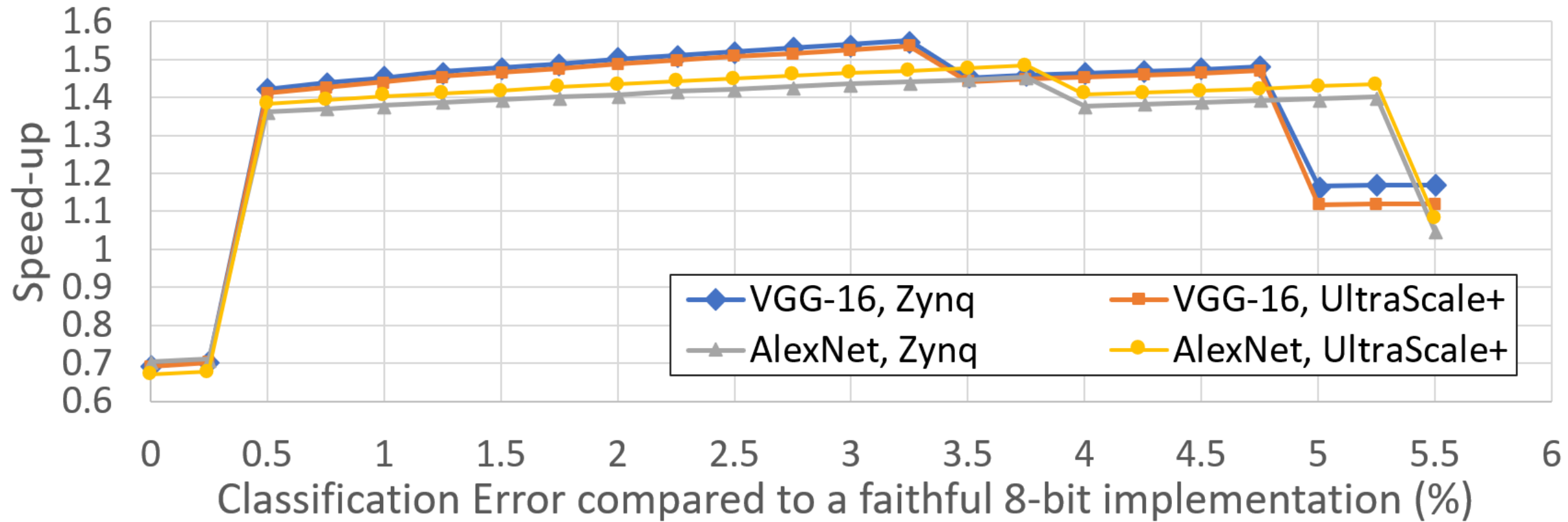
- Pushing quantization below limits of acceptable accuracy to gain performance (high throughput)
- Evaluation of Quality of Prediction to identify and correct error introduced by quantization



Low-Precision Unit:
Degraded accuracy
classification with
high performance

**Confidence
Evaluation Unit:**
Identify
misclassified cases

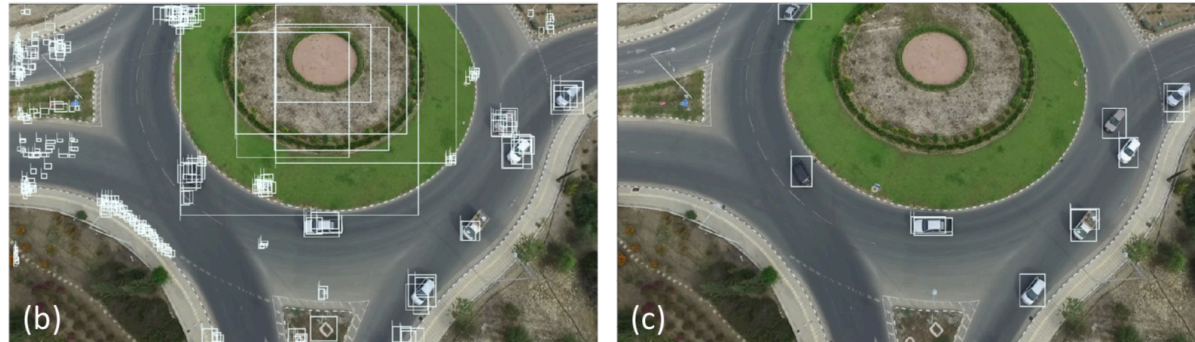
High-Precision Unit:
Correct detected
misclassified samples,
to restore accuracy

Privacy-aware High-Throughput Inference

Conclusions

- Efficient deployment of DNNs on embedded devices requires a holistic approach
- Need of tools to help the designer to address the complexity of the design process

Traffic Detection



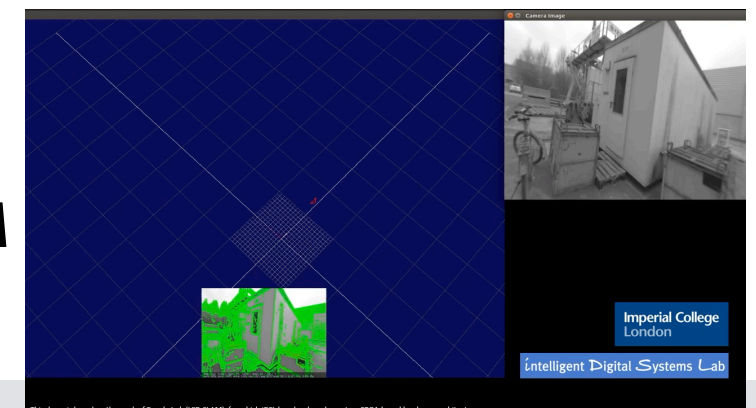
Autonomous Navigation



Pose estimation using ML



Embedded SLAM



Selected Publications

- ✓ Stylianos I. Venieris and Christos-Savvas Bouganis. 2016. **fpgaConvNet: A Framework for Mapping Convolutional Neural Networks on FPGAs**. In 2016 IEEE 24th Annual International Symposium on Field-Programmable Custom Computing Machines (FCCM). 40–47.
- ✓ Stylianos I. Venieris and Christos-Savvas Bouganis. 2017. **fpgaConvNet: A Toolflow for Mapping Diverse Convolutional Neural Networks on Embedded FPGAs**. In NIPS 2017 Workshop on Machine Learning on the Phone and other Consumer Devices.
- ✓ Stylianos I. Venieris and Christos-Savvas Bouganis. 2017. **fpgaConvNet: Automated Mapping of Convolutional Neural Networks on FPGAs** (Abstract Only). In Proceedings of the 2017 ACM/SIGDA International Symposium on Field-Programmable Gate Arrays. ACM, 291–292.
- ✓ S. I. Venieris and C. S. Bouganis. 2017. **Latency-Driven Design for FPGA-based Convolutional Neural Networks**. In 2017 27th International Conference on Field Programmable Logic and Applications (FPL).
- ✓ Alexandros Kouris, Stylianos I. Venieris, and Christos-Savvas Bouganis. 2018. **CascadeCNN: Pushing the performance limits of quantisation**. In SysML.
- ✓ Stylianos I. Venieris, Alexandros Kouris, and Christos-Savvas Bouganis. 2018. **Toolflows for Mapping Convolutional Neural Networks on FPGAs: A Survey and Future Directions**. In ACM Computing Surveys 51, 3, Article 56 (June 2018), 39 pages.
- ✓ Alexandros Kouris, Stylianos I. Venieris, and Christos-Savvas Bouganis. 2018. **CascadeCNN: Pushing the Performance Limits of Quantisation in Convolutional Neural Networks**. In 2018 28th International Conference on Field Programmable Logic and Applications (FPL).
- ✓ S. I. Venieris and C. S. Bouganis. 2018. **f-CNNx: A Toolflow for Mapping Multiple Convolutional Neural Networks on FPGAs**. In 2018 28th International Conference on Field Programmable Logic and Applications (FPL).
- ✓ C. Kyrkou, G. Plastiras, T. Theocharides, S. I. Venieris, and C. S. Bouganis. 2018. **DroNet: Efficient Convolutional Neural Network Detector for Real-Time UAV Applications**. In 2018 Design, Automation Test in Europe Conference Exhibition (DATE). 967–972.
- ✓ Michalis Rizakis, Stylianos I. Venieris, Alexandros Kouris, and Christos-Savvas Bouganis. 2018. **Approximate FPGA-based LSTMs under Computation Time Constraints**. In Applied Reconfigurable Computing - 14th International Symposium, ARC 2018, Santorini, Greece, May 2 - 4, 2018, 3–15.
- ✓ Alexandros Kouris and Christos-Savvas Bouganis. 2018. **Learning to Fly by MySelf: A Self-Supervised CNN-based Approach for Autonomous Navigation**. In IEEE/RSJ International Conf. on Intelligent Robots and Systems (IROS), 2018
- ✓ Stylianos I. Venieris, Alexandros Kouris and Christos-Savvas Bouganis. 2019. **Deploying Deep Neural Networks in the Embedded Space**, in MobiSys18: 2nd International Workshop on Embedded and Mobile Deep Learning (EMDL)
- ✓ Alexandros Kouris, Stylianos I. Venieris, Michalis Rizakis, and Christos-Savvas Bouganis. 2019. **Approximate LSTMs for Time-Constrained Inference: Enabling Fast Reaction in Self-Driving Cars** [Under Review – available on arXiv: <https://arxiv.org/pdf/1905.00689.pdf>]
- ✓ Alexandros Kouris, Christos Kyrkou and Christos-Savvas Bouganis. 2019. **Informed Region Selection for Efficient UAV-based Object Detectors: Altitude-aware Vehicle Detection with CyCAR Dataset**, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2019 [to appear]