DEEP LEARNING FOR AUTOMOTIVE – A HETEROGENEOUS APPROACH

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Table of Content

Introduction

Machine Learning (ML) is one of the classes of Artificial Intelligence (AI) that enables systems to learn from historical data and develop intelligence. The intelligence is used to predict or estimate new outcomes. The types of learning are often categorized as Supervised, Unsupervised, Semi-Supervised, and Reinforcement. In the learning process, the relation between input and target is modelled as linear or nonlinear functions, with thousands of variables that are estimated using algorithms. When the relation between input and target is more complex, millions of variables are used this evolution of learning is termed as Deep Learning.

ML is not a single technology or technique, rather a domain of computation and analytics that incorporates various technologies. The systems with ML algorithms can learn from the past data in their environment. Once learnt, they make predictions and take actions when encountered with a new situation (similar to human decision-making process).

AI has revolutionized the world in various domains, and evolved to ML and to Deep Learning (DL). Artificial Neural Networks is an important class of machine learning model that tries to mimic the human neuro system for learning. In Deep Neural Networks, the architecture will have more layers and variables to learn the deep relation in the data.

Convolutional Neural Networks (CNNs) are one of the most popular Deep Neural Network (DNN) architectures, which in turn are a part of DL

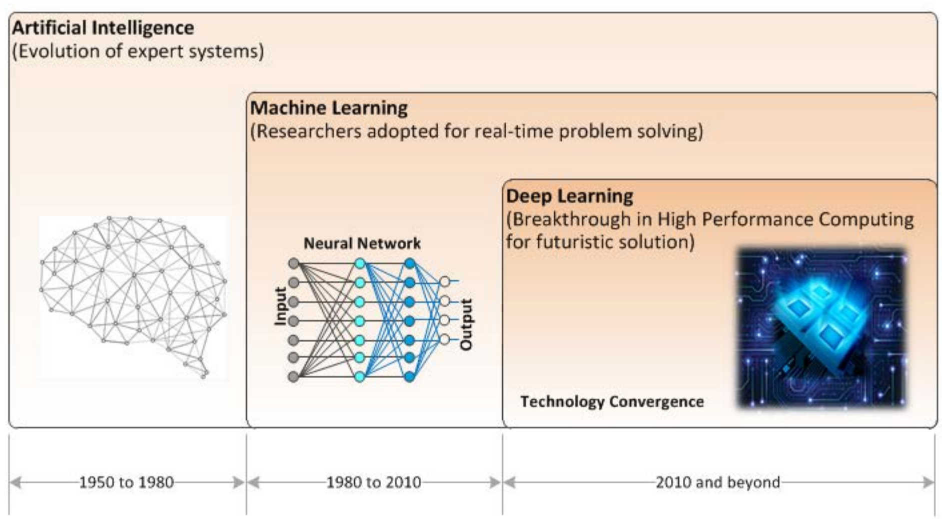

Figure 1: Artificial Intelligence technology evolution

The objective of this paper is to enlighten on the need for DL technology and its adaptation in the industry, as well as ecosystem requirements for solution development. Primarily, this paper focuses on the automotive industry segment.

Deep Neural Network (DNN) Technology Demands

In recent days, DL had firmly expanded its footprint to various domains in problem solving. Recent advances in this technology are used to solve significant real time problems in computer vision, speech recognition, medical, and robotics, etc. CNN based DL or DNN technique is one of cutting-edge methods, which is increasingly being adopted in the industry.

DNNs deliver state-of-art accuracy on many AI tasks, which demand cost of high computational complexity. DL, a frontier area of research within ML uses Neural Networks with many layers (hence forth labeled as DEEP) to push the boundaries of machine capabilities.

Data scientists have made breakthroughs using DL to recognize objects, faces, and gesture to understand and generate language.

Also, reinforcement learning is used to identify and determine the best actions to take in each situation. For instance, heterogeneous data streams produced by smart cars and smart cities can be analyzed)in order to attain the goal of smart travel and smart living.

Presented below are some of the use cases of DL techniques used in various domain for problem solving:

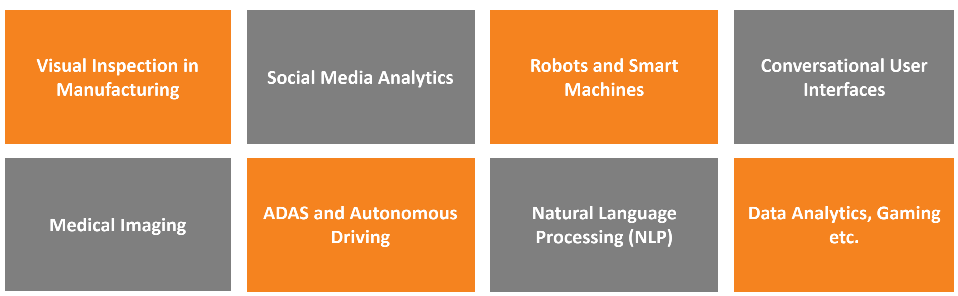

Figure 2: Deep Learning adaptation in different domain areas

Convolutional Neural Network (CNN) for Automotive Solutions

DL technology is bringing out a effecting in the automotive domain over conventional Advanced Driver Assistance Systems (ADAS). This in turn, will have substantial impact on self-driving cars.

When compared to traditional pattern detection methods, CNNs are advantageous because they can be trained efficiently for various scenarios. In future, CNN will be trained for more complex tasks like, judgment and adaptive prediction and strategy driven driving. In particular, when networks become sophisticated enough to recognize actions and context accurately, the ultimate evolutionary goal of self-driving cars be realized

Visual tasks, with enabled by modern sensor networks, connect cars with DL technology will certainly deliver improved and sophisticated ADAS technology to the user. Some of them being:

- Lane Detection (LD)
- Object Detection (OD) Pedestrian Detection (PD)
- Road Signs Recognition
- Blind-Spot Monitoring
- Advanced Parking Assistance
- Trailer Detection
- Adaptive Cruise Control (ACC)
- Forward Collision Warning (FCW)
- Driver Monitoring
- Collision Mitigation by Braking (CMBB)

The algorithm spectrum for the above is not just limited to DL Different signal processing techniques and advancement in sensing technology like, Light Detection and Ranging (LiDAR), RADAR, improved Camera Sensor, and Ultrasonic Sensors will assist the DL technology to mature further and solve complex problems.

For example, DL allows detection of multiple objects, improves perception, supports object classification, enables recognition and prediction of actions, and makes ADAS systems more advanced and robust.

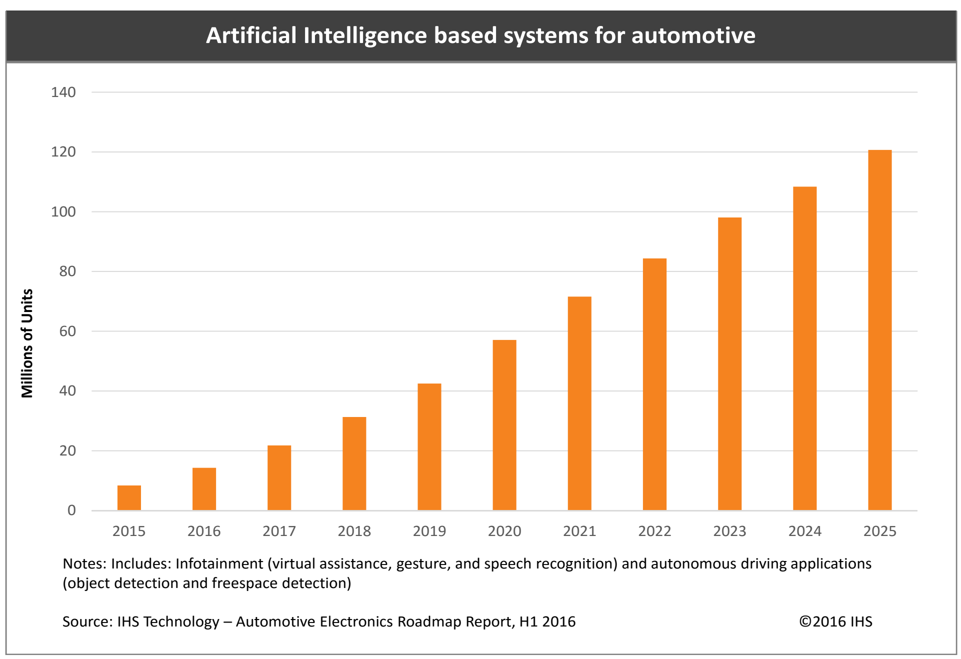

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Figure 3: AI based system for Automotive demand

Deep Learning – A Heterogeneous Composition

DL development constitutes of Hybrid and Heterogeneous environments. To address the real-time demand on ADAS/Autonomous driving a versatile DL ecosystem is needed. In general, to adopt and solve a problem using of Deep Learning technology two main segments are required.

(i) Training a DNN (to solve the problem)

(ii) Detection in real-time (deploying or implementing the trained network on the platform)

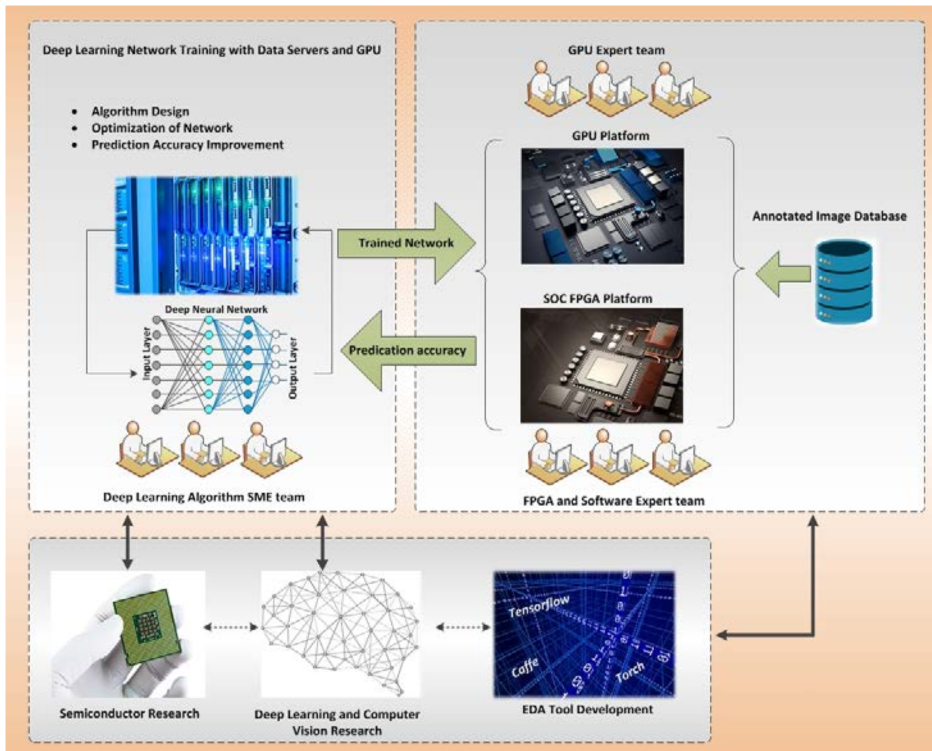

Figure 4: Deep Learning development environment - Overview

For example, image recognition in autonomous vehicles requires the vehicle to process a 360-degree dynamic environment. This demands dual frame processing because collected frames must be combined and considered in context with each other.

In general, the vehicle is equipped with a rotating camera to gather all relevant driving data. The machine must be able to recognize metric, symbolic, and conceptual knowledge. Conceptual knowledge allows the vehicle to understand the traffic and predict the driving scenario. This conceptual knowledge is an essential aspect for being able to detect specific objects and avoid collisions.

As stated in Figure 4, to address the above requirement, the machine vision experts and algorithm experts carefully analyze the captured video data set. An efficient network will be modelled and trained using high-end hardware clusters (CPU/GPU). The modelled network will also be examined using various SOC and FPGA platforms for performance. This ecosystem allows the semiconductor companies to simultaneously research and develop an enriched silicon with large on-chip resources with low power.

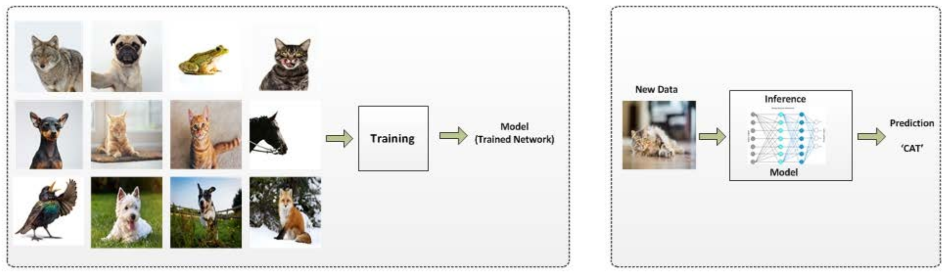

Figure 5: Deep Learning Training and Detection – An example

Training a Network (Deep Neural Network)

To solve a problem in real-time, for example, Pedestrian Detection for an ADAS solution, a suitable AI network has to be identified and trained for various scenarios to improve accuracy. This is huge iterative task, where the DNN structure will be trained on large volumes of data sets for various real life scenarios.

The hardware platform requirements depend on the network type and the volume of data set. Since the DNN largely uses vectorized operations, machines with more computation power having multiple CPU cores or multiple GPU cores are preferred. This helps in better scheduling and pipelining of the mathematical task.

A selection of tools/libraries is essential for fast prototyping like Tensorflow, Caffe, Theano, Torch, and Keras, etc. Nearly all of these DL libraries provide support for CPU/GPU computation.

Detection in Real-time

The trained network model can be implemented in various semiconductor hardware platforms (for example, GPU, CPU or FPGA) and can be deployed in the vehicle for real-time problem solving. Since the emerging DNN algorithms provide improved accuracy with substantial increase in network layers/size and parameters, the selection of platform is vital.

Considering the computational efficiency, memory bandwidth, power, data storage, and system, a suitable hardware platform should be selected. In addition, selection of semiconductor device with automotive grade (AEC-Q100) is an essential in-vehicle deployment.

Heterogeneous Computing with FPGA

Implementing DNN solution on hardware platform for a safety-critical application with high system throughput and performance needs a careful tradeoff analysis on factors like power consumption, throughput, memory, device qualification for automotive compliance, and cost. Even though many OEM and suppliers develop solution around the multicore GPU and CPU, the FPGA solution is advantageous due to better energy efficiency (performance/Watt), as compared to high-end CPU and GPUs.

Since, SOC FPGA devices have massive reconfigurable fabric with on-chip multicore processor, they are the right choice for implementing DNN algorithms. The powerful multicore ARM-A53 + Reconfigurable fabric enables solution developers to make perfect hardware/software partitioning with better system performance. For a simple lightweight and less throughput DNN solutions, the SOC FPGA devices with ARM-Cortex + reconfigurable fabric can be adopted.

Also, the SOC FPGA allows for fast prototyping using HDL, OPENCL or C/C++ based High Level Synthesis (HLS) flow.

Network computation goes through each layer in the network and for every layer, each neuron value is calculated by “multiplying and accumulating” the previous layer’s neuron values and weights. The computation, to a great extent, depends on multiply-accumulate (MAC) operations.

The reduction in technology node to 20nm and 14nm, allows for more on-chip resources with lesser power. Today’s SOC FPGA provides greater flexibility for implementing DNN solutions because of:

- Several thousands of hardened DSP blocks, which enable, for kernel multiplications
- Several MB of on-chip RAMs for handling multiple line buffer.
- High bandwidth interface facilitates easy access to on chip HOST and external memories.
- Reconfigurable logic blocks
- Multicore Processor Subsystem which helps in scheduling and other algorithm task
- Processor with OS and without OS (bare metal code) possible
- Device with automotive grade (AEC-Q100)
- Better power advantage over GPU/CPU

The above mentioned benefits enable FPGA as a potential option for mass volume production and for in-vehicle deployment. For example, the FPGA fabric can have Processing Engine (PE), which does the core hardware acceleration for convolution. Also, the PE can be configured for different convolution kernel via host processor. Based on the FPGA on-chip resources, multiple instances can be integrated. Also, this allows parallel and pipelined accelerators for better system performance.

HCL – Capability and Collaboration Scope

HCL Technologies Ltd. understands the DL ecosystem and its vast domain and technology experience can be leveraged for developing DNN based solution.

Algorithm Development and Consultation

- Good understanding of DL and CNN
- Understanding of various CNN topology (AlexNet, GoogLeNet, Residual Network)
- Image recognition, localization, semantic segmentation
- Caffe/TensorFlow/Torch
- Ground truth estimation and benchmarking

SoC FPGA

- CNN implementation using, custom RTL design
- CNN fast prototyping with OPENCL
- Develop reusable and optimized embedded solution library components
- Optimized network for performance and accuracy
- Design benchmarking

Other possibilities

- Study and analysis of various Vision and Deep Net algorithms for automotive application
- Collaboration for CNN training and optimization
- Benchmarking analysis for various platforms
- Custom SOC FPGA platform development with camera sensor interface
- CNN implementation on GPU Platform

HCL SOC FPGA experience leveraging Deep Learning development.

Understanding on various Deep Learning algorithms	Expertise in Xilinx and Altera FPGA platform	Expertise in SOC FPGA and MPSOC	Experience in ASIC design and development
Good understanding of HW and SW partition for CNN	Experience in OPENCL and DSP algorithm design	Experience in various embedded platform/validation	Experience in driver development and OS porting

Conclusion

On a larger context, to make the driving experience safe and smooth, intelligent transportation system is essential. Emerging technologies and concepts like Connect Cars, IoT ADAS, and high-end Sensor Networks are gradually converging. To handle large real-time data sets and enable the vehicle to adopt to the environment, scenario, local governing road rules, and geography AI is necessary. The R&D on the DL technology, tools, and semiconductor will certainly help build SMART, INTELLIGENT, and USER FRIENDLY vehicles in future.

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Sai is part of HCL ERS-XMS-SPP Team, he works on computer vision and image processing. He has contributed 120 technical publications in International Journals and Conferences, as well as 40 US patent filed in the field of image processing. Sai's areas of interest are document imaging and machine learning.

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