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Training Neural Networks on Embedded Devices

Comparing Training on Neural Network Frameworks vs

Systems Programming Languages like C/C++

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Short abstract

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Part I: Introduction

Embedded systems are equipped with a combination of hardware and software components to achieve a specific task. Often, embedded systems are built into a larger device or system where they are used to collect, store, process, and analyse data, as well as to control the device's behaviour.

Scania employs embedded devices called Electronic Control Units (ECUs) in their trucks to supervise and regulate essential subsystems such as the engine, transmission, braking, and electrical systems. Each of these subsystems has one or more ECUs to gather system data and transmit it to a central communicator via the Controller Area Network (CAN) interface. The existing fleet of trucks will receive upgraded ECU's and communicators with higher performance hardware enabling faster and advanced data collection. This upgrade presents an opportunity to reuse the on-board hardware that is currently operational.

Machine learning (ML) on embedded systems is becoming increasingly popular due to its ability to provide real-time insight and intelligence to devices. But this technology presents a unique set of challenges due to the limited resources available on these systems. Embedded systems are designed to be power efficient, have limited memory and processing power, and require closely tailored algorithms, making it difficult to use pre-existing machine learning models. Furthermore, embedded systems often have expectations such as real-time behaviour which can complicate the ML development process. Despite these challenges, machine learning on embedded systems has potential applications in a variety of areas, such as in the fields of robotics and autonomous vehicles.

One such application Scania has been working on in their LOBSTR [1] and FAMOUS projects is anomaly and fault detection. Targeting to run the anomaly detection models on the existing ECUs with limited resources provides many benefits.

Scania currently runs a massive fleet of more than 100,000 trucks and has been adding another 60,000 trucks annually since 2014. The company's truck sales make up 62% of its global sales. Scania has a substantial fleet of connected trucks with electronic control units (ECUs) and communication devices that are due for an upgrade. However, this upgrade will result in a massive amount of e-waste, which could be prevented. Scania is actively working towards a sustainable and autonomous future by devising strategies to promote a shift towards eco-friendly transport systems.

As part of this commitment, Scania is exploring the possibility of repurposing existing ECU's to run machine learning models. This innovative approach aligns with Scania's vision of leading the way towards a sustainable future.

Among the ML approaches to take, Artifical Neural Networks are especially interesting for anomaly detection due to several factors such as minimal data preprocessing . . . To get the best out of this approache, training of the model needs to be performed on-board. However much of the potential of running machine learning applications on these devices remain unattained due to the difficulties in creating these applications and running training on-board.

The scope of the thesis is to explore the challenges of building and training artificial neural networks on embedded devices using different approaches and evaluating their performance.

1. Background

The development and maintainance of neural network applications on a fleet of embedded devices has several design considerations and relies heavily on technological innovations. This makes embedded linux an attractive platform to build these applications and motivates an examination of build systems that target embedded environments.

1.1 Development For Embedded Linux

1.1.1 The Yocto Project

The Yocto Project is an open source collaborative project that provides users with a set of tools to create custom Linux-based systems for embedded products. It's based on the OpenEmbedded framework and is backed by the Linux Foundation. The Yocto Project works with hardware vendors, open source communities, and hundreds of developers to provide a robust development environment for embedded products

Yocto Project allows developers to create unique Linux-based systems for embedded devices. Yocto Project provides developers with the tools to customise their embedded Linux systems to meet the specific needs of their products.

1.1.2 Toolchains & Cross compilers

Describe their usage. Will show up again in Development chapter

Support for embedded hardware requires a stack that includes several components covered in this chapter. The initial target machine was an ECU filling the role of a coordinator on the truck, however due to certain components missing from are contained in the Appendix []

1.2 Training on Device

1.2.1 Federated Learning

1.3 Development Of Neural Network Application

Contrast general purpose frameworks - TFlite etc with handwritten applications

- *Include literature study elements from Tiny ML*

1.3.1 Different Programming Paradigms

Approaches to doing Machine Learning in Embedded Environments. Emphasis on how these applications are developed - e.g TFLite

1.4 General Distribution of Work

2. Theory

2.1 Artificial Neural Networks

General introduction to ANNs. Explaining topics from inference, training, till federated learning systems

2.2 ANN Performance Optimisations Techniques

Contrast traditional implementations in resource rich environments and the constraints of embedded environment. Layout general strategies to acquire performance improvements with little losses to accuracy - Purning, Quantisation

2.3 Hardware Support for Neural Networks

Introduction to ARM-NN kernels, mentioned again in Development chapter

2.4 Embedded Linux

Describe the process of boot flow introducing concepts such as Boot ROM, eMMC, IVT, bootloader, kernel, file systems etc.

2.5 Software Development Kits for Embedded Targets

2.6 Performance Evaluation

Describe and motivate performance measures used in the Results chapter

Part II: Implementation

ANN training presents an important gap in the current efforts in Tiny ML. This section contains the description of benchmark ANN training applications created to test the performance of an ANN training cycle on an embedded board. The neural network structure, learning algorithm, and the dataset remain the same but the implementations are completed in traditional general purpose neural network frameworks as well as straightforward implementations in C and other languages

3. Design

The benchmark applications test the training phase of a Handwritten Digit Recognition Neural Network (HDR-NN) on the MNIST [2] dataset. MNIST is a popular dataset of handwritten digits commonly used for training image processing systems. It is a popular starting point for neural network implementations and has been used as the primary dataset in the benchmark experiments. The target embedded device is an Electronic Control Unit (ECU) board based on an iMX6 series processor

3.1 ANN Development Process

The target environment necessitates the use of cross compilers and as part of the development process multiple build environments and systems were examined. Ultimately, the primary platform that ended up being used was the Yocto Project extensible SDK (eSDK) based application development process running on a standard linux based build environment

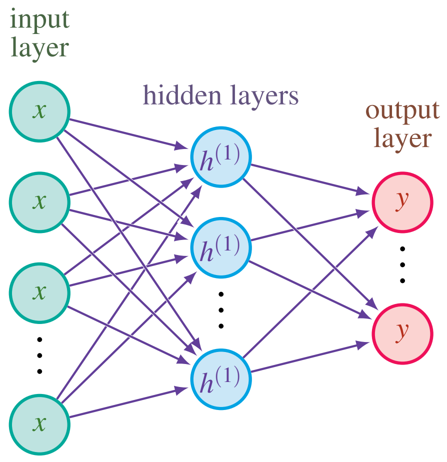
3.1.1 Compiler Toolchains & Yocto Recipes

The *meta-freescale* Yocto BSP layer by NXP supports the target processor and in combination with Poky can provide an eSDK that was primarily used to test and develop the benchmark applications.

GCC based cross compilers and debuggers were usefull for the C, C++ programs. The general portability of the benchmark applications and the Yocto project allows for further experiments to be conducted on different target architectures as well. For further optimisations that relies on hardware specific features such as ARM's CMSIS-NN cannot be so easily ported however

3.2 HDR-NN Benchmark Programs

The handwritten digit recognition neural network is a fully connected neural network and derives from the popular neural network textbook neuralnetworksanddeeplearning.com



The input layer has 784 neurons corresponding to 28 x 28 pixel images of the MNIST dataset and the output layer has 10 neurons corresponds to 10 different possible digits. The dimensions and depth of hidden layers of the network is configurable as well as other properties of the learning algorithm

3.2.1 The Learning Algorithm

The HDR-NN benchmark applications will all share the same standard training algorithm, namely Backpropagation with Stochastic Gradient Descent. Describing this algorithm in general purpose neural network frameworks is straight forward and plenty of general implementations of the algorithm exists in the wild, making the development process easier to target multiple programming paradigms. The configurable parameters of the learning algorithm in through out the implementations are the learning rate, the total number of epochs for training, and the batch size for gradient descent iterations

3.2.2 Verifying Correctness

The model structure can be configured in the same manner across the implementations, as well as the learning algorithm configuration. To verify their mutual correctness, all the implementations initialize HDR-NN using the same PRNG

4. Development

The HDR-NN benchmark application were completed in different programming languages and in neural network frameworks like Tensorflow. Details about the target environment and the benchmark implementations are layed out in this chapter

4.1 Targetting an i.MX6 based custom board

Exploring the target ECU board involved several examinations of a known state of the board. The linux kernel binaries were made via the Yocto project however there was no access to source code such as the recipes or the meta-layers themselves

The i.MX SoCs have a special boot mode named Serial Download Mode (SDM) typically accessible through boot switches. When configured into this mode, the ROM code will poll for a connection on a USB OTG port

4.1.1 i.MX6 Overview

The iMX6 series is designed for high performance low power applications and target boards are configured with a single Cortex A9 core with the ARMv7 ISA. The processor supports NEON single-instruction multiple-data (SIMD) instructions, allowing for SIMD vector operations within the training program

4.1.2 Testing on Device

The benchmark tests were performed on ... using the perf tool

4.2 HDR-NN Implementation

With the primary focus on training, MNIST dataset was primarily loaded in an easily readable format appropriate to the corresponding paradigms and the correctness verification routines and execution statistics measurement runs were seperated. The benchmark executions did not produce disk I/O after the dataset was read, unlike the correctness verification runs which produced the final weights from the execution runs that were subsequently compared with the other benchmark program execution output weights

4.2.1 The Reference HDR-NN in Python

This is the baseline implementation and follows close to the implementation exhibitied on neuralnetworksanddeeplearning.com. The implementation uses the n-dimensional array data structure present in the popular Python programming language library Numpy

4.2.2 Tensorflow Lite based HDR-NN

Developing ANNs on tensorflow using Keras is straightforward with good support and well documented APIs. Building the same model for a Tensorflow Lite (TFLite) was more involved however still straightforward

4.2.3 C based HDR-NN

The C implementation had the least amount of external dependencies and contained the network in float arrays within structs.

4.2.4 CPP based HDR-NN

Part III: Analysis

Results from the implementation

5. Results

The HDR-NN training implementations were benchmarked on the iMX6SDB evaluation board. Model accuracy, execution time and peak memory utilised during the training of the model is compared while varying the number of layers and the neurons in each layer

5.1 HDR-NN comparisons

The execution times for HDR-NN training were recorded for different network configurations such as differing hidden layer sizes of 2, 8, 32, and 128. The run times increased exponentially with the number of parameters. This is due to the fact that the amount of calculation in a fully connected network increases with the number of neurons, leading to longer training times

Further, when the number of neurons in a single layer exceeds 32, the accuracy of the model is observed to decrease due to overfitting. To improve accuracy, adding another layer with 16 neurons is found to be beneficial without significantly increasing the time required for computation. In fact, for larger network sizes, it is observed to even reduce the computation time required

Regardless of the hidden layer sizes, the peak memory utilisation remains constant for the same application regardless of the network configuration

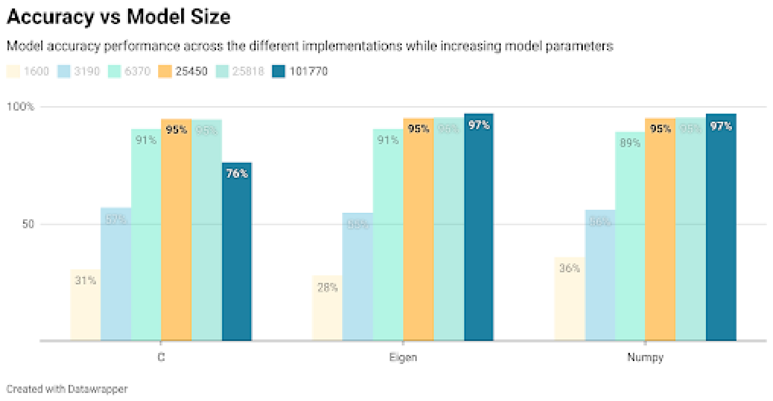


Figure 5.1. Comparing the accuracy of the different HDR-NN implementations

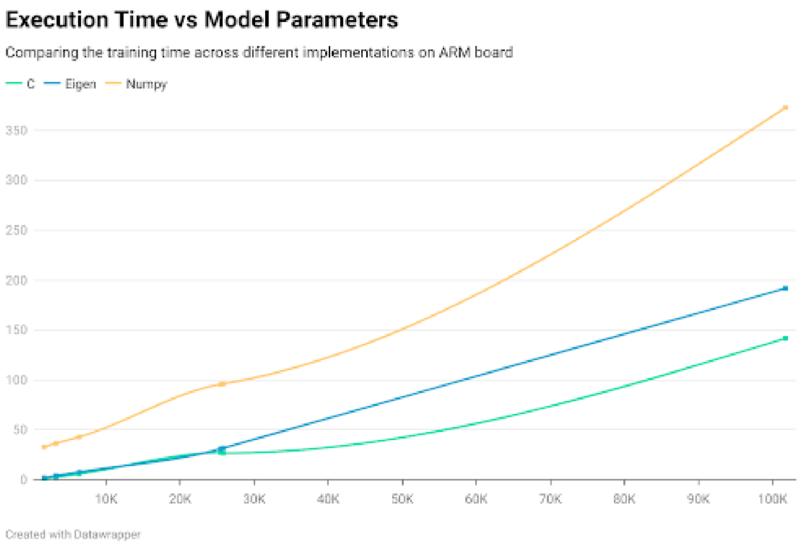


Figure 5.2. Comparing total run time for training the different HDR-NN programs

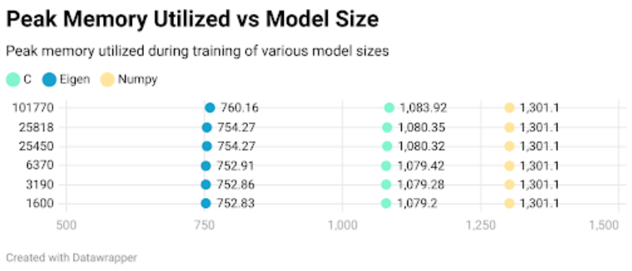


Figure 5.3. Peak Memory Utilized during training with different model sizes remain similar within the same implementation

5.1.1 Python Numpy based HDR-NN

The Numpy implementation consistantly took longer duration to perform the same training cycle as compared to the C implementation

5.1.2 Tensorflow-Lite based HDR-NN

Benchmark pending . . .

5.1.3 C based HDR-NN

C implementation had lower execution times and memory usage

5.1.4 CPP based HDR-NN

Benchmark pending . . .

5.2 CMSIS-NN based Optimisations to Training

Further breakdown of the performance achieved from different optimisation techniques

5.2.1 Quantisation

future: Training Network with Quantized weights

5.2.2 Pruning the Network

future

6. Discussion

- *Contrast development process for the ML programming paradigms*
- *Which optimisation approaches gave the most in improvement?*

7. Conclusion and Future Work

What does it all mean? Where do we go from here?

References

[1] Juan Carlos Andresen. Lobstr learning on-board signals for timely reaction, 2020.

[2] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition, 1998.

Appendixes

Scania C300 Communicator