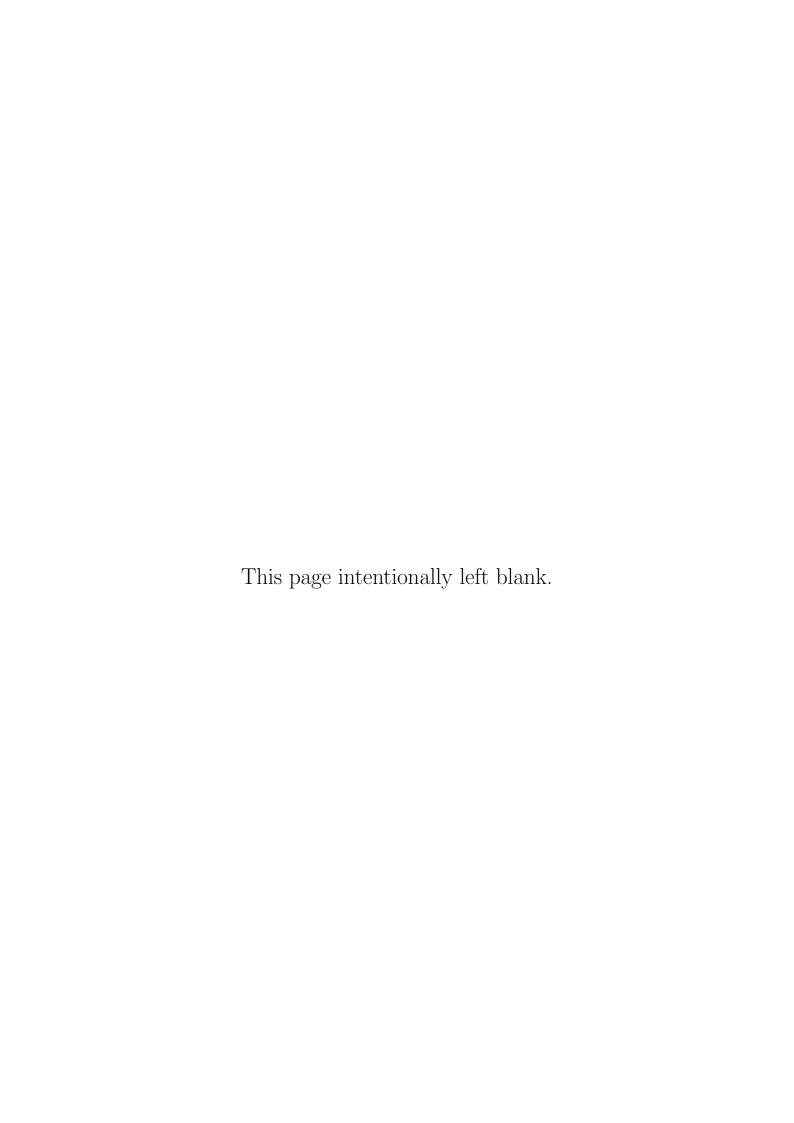
Vision Transformer Accelerator ASIC for In-Ear Sleep Staging

by Tristan Robitaille

Supervisor: Professor Xilin Liu April 2024

B.A.Sc. Thesis





ESC499 Engineering Science Thesis

Vision Transformer Accelerator ASIC for In-Ear Sleep Staging

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April 12th, 2024

Abstract

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Keywords: Sleep staging, ASIC accelerator, vision transformer, computer architecture

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In addition, I owe much to the professors who have taught me the fundamentals of computer architecture at the University of Toronto - Profs. Jason Anderson, Natalie Enright-Jerger, Andreas Moshovos and Mark C. Jeffrey.

Throughout this project, I have made extensive use the Compute Canada cluster, which has provided me with the computational resources I needed to run the simulations and train the model. I would like to thank the staff at Compute Canada for their initiative. I am also appreciative of the tools provided by the Canadian Microelectronics Corporation, which have been instrumental in the hardware implementation of the accelerator.

I would also like to acknowledge the work of Professors Lisa Romkey and Alan Chong who organized this thesis project for us, ensuring a structured and productive environment.

Finally, I would like to thank my family and friends for their support and encouragement throughout this project. I am grateful for their patience and understanding during this time.

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List of Abbreviations

ADC Analog-to-Digital Converter

ASIC Application-Specific Integrated Circuit

CiM Compute-in-Memory

CMOS Complimentary Metal Oxide Semiconductor

CSV Comma-Separated Values

EEG Electroencephalography

HDL Hardware Description Language

HDF5 Hierarchical Data Format 5

IP Intellectual Property

MAC Mulitiply-Accumulate

MASS Montreal Archive of Sleep Studies

PSG Polysomnography

RTL Register Transfer Level

TSMC Taiwan Semiconductor Manufacturing Company

VCD Value Change Dump

See [1]. I am making an Application-Specific Integrated Circuit (ASIC). It's small, low-power and fast. It's better than Google's.

1 Introduction

2 Background

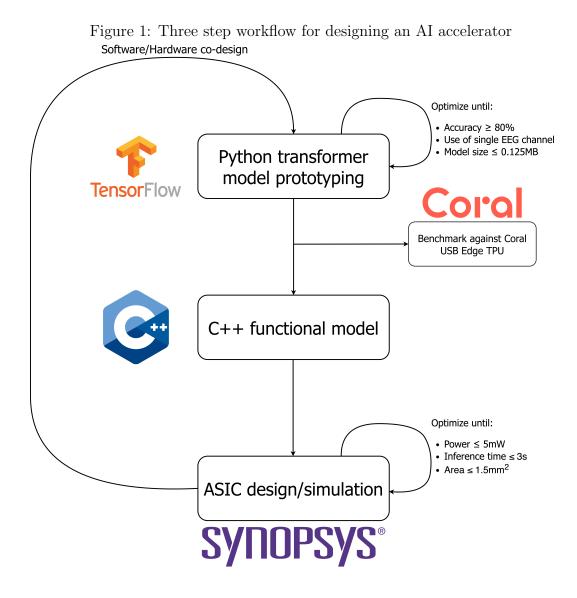
2.1 Problem Statement

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2.2 Technical Goals and Requirements

3 How to Design an AI Accelerator

This section describes the workflow used for this project, which was divided into three main steps: model prototyping, accelerator functional simulation and accelerator hardware implementation. The tools used in each step are described in the following sections. The goal is to expose progressively more layers of abstraction to make hardware/software co-design and debugging easier. As can be seen in Figure 3, these three steps allow iterations to converge on a design that meets the requirements.



3.1 Model Prototyping, Data Processing and Accuracy Measurements

The first step in designing an accelerator is prototyping the model that the accelerator will run. Here, we prioritize productivity of development and profiling over performance. In this project, the model was developed in TensorFlow, a widely-used Python framework

maintained by Google. Its popularity implies that it has a large community of developers and is well-documented. TensorFlow also provides a high-level API that allows for rapid prototyping of models. The model was developed in Python 3.11 and TensorFlow 2.14. The model was trained on the Montreal Archive of Sleep Studies (MASS) SS3 dataset, which contains 62 nights of Polysomnography (PSG) recordings with 21 Electroencephalography (EEG) channels [2]. The 16-bit raw PSG data was preprocessed manually with the following steps:

- Pruning of epochs of unknown sleep stage.
- Downsampling from 256Hz to 128Hz to reduce model size and inference energy.
- Filtering with 60Hz notch filter to remove noise from AC mains coupling.
- Filtering with 0.3-100Hz bandpass filter to remove noise (as recommended in [3]).
- Offset by half of the scale to replicate the unsigned 16-bit format expected from the Analog-to-Digital Converter (ADC) in the final hardware.

In addition, the two light sleep stages (N1 and N2) were merged into one stage to simplify the model. Finally, the nights were concatenated and shuffled. All training and hyperparameter search took place on the Compute Canada Cedar cluster through remote SSH access.

Accuracy against PSG ground truth was assessed through repeated 31-fold validation: the model is trained on 60 nights and tested on the remaining two nights. The best accuracy of 5 runs is recorded, and the process is repeated another 30 times until all pairs of nights have been tested. The training set represents 90% of the 60 training nights. The final accuracy is the average of the best accuracies of each validation fold. This provides measurements that are robust against night-to-night variability in the dataset and resulting inference performance. Table I shows the hyperparameters used for training the model. These have been empirically determined to yield the best accuracy with reasonable training time. Figure 3.1 shows the accuracy of the model as a function of the number of epochs, which is shown to converge at around 100 epochs.

3.2 Accelerator Functional Simulation

To prototype the accelerator architecture, run more accurate studies to determine the impact of design choices and write the model in a way that can be easily translated to hardware, a functional simulation was written. The simulation is written in C++ and, in the aim of helping subsequent SystemVerilog development, uses a similar structure to the SystemVerilog code (cycle-level parallelism, use of FSM, limited function calls). It is organized identically to the hardware design, with a master module controls high-level

Table I: Training hyperparameters for vision transformer model

Hyperparameter	Value			
Learning rate schedule	$\sqrt{d_{model}} * min(\sqrt{step}, step/4000^{1.5})$			
Initial learning rate	0.001			
Batch size	16			
# of epochs	100			
Dropout rate	30%			
Class weights	$1.0 \forall \{Wake, REM, N1/N2, N3/N4\}$			
Optimizer	Adam			
Data downsampling	$256 \mathrm{Hz} \rightarrow 128 \mathrm{Hz}$			
Data filtering	60Hz notch \rightarrow 0.3-100Hz bandpass \rightarrow 16b quantization			

operation of CiM modules. It also makes use of compute modules written using the same fixed-point format and approximation as the hardware. This functional simulation is used to collect metrics that are difficult to measure in hardware, such as the distribution of inputs to certain operations, the distribution of intermediate results, the exact number of all types of operations, etc. This information can be used to optimize the hardware design. Finally, it provides an easy way to validate the operations by cross-checking each step with reference outputs from the TensorFlow model. The only non-standard libraries used are armadillo for compute verification, HighFive for Hierarchical Data Format 5 (HDF5) file I/O (storing model parameters and EEG data) and rapidcsv for Comma-Separated Values (CSV) file I/O (storing fixed-point accuracy study results).

3.3 Accelerator Hardware Implementation

The final step in the workflow is the hardware implementation of the accelerator. The hardware is written in SystemVerilog and uses the same structure as the functional simulation. Several tools are used to design the hardware:

- Verilator: Register Transfer Level (RTL) compiler and linter.
- CocoTB: Python testbenching framework.
- Gtkwave: Value Change Dump (VCD) waveform viewer.
- ARM Artisan Physical IP: SRAM compiler.
- Synopsys Design Compiler: Synthesis and performance evaluation tool.

The first three tools are open-source and compatible with all major operating systems, providing a familiar, local and OS-agnostic development environment. The last two tools are proprietary and are used to evaluate the performance of the design against requirements.

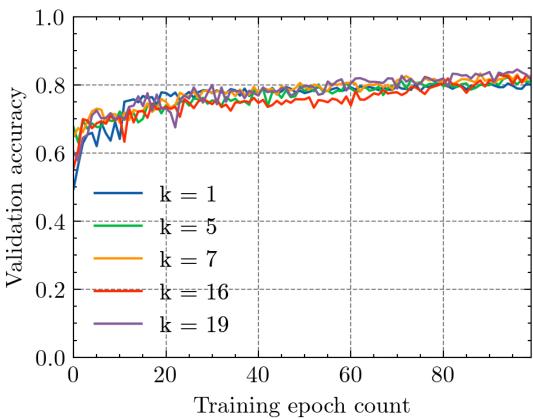


Figure 2: Testing set accuracy for 5 randomly-selected folds as a function of epoch

4 Vision Transformer Model Design

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5 ASIC Accelerator Architecture

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- 5.1 Centralized vs. Distributed Architecture
- 5.2 Master Architecture
- 5.3 Data and Control Bus
- 5.4 Compute-in-Memory: Fixed-Point Accuracy
- 5.5 Compute-in-Memory: Memory
- 5.6 Compute-in-Memory: Compute Modules

This section describes the design and performance metrics of the various compute Intellectual Property (IP) modules use by the Compute-in-Memory (CiM) modules. Each is custom-designed for this project. Each module works with signed (2's complement) fixed-point representation. To avoid overflow, the modules use internal temporary variables of fixed-point format Q22.10. Table II shows the performance metrics of the compute modules. The working principles of each modules is described briefly in subsequent sections.

Note that all measurement in Table II are given for standard 65nm Taiwan Semiconductor Manufacturing Company (TSMC) process with a 100MHz clock. To determine these metrics, the following methodology was used with Synopsys Design Compiler 2017.09 running on UofT's EECG cluster:

- Area: Synthesis with the area optimization effort set to high, and the area was extracted from the report_area command report.
- Cycle/op: The latency was observed when running a single operation on a presynthesis simulation.
- Energy/op: A single-instance testbench running 10000 operations was designed, and a .saif file was generated from the VCD dump file of the testbench using Synopsys' vcd2saif utility. This provides an average activity factor for each node, yielding an accuracy that is adequate for this discussion. The energy per operation

Table II: Performance metrics of the compute modules

Module	Area	Cycle/op	Energy/op	Leakage power	F_{max}
Adder	$450.4 \mu m^2$	1	0.99pJ	11.87μW	6.67GHz
Multiplier	$3535.2 \mu m^2$	1	$7.05 \mathrm{pJ}$	$90.50 \mu W$	$1.59\mathrm{GHz}$
Divider	$1719.9 \mu m^2$	35	$23.44 \mathrm{pJ}$	$34.56 \mu W$	$1.11\mathrm{GHz}$
Exponential	$2442.2 \mu m^2$	24	$62.73 \mathrm{pJ}$	$47.10 \mu W$	$7.14\mathrm{GHz}$
Square Root	$1325.2 \mu m^2$	17	$18.32 \mathrm{pJ}$	$26.30 \mu W$	$0.758\mathrm{GHz}$
$\mathrm{MAC^1}$	_	386	$820.20 \mathrm{pJ}$	_	
MAC^2	$3129.8 \mu m^2$	391	$839.32 \mathrm{pJ}$	$69.40 \mathrm{pJ}$	$2.17\mathrm{GHz}$
$\mathrm{MAC^3}$	_	456	$941.68 \mathrm{pJ}$	_	
Softmax	$2341.1 \mu m^2$	2024	$1972.5 \mathrm{pJ}$	$51.47 \mu W$	$1.20\mathrm{GHz}$
LayerNorm	$3836.89 \mu\mathrm{m}^2$	1469 + 494	$1705.7 \mathrm{pJ}$	$78.39 \mu W$	$0.877\mathrm{GHz}$
Total	$18780.69 \mu m^2$	N/A	N/A	$409.59 \mu W$	0.758GHz

¹ No activation function applied

was calculated by multiplying the total dynamic power by the time to complete the 10000 operations, divided by 10000.

- Leakage power: Synthesis with the power optimization effort set to high, and the leakage power was extracted from the report_area command report.
- F_{max} : The report_timing command was used to determine the maximum frequency of the design.

It must be noted that the measurements for all composite compute units (i.e. units that make use of shared resources) exclude the area/power/etc. of the shared resources. Including them would result in misleadingly high figures, given that they are explictly designed to share resources. The total area of the CiM provides figures more representative of this integration.

5.6.1 Adder

The adder is a single-cycle, combinational module that adds two fixed-point numbers. It uses a ripple-carry adder architecture. The adder has a latency of 1 cycle, which simplifies the logic that uses it. It also provides an overflow flag. To reduce dynamic power consumption, the adder only updates its output when the refresh signal is high.

² Linear activation function applied

³ Swish activation function applied

5.6.2 Multiplier

The multiplier is very similar to the adder. One difference is that it uses Gaussian rounding (also known as banker's rounding). This rounding method rounds 0.5 to the nearest even number. This reduces the bias in the output that is commonly observed with standard rounding methods, which is particularly important in MAC operations where the error can accumulate. The multiplier also has a latency of 1 cycle and provides an overflow flag. Like the adder, the multiplier only updates its output when the refresh signal is high.

5.6.3 Divider

The divider is more complicated than the adder and multiplier. It performs bit-wise long-division and has a latency of N+Q+3 cycles, where N is the number of integer bits and Q is the number of fractional bits. The divider also provides flags for overflow and divide-by-zero and done/busy status signals. The module start division on an active-high pulse of the start signal and provides the result when the done signal is high. The divider module is mostly used in the MAC module during computation of the Swish activation function.

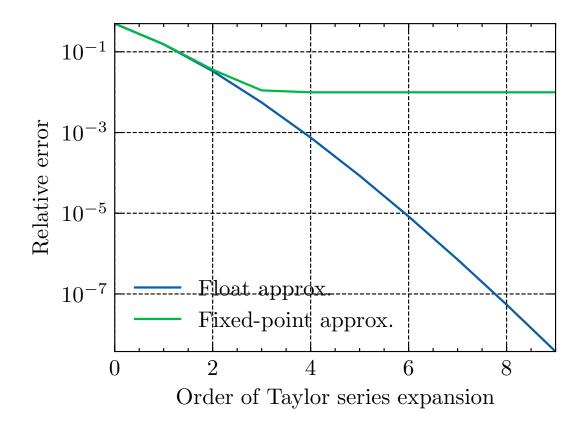
5.6.4 Exponential

The exponential module computes the exponential e^x of a fixed-point number x. It uses a combination of the identities of exponential and a Taylor series approximation around zero to compute the exponential. Specifically, the module transforms the exponential as such:

$$e^x = 2^{\frac{x}{\ln(e)}} = 2^z = 2^{\lfloor z \rfloor} 2^{z - \lfloor z \rfloor} \tag{1}$$

The compute can then easily compute $2^{\lfloor z\rfloor}$ as an inexpensive bit-shift operation and $2^{z-\lfloor z\rfloor}$ as a Taylor series approximation. To determine a reasonable number of terms to use for the Taylor series expansion, an accuracy study was ran. Figure 5.6.4 shows the relative error of the exponential module as a function of the order of the Taylor series expansion for both fixed-point (Q22.10) approximation and float (64b) approximation. As can be seen, the error decreases with an increase in the order of the expansion. However, for the fixed-point approximation, it converges to a minimum error of $\tilde{0}.992\%$. This is because the quantization of fixed-point dominates the Taylor series error. Therefore, using a 3rd order Tarlor series expansion to appriximate the exponential function is a good balance between accuracy and latency/energy. Note that these error was measured over the input range of [-4, 4]. According to the functional simulation, this corresponds to roughly ± 3 standard deviations from the mean of inputs to the exponential function. To further speed up the computation, the exponential module uses a lookup table to

Figure 3: Error of exponential approximation as a function of Taylor series expansion order



store the Taylor series coefficients as well as 1/ln(e). To reduce area, the exponential module does not instantiate its own adder and multiplier modules. Rather, it accesses the adder and multiplier modules in the CiM module shared with other compute units. The latency is 24 cycles.

5.6.5 Square Root

The square root module computes the square root of a fixed-point number using an iterative algorithm. It has a latency of (N+Q)//2+1 cycles, where // denotes integer division. The module provides flags for overflow and negative radicand and start/busy/done signals. The module starts computation on an active-high pulse of the **start** signal and provides the result when the **done** signal is high.

5.6.6 Multiply-Accumulate

The MAC module performs a vector dot-product for a given pair of base addresses for the data and length of the vector and applies a selectable activation function to the result. Similar to the exponential module, it uses shared adder, multiplier, divider and exponential modules in the CiM module. It can implement three activation functions: none, linear and Swish. For a nominal length of 64 (which corresponds to the embedding depth of the model, a very common value for matrix dimensions in the model) and Q22.10 formate, the latencies are 386, 391 and 456, respectively. Note that, although the Swish activation function comprises a divider operation, the MAC compute latency can still be kept fairly short because the divisor is the same for all elements. The module can thus perform the division once and multiply by the inverse, which is a single-cycle operation. Finally, the MAC module can be directed to choose the second vector from weights or intermediate results memory.

5.6.7 Softmax

The softmax module computes the softmax function of a vector of fixed-point numbers. Similarly to the MAC module, it uses shared adder, mulitplier, divider and exponential modules and provides busy and done signals. For a 64-element Q22.10 vector, the latency is 2024 cycles. This is significantly longer than other vector compute modules such as the MAC because, in the softmax operation, each element is exponentiated individually.

5.6.8 LayerNorm

The final compute module is the LayerNorm module. It computes the Layer Normalization of a vector of fixed-point numbers. As described in section 4, the LayerNorm operation consists of a normalization of the vector on the horizontal dimension followed by scaling and shifting using learnable parameters on the vertical dimension. Because each CiM module stores one vector at a time, the LayerNorm operation must be separated into two stages with a matrix transpose broadcast between the two. The latency for the first half is 1469 cycles and the latency for the second half is 494 cycles. The module provides busy and done signals and is controlled with a half-select and start pulse signals. Because the length of the vector is constrained to be a power of two, the module uses bit-shifting instead of division for the normalization operation to decrease latency and energy per operation.

5.7 A Note About Software-Hardware Co-Design

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6 Evaluation of Performance Metrics

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6.1 Vision Transformer

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6.2 Accelerator

7 Future Work

8 Conclusion

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A Codebase Statistics

It may be interesting to the reader to appreciate the size of the codebase needed to develop a project of similar scale. The code for this project is available in my GitHub repository. The following table provides a breakdown of the number of lines of code in the project.

Table III: Line and file count per file type in the codebase

File type	File count	Line count	Percent of total
Python	12	3000	33.7%
SystemVerilog	12	2500	30.4%
C++	12	1250	18.9%
TeX	12	670	8.2%
Shell	12	300	4.3%
Other	12	20	4.5%
Total	60	13,000	100%

In addition, there have been 200 commits to the repository.

B Reflection on Learnings and Experience Gained

