

INTEGRATED CIRCUIT DESIGN OF A MULTIPLIER-ACCUMULATOR  
FOR CONVOLUTIONAL NEURAL NETWORK BASED ON  
CARRY-SAVE ADDER ARCHITECTURE

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## ABSTRACT

Convolutional Neural Networks (CNNs) are hierarchical biologically-inspired models that may be taught to perform a variety of detection, identification, and segmentation tasks. The key processing requirements in the CNNs process are the multiplier-accumulator (MAC) operations in the convolution layer. A perfect fusion of various multipliers and adders would yield an ideal MAC for CNNs' convolution layer. Besides this, different kernel mask sizes are required throughout the convolution layer in CNNs, depending on demand. In general, each size of kernel mask requires a unique MAC architectural configuration, thus lengthening the time spent in research and development. To overcome this problem, a flexible MAC design has been developed that allows users to choose between different sizes depending on the requirements of the CNNs. This method, known as Selective Kernel Size, may activate kernel sizes from  $1 \times 1$  to  $7 \times 7$ . This thesis also proposes a new MAC architecture called Multiplier-Accumulator with Carry-Save-Adder ( $MAC_{CSA}$ ) to improve the MAC performance by efficiently computing the sum of three or more bits of input. Each proposed design is synthesized to Silterra 180 nm technology, and the time, power consumption, and cell area are all compared. Selective Kernel Size architecture demonstrates a substantial gain in terms of cell area and power from 56% to 80% when compared to mixing different sizes of MAC design in specific CNNs network, with some degradation in time delay. When comparing the classical addition structure to the proposed MAC with the CSA structure, results show that while the MAC with CSA is only slightly faster than the classical MAC, the power and cell area are improved by 4% to 10%.

## ABSTRAK

Rangkaian Neural Konvolusi (CNN) ialah model hierarki yang diilhamkan secara biologi yang boleh diajar untuk melaksanakan pelbagai tugas pengesanan, pengenalan, dan pembahagian. Keperluan pemprosesan utama dalam proses CNN ialah operasi darab-tambah (MAC) dalam lapisan konvolusi. Gabungan sempurna pelbagai pendarab dan penambah akan menghasilkan MAC yang ideal untuk lapisan konvolusi CNN. Selain itu, topeng kernel saiz berbeza diperlukan di seluruh lapisan konvolusi dalam CNN, bergantung kepada permintaan. Secara amnya, setiap saiz topeng kernel memerlukan konfigurasi seni bina MAC yang unik, dengan itu memanjangkan masa yang diperlukan dalam penyelidikan dan pembangunan. Untuk mengatasi masalah ini, reka bentuk MAC yang fleksibel telah dibangunkan yang membolehkan pengguna memilih antara saiz yang berbeza bergantung kepada keperluan CNN. Kaedah ini, dikenali sebagai Saiz Kernel Selektif, boleh mengaktifkan saiz kernel dari  $1 \times 1$  hingga  $7 \times 7$ . Tesis ini juga mencadangkan seni bina MAC baharu yang dipanggil Multiplier-Accumulator dengan Carry-Save-Adder ( $MAC_{CSA}$ ) untuk meningkatkan prestasi MAC dengan menggabungkan tiga atau lebih bit input untuk operasi penambahan. Setiap reka bentuk yang dicadangkan disintesis kepada teknologi Silterra 180nm, dan masa, penggunaan kuasa, dan keluasan sel semuanya dibandingkan. Seni bina Saiz Kernel Selektif menunjukkan peningkatan yang besar dari segi keluasan dan kuasa sel daripada 56% hingga 80% jika dibandingkan dengan reka bentuk MAC yang berbeza dalam rangkaian CNN tertentu, dengan sedikit kemerosotan dari segi masa. Apabila membandingkan struktur penambahan klasik kepada MAC yang dicadangkan dengan struktur CSA, keputusan menunjukkan bahawa walaupun MAC dengan CSA adalah lebih pantas sedikit daripada MAC klasik, kuasa dan kawasan sel adalah lebih baik sebanyak 4% hingga 10%.

## TABLE OF CONTENTS

	<b>TITLE</b>	<b>PAGE</b>
	<b>DECLARATION</b>	<b>iii</b>
	<b>DEDICATION</b>	<b>iv</b>
	<b>ACKNOWLEDGEMENT</b>	<b>v</b>
	<b>ABSTRACT</b>	<b>vi</b>
	<b>ABSTRAK</b>	<b>vii</b>
	<b>TABLE OF CONTENTS</b>	<b>viii</b>
	<b>LIST OF TABLES</b>	<b>xi</b>
	<b>LIST OF FIGURES</b>	<b>xiv</b>
	<b>LIST OF ABBREVIATIONS</b>	<b>xviii</b>
	<b>LIST OF SYMBOLS</b>	<b>xxii</b>
	<b>LIST OF APPENDICES</b>	<b>xxiii</b>
<b>CHAPTER 1</b>	<b>INTRODUCTION</b>	<b>1</b>
1.1	Problem Statement	2
1.2	Objective	3
1.3	Scope of Study	3
1.4	Contribution	4
1.5	Organization in Thesis	4
<b>CHAPTER 2</b>	<b>BACKGROUND AND LITERATURE REVIEW</b>	<b>7</b>
2.1	Convolutional Neural Networks (CNNs)	7
2.2	Kernel Mask	8
2.3	Multiplier-Accumulator (MAC)	16
2.4	Multiple-Accumulator (MAC) used in CNNs application	18
2.5	Multiplier	20
2.5.1	Array Multiplier (AM)	22
2.5.2	Wallace-Tree Multiplier (WT)	25
2.5.3	Wallace-Tree Multiplier with Carry Look Ahead Adder at Carry Propagation Generator (WT-CLA)	27

2.5.4	Wallace-Tree Multiplier with Kogge-Stone Adder at Carry Propagation Generator (WT-KSA)	28
2.5.5	Booth Multiplier (BM)	28
2.6	Adder	30
2.6.1	Ripple Carry Adder (RCA)	31
2.6.2	Carry Look Ahead Adder (CLA)	33
2.6.3	Kogge-Stone Adder (KSA)	38
2.6.4	Brent-Kung Adder (BKA)	41
2.7	Carry Save Adder (CSA)	43
2.8	Summary	44
<b>CHAPTER 3</b>	<b>METHODOLOGY AND PROPOSED ALGORITHM</b>	<b>47</b>
3.1	Project Methodology	47
3.1.1	Project Flow	48
3.1.2	Design Tools	49
3.1.2.1	Quartus II	49
3.1.2.2	Synopsys EDA Tool	50
3.2	Proposed MAC for CNNs	52
3.2.1	MAC Implementation for Selective Kernel Size	52
3.2.2	The Proposed MAC with CSA arrangement Architecture	59
3.3	Summary	63
<b>CHAPTER 4</b>	<b>RESULTS AND DISCUSSION</b>	<b>65</b>
4.1	Selected Adder and Multiplier	65
4.1.1	Adder in 16-bit	66
4.1.2	Multiplier with 8-bit input	70
4.2	MAC Architecture with Selective Kernel Size and CSA Arrangement	75
4.2.1	Performance of MAC Architecture with CSA Arrangement	75
4.2.2	Performance of MAC Architecture with Selective Kernel Size in CNNs Network	85

4.3	Summary	99
<b>CHAPTER 5</b>	<b>CONCLUSION AND FUTURE WORK</b>	<b>101</b>
5.1	Summary of the Thesis	101
5.2	Conclusion	102
5.3	Future Work	104
<b>REFERENCES</b>		<b>107</b>
<b>LIST OF PUBLICATIONS</b>		<b>171</b>

## LIST OF TABLES

<b>TABLE NO.</b>	<b>TITLE</b>	<b>PAGE</b>
Table 2.1	Kernel matrix size in current CNNs Network.	9
Table 2.2	Summary of previous works in general Multiplier-Accumulator (MAC) architecture.	17
Table 2.3	Summary of related works in MAC for CNNs.	19
Table 2.4	Characters used in Booth Multiplier (BM).	29
Table 2.5	Adding action based on condition in BM process.	29
Table 2.6	Characteristics of different type of multiplier in this study.	30
Table 2.7	Characteristics of different type of adder in this study.	43
Table 3.1	The effect of Condition value to $Sm_{new}$ $Sr_{new}$ .	56
Table 3.2	Relationship between value $Sm_{new}$ to $control_m$ .	57
Table 3.3	Relationship between each bit of $control_m$ with the group A input value.	57
Table 3.4	Relationship between each bit of $control_m$ with the group C input value.	58
Table 4.1	Adder Simulation Results.	66
Table 4.2	Multiplier Simulation Results.	71
Table 4.3	Total Power ( $\mu$ W) for MAC and Multiplier-Accumulator with Carry Save Adder structure after multiplier product ( $MAC_{CSA}$ ) Simulation Results.	76
Table 4.4	Dynamic Power ( $\mu$ W) for MAC and $MAC_{CSA}$ Simulation Results.	76
Table 4.5	Leakage Power ( $\mu$ W) for MAC and $MAC_{CSA}$ Simulation Results.	76
Table 4.6	Cell Area ( $\mu$ m <sup>2</sup> ) for MAC and $MAC_{CSA}$ Simulation Results.	76
Table 4.7	Time Delay (ns) for MAC and $MAC_{CSA}$ Simulation Results.	76
Table 4.8	Average Performance for MAC and $MAC_{CSA}$ Simulation Results.	77
Table 4.9	Best Performance for MAC and $MAC_{CSA}$ Simulation Results.	77

Table 4.10	Total Power ( $\mu W$ ) between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	86
Table 4.11	Dynamic Power ( $\mu W$ ) between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	86
Table 4.12	Leakage Power ( $\mu W$ ) between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	86
Table 4.13	Cell Area ( $\mu m^2$ ) between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	87
Table 4.14	Time Delay (ns) between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_v1.	87
Table 4.15	Time Delay (ns) between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_v3.	87
Table 4.16	Time Delay (ns) between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_Resnet.	88
Table 4.17	Average Performance between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_v1.	88
Table 4.18	Average Performance between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_v3.	88
Table 4.19	Average Performance between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_Resnet.	89
Table 4.20	Best Performance between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_v1.	89

Table 4.21	Best Performance between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_v3.	90
Table 4.22	Best Performance between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_Resnet.	90

## LIST OF FIGURES

<b>FIGURE NO.</b>	<b>TITLE</b>	<b>PAGE</b>
Figure 2.1	Basic Idea for CNNs.	7
Figure 2.2	Kernel width and height for Input and Output Channels.	9
Figure 2.3	VGG-16 Architecture.	10
Figure 2.4	Inception-v1 architecture.	10
Figure 2.5	Inception-v3 architecture.	11
Figure 2.6	Inception-v4 architecture.	12
Figure 2.7	Inception-ResNet-V2 architecture.	13
Figure 2.8	ResNet-50 architecture.	13
Figure 2.9	Simple Block of ResNet-50.	14
Figure 2.10	Xception architecture.	15
Figure 2.11	ResNeXt architecture.	15
Figure 2.12	Basic Block Diagram of Multiplier.	21
Figure 2.13	Partial Product representation for 8-bit multiplication.	22
Figure 2.14	Top entity for Array Multiplier (AM).	23
Figure 2.15	Full Adder (FA) for AM.	24
Figure 2.16	Half Adder (HA) for AM.	24
Figure 2.17	Mathematics Process For Wallace-Tree Multiplier (WT).	25
Figure 2.18	Top entity for WT.	27
Figure 2.19	Top entity for Wallace-Tree Multiplier with Carry Look Ahead Adder at Carry Propagation Generator (WT-CLA).	28
Figure 2.20	Top entity for Wallace-Tree Multiplier with Kogge-Stone Adder at Carry Propagation Generator (WT-KSA).	28
Figure 2.21	Basic Logic Circuit for Adder.	31
Figure 2.22	Top entity for Ripple-Carry Adder (RCA).	32
Figure 2.23	FA for RCA.	32
Figure 2.24	Block Diagram in getting the sum for Parallel Prefix Adder.	33
Figure 2.25	Architecture of Propagator and Generator (PG) Block.	33
Figure 2.26	Architecture of Various Carry Generator (PPC) Block.	34
Figure 2.27	Architecture of 8-bit Carry Look Ahead Adder (CLA).	34

Figure 2.28	Top entity for CLA.	35
Figure 2.29	PG block for CLA.	35
Figure 2.30	CLA-Level 1 generator/CLA generator for CLA.	36
Figure 2.31	4-bit 4-bit of PG block (PG-4) Block for CLA.	37
Figure 2.32	4-bit 4-bit of Various Carry Generator (PPC-4) for CLA.	37
Figure 2.33	Top entity for Kogge-Stone Adder (KSA).	39
Figure 2.34	PPC block for KSA.	40
Figure 2.35	Fundamental Carry Operator (FCO) block for KSA.	40
Figure 2.36	Arrangement of FCO block for 16-bit KSA.	41
Figure 2.37	Top entity for Brent-Kung Adder (BKA).	41
Figure 2.38	Arrangement of FCO block for 16-bit BKA.	42
Figure 2.39	Block diagram 4-bit Carry Save Adder (CSA).	44
Figure 3.1	Flow Chart for Overall Project.	48
Figure 3.2	Flow Chart for Adder and Multiplier architecture simulation.	49
Figure 3.3	Electronic Design Automation (EDA) Tool Design Flow Chart.	51
Figure 3.4	Folder Required in EDA Tools.	52
Figure 3.5	Top entity for MAC architecture for Selective Kernel Size.	54
Figure 3.6	3 x 3 matrix of Kernel Mask.	55
Figure 3.7	Control Unit (CU) for Selective Kernel Size MAC architecture.	56
Figure 3.8	Algorithm State Machine (ASM) of CU block in Selective Kernel Size MAC architecture.	59
Figure 3.9	Data Unit (DU) with Classical Additional Arrangement for Selective Kernel Size MAC architecture.	60
Figure 3.10	DU with CSA Arrangement for Selective Kernel Size MAC architecture.	61
Figure 3.11	16-bit CSA	62
Figure 4.1	Time Delay for 16-bit Adder.	66
Figure 4.2	Speed Up Graph for 16-bit Adder.	67
Figure 4.3	Cell Area for 16-bit Adder.	68
Figure 4.4	Leakage Power for 16-bit Adder.	68
Figure 4.5	Dynamic Power for 16-bit Adder.	69

Figure 4.6	Performance Result for 16-bit Adder.	70
Figure 4.7	Time Delay for 8-bit Multiplier.	71
Figure 4.8	Speed Up Graph for 8-bit Multiplier.	72
Figure 4.9	Cell Area for 8-bit Multiplier.	72
Figure 4.10	Leakage Power for 8-bit Multiplier.	73
Figure 4.11	Dynamic Power for 8-bit Multiplier.	74
Figure 4.12	Performance Result for 8-bit Multiplier.	74
Figure 4.13	Time Delay for MAC and MAC <sub>CSA</sub> Simulation Results.	78
Figure 4.14	Speed Up Graph for MAC and MAC <sub>CSA</sub> Simulation Results.	79
Figure 4.15	Cell Area for MAC and MAC <sub>CSA</sub> Simulation Results.	79
Figure 4.16	Total Power for MAC and MAC <sub>CSA</sub> Simulation Results.	80
Figure 4.17	Leakage Power for MAC and MAC <sub>CSA</sub> Simulation Results.	81
Figure 4.18	Dynamic Power for MAC and MAC <sub>CSA</sub> Simulation Results.	82
Figure 4.19	Performance Result for MAC and MAC <sub>CSA</sub> Simulation Results.	83
Figure 4.20	Percentage Difference for MAC and MAC <sub>CSA</sub> Simulation Results.	84
Figure 4.21	Time Delay between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_v1.	91
Figure 4.22	Time Delay between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_v3.	91
Figure 4.23	Time Delay between mixing of different size of MAC design and Selective Kernel Size MAC design in Inception_Resnet.	92
Figure 4.24	Speed Up Graph between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	93
Figure 4.25	Cell Area for between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	94
Figure 4.26	Total Power between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	95

Figure 4.27	Leakage Power between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	96
Figure 4.28	Dynamic Power between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	97
Figure 4.29	Performance Result between mixing of different size of MAC design and Selective Kernel Size MAC design in different CNNs network.	98
Figure C.1	Layout of 16-bit Ripple Carry Adder.	155
Figure C.2	Layout of 16-bit Carry Look Ahead Adder.	156
Figure C.3	Layout of 16-bit Kogge Stone Adder.	157
Figure C.4	Layout of 16-bit Brent-Kung Adder.	157
Figure C.5	Layout of 16-bit Array Multiplier.	158
Figure C.6	Layout of 16-bit Booth Multiplier.	159
Figure C.7	Layout of 16-bit Wallace-Tree Multiplier.	159
Figure C.8	Layout of 16-bit Wallace-Tree Multiplier with KSA.	160
Figure C.9	Layout of 16-bit Wallace-Tree Multiplier with CLA.	160
Figure C.10	Layout of MAC with fusion between WT and CLA.	161
Figure C.11	Layout of MAC with fusion between WT and KSA.	162
Figure C.12	Layout of MAC with fusion between WT-CLA and CLA.	163
Figure C.13	Layout of MAC with fusion between WT-CLA and KSA.	164
Figure C.14	Layout of MAC with fusion between WT-KSA and CLA.	165
Figure C.15	Layout of MAC with fusion between WT-KSA and KSA.	166
Figure C.16	Layout of MAC with fusion between WT and CLA.	167
Figure C.17	Layout of MAC with fusion between WT and KSA.	168
Figure C.18	Layout of MAC with fusion between WT-CLA and CLA.	169
Figure C.19	Layout of MAC with fusion between WT-CLA and KSA.	170
Figure C.20	Layout of MAC with fusion between WT-KSA and CLA.	171
Figure C.21	Layout of MAC with fusion between WT-KSA and KSA.	172

## LIST OF ABBREVIATIONS

ASIC	–	Application Specific Integrated Circuit
ASM	–	Algorithm State Machine
AM	–	Array Multiplier
BKA	–	Brent-Kung Adder
BM	–	Booth Multiplier
$C_i$	–	Carry Signal
$C_{in}$	–	Carry in
$C_{out}$	–	Carry out
CAVM	–	Constant Array Vector Multiplication
CLA	–	Carry Look Ahead Adder
CSA	–	Carry Save Adder
CSDC	–	Computation Sharing Differential Coefficient
CNNs	–	Convolutional Neural Networks
CPG	–	Carry Propagation Generator
$control_m$	–	control value from CU to control the high for the Kernel matrix size
$control_r$	–	control value from CU to control the length for the Kernel matrix size
CU	–	Control Unit
DSP	–	Digital Signal Processing
DU	–	Data Unit
EDA	–	Electronic Design Automation
FA	–	Full Adder
FCO	–	Fundamental Carry Operator

FWBM	–	fixed-width Booth multiplier
FIR	–	Finite Impulse Response
FPGA	–	Field Programmable Gate Arrays
G	–	Generator
$G_i$	–	Generation Signal
HA	–	Half Adder
IC	–	Integrated Circuit
ICC	–	Integrated Circuit Compiler
KSA	–	Kogge-Stone Adder
LSB	–	Least Significant Bit
LUT	–	Lookup Table
MAC	–	Multiplier-Accumulator
MAC-WT-CLA	–	Multiplier-Accumulator normal structure with Wallace-Tree Multiplier combine and Carry Look Ahead Adder
MAC-WTK-KSA	–	Multiplier-Accumulator normal structure with Wallace-Tree Multiplier combine and Kogge-Stone Adder
MAC-WTC-CLA	–	Multiplier-Accumulator normal structure with WT-CLA combine and Carry Look Ahead Adder
MAC-WTC-KSA	–	Multiplier-Accumulator normal structure with WT-CLA combine and Kogge-Stone Adder
MAC-WTK-CLA	–	Multiplier-Accumulator normal structure with WT-KSA combine and Carry Look Ahead Adder
MAC-WTK-KSA	–	Multiplier-Accumulator normal structure with WT-KSA combine and Kogge-Stone Adder
$MAC_{CSA}$	–	Multiplier-Accumulator with Carry Save Adder structure after multiplier product
$MAC_{CSA}$ -WT-CLA	–	$MAC_{CSA}$ structure with Wallace-Tree Multiplier combine and Carry Look Ahead Adder

$MAC_{CSA}$ -WT-KSA-		$MAC_{CSA}$ structure with Wallace-Tree Multiplier combine and Kogge-Stone Adder
$MAC_{CSA}$ -WTC-CLA-		$MAC_{CSA}$ structure with WT-CLA combine and Carry Look Ahead Adder
$MAC_{CSA}$ -WTC-KSA-		$MAC_{CSA}$ structure with WT-CLA combine and Kogge-Stone Adder
$MAC_{CSA}$ -WTK-CLA-		$MAC_{CSA}$ structure with WT-KSA combine and Carry Look Ahead Adder
$MAC_{CSA}$ -WTK-KSA-		$MAC_{CSA}$ structure with WT-KSA combine and Kogge-Stone Adder
MUX	–	Multiplexer
OGA	–	Orthogonal Genetic Algorithm
P	–	Propagator
$P_i$	–	Propagation Signal
PG	–	Propagator and Generator
PG-4	–	4-bit of PG block
POT	–	Powers of Two
PPA	–	performance, power and area
PPC	–	Various Carry Generator
PPC-4	–	4-bit of Various Carry Generator
PPG	–	Partial Product Generator
PPRT	–	Partial Product Reduction Tree
QCA	–	Quantum-dot Cellular Automata
RCA	–	Ripple-Carry Adder
RMACA	–	Reconfigurable MAC Systolic Array Architecture
RTL	–	Register Transfer Level
$size_m$	–	input value to control the high for the Kernel matrix size
$size_r$	–	input value to control the length for the Kernel matrix size

Sm	–	carry value of size <sub>m</sub> after one clock cycle
Sr	–	carry value of size <sub>r</sub> after one clock cycle
STA	–	Static Timing Analysis
Sum <sub>i</sub>	–	Sum Signal
TEC	–	Truncation Error Compensation
VLSI	–	Very-Large-Scale Integration
VHDL	–	Very High Speed Integrated Circuit Hardware Description Language
WT	–	Wallace-Tree Multiplier
WT-CLA	–	Wallace-Tree Multiplier with Carry Look Ahead Adder at Carry Propagation Generator
WT-KSA	–	Wallace-Tree Multiplier with Kogge-Stone Adder at Carry Propagation Generator

## LIST OF SYMBOLS

$\oplus$	–	xor gate description
$\leq$	–	less and equal description
$\geq$	–	less and equal description
$\cdot$	–	and gate description
$ $	–	or gate description
$+$	–	symbol of adding process
$\times$	–	symbol of multiply process
$\%$	–	symbol of percentage
$\mu$	–	symbol of unit prefix in the metric system denoting a factor of $10^{-6}$
$\checkmark$	–	check-mark for simulation results compare to theoretical

## LIST OF APPENDICES

<b>APPENDIX</b>	<b>TITLE</b>	<b>PAGE</b>
Appendix A	Coding in Verilog Code	115
Appendix B	Testbench code for simulation	145
Appendix C	Post Layout	155

# CHAPTER 1

## INTRODUCTION

Convolution Neural Networks (CNNs) is the fundamental technology that is utilised in image processing task such as image classification. In order to manage image classification task, a computer or system must be able to search for low-level characteristics in the kernel mask, such as edges and curves. The CNNs system can output the input image of a probability class to provide it the best description based on the mapping of the original input image with kernel mask. All of these processes will eventually add up to additional learning concepts spread across a network of convolution layers in CNNs.

When traversing through the convolution layer in CNN, a bundle of Multiple Accumulation (MAC) process blocks of varying sizes appear. A new MAC architecture for CNNs application will be introduced in this work. MAC is basic component used in CNNs to perform the multiply-accumulation process, which includes multiple registers as a Lookup Table (LUT) to store the feature maps and kernels for image classification class. For example, with  $3 \times 3$  kernel mask used, the values of first 3 columns are multiplied by the first value of the kernel mask used respectively and accumulated for a value. The operation will be repeated for the remaining values in the kernel mask table. The output result is primarily about the MAC between the pixels of the input image with kernel size, which is significant in the convolution layer process. Because it is the primary function of convolution layers, the type of MAC utilised has a direct impact on the performance of the CNNs process.

In this study, the MAC is developed with a control unit (CU) block that allows it to traverse any Kernel Size used in different CNNs networks without changing the MAC architecture or arrangement. As a result, this MAC design increases its flexibility and covers practically all significant kernel mask sizes to suit the requirements of every sort of CNNs network. The flexibility of the MAC architecture designed also contributes

significantly to the innovation of CNN networks. The Selective Kernel Size algorithm, which is employed in MAC, will be explained in further detail in Chapter 3.

MAC is defined in two architectures throughout this work. This study's  $MAC_{CSA}$  architecture will present one with classical addition and another MAC architecture. Before the accumulator,  $MAC_{CSA}$  will replace the adding component of MAC. A normal adder can only add two groups of numbers at a time, whereas CSA can add up to three groups of numbers at once. This new design architecture is described in detail in this thesis.

To identify an effective MAC, simulation of many types of multiplier and adder is required to select the best architecture for MAC design. Dynamic Power, Leakage Power, Cell Area, and Time Delay are all important parameters to consider. For the Multiplier, it will be compared between WT, BM, and the AM benchmark. WT will have three distinct designs due to the employment of different Adders in its Carry Propagation Generator (CPG). KSA, CLA, and the default adder in EDA Tool are among the adders utilised. On the other hand, adder will be compared in the simulation between KSA, CLA, and BKA by using RCA as benchmark.

## **1.1 Problem Statement**

The MAC is a fundamental unit block in all Digital Signal Processing (DSP) systems and plays critical functions in CNNs. Because it is a lower level component in a system, the time delay and power consumption will have a direct impact on the entire system. As a result, an efficient MAC may increase the overall performance of CNNs.

Each convolution layer in CNNs requires a different size kernel mask. According to earlier research, each size of kernel mask necessitates a separate MAC architectural configuration [1]. This lengthens the trial-and-error process of determining the best MAC size and layout of those MAC architectures for the simulation process. With the Selective Kernel Size technique, the user can quickly change the size of the MAC by entering 0 or 1 into the control unit. In other words, just one MAC

design is required for the entire convolution Layer in CNNs. Selective Kernel Size has a function in the flexibility of arrangement between each MAC when going through the invention of CNNs model.

CSA is a binary adder that can easily compute the sum of three or more bits of data. Typically, MAC for CNNs must include at least three numbers of data. In this thesis, CSA may sum three 16-bit numbers concurrently. This will undoubtedly boost MAC performance.

## **1.2 Objective**

1. To study and compare the speed, area and power of multiplier and adder and select for MAC fusion design used in CNNs for Application Specific Integrated Circuit (ASIC) implementation.
2. To propose and implement ASIC Selective Kernel Size MAC to match the different requirement of each type of CNNs networks.
3. To propose and implement  $MAC_{CSA}$  architecture and compare with classical addition MAC architecture.

## **1.3 Scope of Study**

1. The type of adder used in MAC:
  - (a) CLA
  - (b) KSA
2. The type of multiplier used in MAC:
  - (a) WT with EDA Tool default adder used in CPG (WT)
  - (b) WT with CLA used in CPG (WT-CLA for Multiplier, WTC for MAC)
  - (c) WT with KSA used in CPG (WT-KSA for Multiplier, WTK for MAC)

3. This thesis discusses the kernel mask size of a convolution layer ranging from  $1 \times 1$  matrix to  $7 \times 7$  matrix.
4. The developed MAC design with 8-bit input is used in each convolution layer of CNNs using the Selective Kernel Size technique.

#### **1.4 Contribution**

The contribution of this research is as follows:-

1. Investigate various adder and multiplier architectural designs in synthesis and analysis. They are combined to discover the ideal MAC architecture design in terms of performance, power and area (PPA).
2. Redesign the classical MAC architecture so that it can be selective in the kernel matrix size utilised by the convolution layer of various types of CNNs. Only one MAC design is necessary because it can cover the majority of kernel matrix sizes utilised by the convolution layer of various types of CNNs.
3. Redesign the MAC architecture that is used in the convolution layer. The traditional MAC adds two groups of numbers before adding the preceding result. In this paper, we replace the adder with CSA, which can add up to three groups of numbers at once before accumulating with the preceding result.

#### **1.5 Organization in Thesis**

The thesis is organized as follows:-

1. The history and operation of CNNs will be covered in Chapter 2. The kernel matrix size utilised for each well-known type of CNNs will be listed. As the study's outcome is a new architecture design of MAC, the major context will be MAC used for convolution layer. Finally, a full examination of the multiplier and adder utilised in MAC architecture.

2. Chapter 3 discusses each algorithm employed, from research through design to algorithm verification. The discussion starts with how MAC performs in the Selective Kernel Size architecture and progresses to the later stages of adding multiplier and adder. The proposed working techniques for this thesis, which include all algorithmic function blocks, will be presented in depth. The classic addition MAC in Selective Kernel Size Architecture will be illustrated first, followed by the  $MAC_{CSA}$  method of selected adder and multiplier. Each method available for producing algorithm design, verify the functionality of proposed design, and simulation result of each design will also be presented.
3. The simulation results of all designs are discussed in Chapter 4 according to their level. This includes the results for the selected 16-bit adder and 8-bit multiplier, followed by the MAC architecture results for the proposed Selective Kernel Size MAC and the new MAC-CSA architecture. For each explored designs, results are presented in terms of performance, power, and area.
4. Chapter 5 provides a summary of this thesis. This includes the summary of the work that has been done, as well as the contributions. The chapter also gives a conclusion on the overall perspective of the work, and with the final section on several possible future directions for the work.

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