## **LAB 4: STUDENT WORKSHEET**

## **Machine Learning Hardware Optimization**

Student	ID:				
Date:					
		_	NCE BENCHMAR		platforms:
Model	Hardware	Training Time (s)	Samples/Second	Valid	dation Accuracy (%)
CNN	CPU				
CNN	GPU				
FCNN	CPU				
FCNN	GPU				
	· 		Inference Time (ms)	ardware	· 
Model	Hardware	Batch Size	Inference Time (ms)	ardware	e platforms:  Samples/Second
<b>Model</b> CNN	<b>Hardware</b> CPU	Batch Size	T	ardware	· 
Model CNN CNN	Hardware CPU CPU	Batch Size  1 32	T	ardware	· 
	<b>Hardware</b> CPU	Batch Size	T	ardware	· 
Model CNN CNN CNN	Hardware CPU CPU GPU	Batch Size  1 32	T	ardware	· 
Model CNN CNN CNN CNN FCNN	Hardware CPU CPU GPU GPU	Batch Size  1 32 1 32	T	ardware	· 
Model CNN CNN CNN CNN	Hardware CPU CPU GPU GPU CPU	Batch Size  1 32 1 32 1	T	ardware	· 
Model CNN CNN CNN CNN FCNN	Hardware CPU CPU GPU GPU CPU CPU	Batch Size  1 32 1 32 1 32 1 32	T	ardware	· 
Model CNN CNN CNN CNN FCNN FCNN FCNN	Hardware CPU CPU GPU GPU CPU CPU CPU CPU	Batch Size  1 32 1 32 1 32 1 32 1	T	ardware	· 
Model CNN CNN CNN CNN FCNN FCNN FCNN FCNN	Hardware CPU CPU GPU GPU CPU CPU CPU CPU	Batch Size  1 32 1 32 1 32 1 32 1	T	ardware	· 
Model CNN CNN CNN CNN FCNN FCNN FCNN FCNN FC	Hardware  CPU CPU GPU CPU CPU CPU GPU GPU GPU GPU GPU GPU your results:	Batch Size  1 32 1 32 1 32 1 32 1 32 1 32	T	ardware	· 

PART 2: MODE	L QUANTIZAT	ION		
Record the perform	nance metrics for d	ifferent quanti	zation techniques:	
Model	Accuracy (%)	Model	Size (MB)	Size Reduction (%)
Original Model				N/A
TFLite (Float32)				
TFLite (Float16)				
TFLite (Int8)				
accuracy loss?		vould you reco	ommend int8 quar	ntization, despite potentia
accuracy loss?  PART 3: MODE				ntization, despite potentia
accuracy loss?  PART 3: MODE ecord the perform	EL PRUNING			
PART 3: MODE ecord the perform	EL PRUNING	ifferent prunin	g techniques:	
PART 3: MODE ecord the perform Model Original Model	EL PRUNING	ifferent prunin	g techniques:	) Size Reduction (%)
accuracy loss?  PART 3: MODE ecord the perform  Model  Original Model  Pruned Model	EL PRUNING  nance metrics for di	ifferent prunin	g techniques:	) Size Reduction (%)
accuracy loss?  PART 3: MODE	EL PRUNING nance metrics for di	ifferent prunin	g techniques:	) Size Reduction (%)

1. How effective is pruning at reducing model size while maintaining accuracy?

2. What are the	e combined effects of prur	ning and quantization?
3. What hardwa	are benefits would you exp	pect from a pruned model (beyond size reduction)?
-	LOYMENT FORMAT	
Format	Model Size (MB)	Size Relative to Original Keras Model (%)
Keras (H5)		100%
TensorFlow Lite		
ONNX		
SavedModel		
TensorFlow.js		
Based on your re		e-efficient? Why might this be the case?
	-	choosing a deployment format beyond size?
		ich format would you recommend and why?
PART 5: COM	IPREHENSIVE ANA	LYSIS

PART 6: REFLECT  Vrite a short reflection mportance for ML mo	n (100-150 w		what you lea	rned abou	t hardware opti	mization and its
PART 6: REFLECT	n (100-150 w		what you lea	rned abou	t hardware optii	mization and its
PART 6: REFLECT	n (100-150 w		what you lea	rned abou	t hardware optii	mization and its
	ION					
model for a smare						
3. What would be yo model for a smart		nded app	roach for op	timizing a	real-time comp	uter vision
2. If you needed to combine?	deploy a mod	del with <	1MB size, wh	iich optimi	zation techniqu	es would you
1. What optimization	n technique բ	provides t	he best accu	racy-per-N	1B efficiency?	
Based on your compre	ehensive ana	lysis:				
Server Deployment						
Mobile Deployment						
Trade on						
Best Accuracy/Size Trade-off						

Accuracy

(%)

Size

(MB)

Best

Model/Technique

**Priority** 

**Highest Accuracy** 

Grade: \_\_\_\_\_/ \_\_\_\_\_

**Accuracy Loss** 

(%)

**Size Reduction** 

(%)