SqueezeNet for Leaf Disease Detection

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CSC14116 - Applied Parallel Programming

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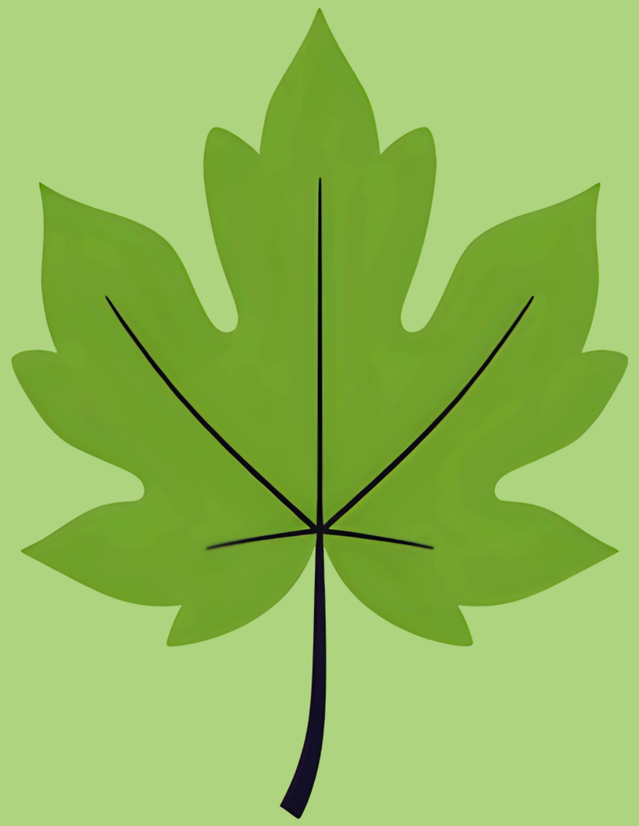
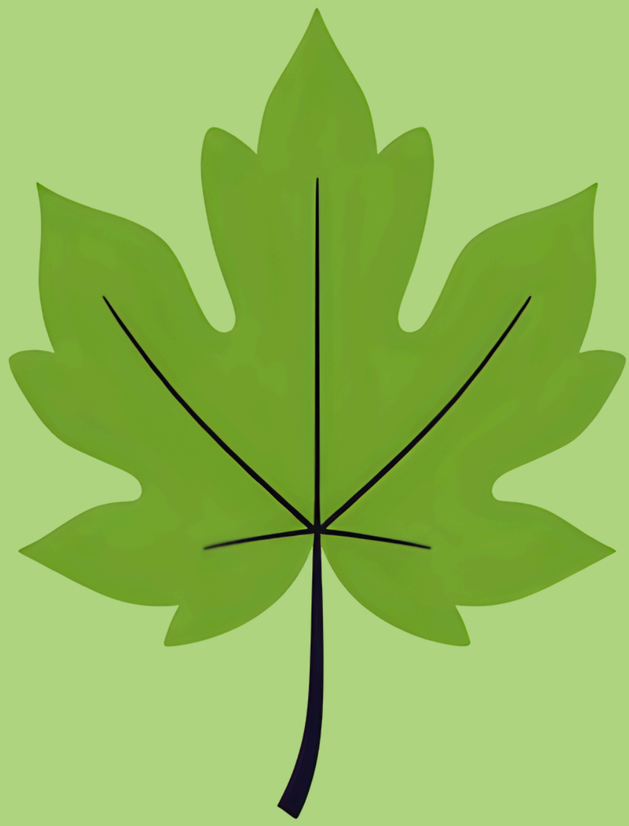
- Nguyễn Trần Duy Minh

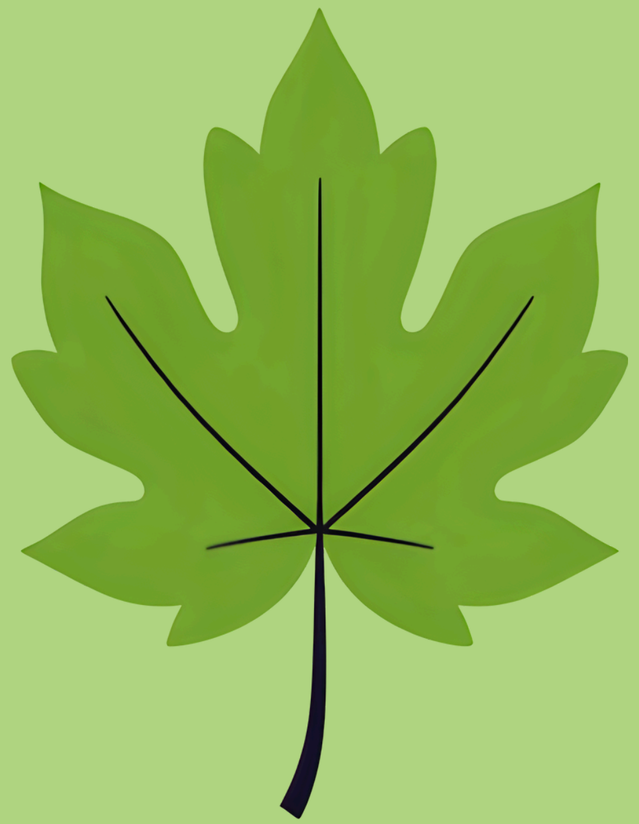
Innovative solutions for agricultural challenges



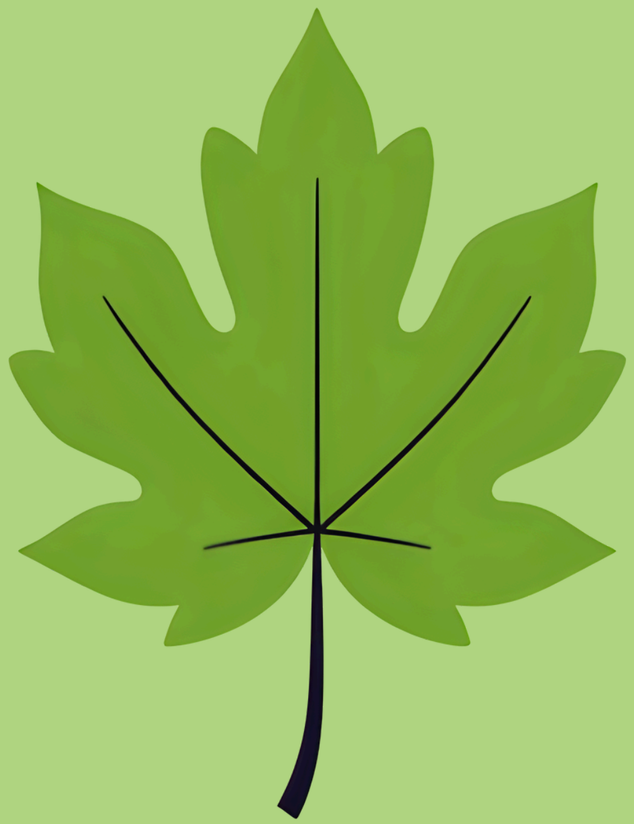
Deleveriables Overview



Type of Passing	Modules		Versions		
			CPU-based	CUDA	CUDA with Shared Memory
Inference	***2D Convolution***	• Convolution 1x1 • Convolution 3x3 • Convolution 7x7	✅	✅	✅
	Pooling	• Max Pooling • Global Average Pooling	✅	✅	
	Activations	• ReLU • softmax	✅	✅	
	Concat		✅	✅	
Gradient calculation	***Gradient w.r.t input***	2D Convolution Bias	✅	✅	
		Pooling: • Max Pooling • Global Average	✅	✅	
		Activations: • ReLU • softmax	✅	✅	
	Gradient w.r.t filters	2D Convolution	✅	✅	
	Fire Module (Inference and gradient)		✅	✅	



Inference



Convolution

		CPU-based	CUDA	CUDA shared Memory	Pytorch
Input		**Images X** → 4D np.ndarray / tensor **Filters W** → 4D np.ndarray / tensor **Biases B** → 1D np.ndarray / tensor **Stride S** → int **Padding P** → int			
			Thread Per Block TPB → 16 x 16		
Output		**out**→ 4D np.ndarray / tensor			
Description		2D sliding window algorithm with stride and padding	1 thread per ouput cell, read directly from global memory, coalesced	Load the input tile into shared memory; reuse the data to reduce global memory access; each block computes the output cells within the tile.	
Time	**1x1**	**2.894**	**0.00691 (x419)**	**0.00894 (x324)**	**0.00122 (x2364)**
	7x7	**55.707**	**0.02662 (x2092)**	**0.01474 (x3779)**	**0.00106 (x52236)**

Max Pooling

	CPU-based	CUDA	Pytorch
Input	**Images X** → 4D np.ndarray / tensor **Stride S** → int **Padding P** → int		
		Thread Per Block TPB → 16 x 16	
Output	**out** → 4D np.ndarray / tensor		
Description	• 2D sliding window algorithm with stride	• 1 thread per ouput cell, read directly from global memory, coalesced	
Time	**9.01628**	**0.0058 (x1554)**	**0.00054 (x16522)**

Global Average Pooling

	CPU-based	CUDA	Pytorch
Input	**Images X** → 4D np.ndarray / tensor		
		Thread Per Block TPB → 16 x 16	
Output	**out** → 4D np.ndarray / tensor		
Description	• Every cell is divided by (HxW)	• 1 thread per ouput cell, read directly from global memory, coalesced	
Time	**0.00024**	**0.00429 (x0.55)**	**0.00077 (x0.308)**

ReLU

<table>
<tr><th></th><th>CPU-based</th><th>CUDA</th><th>Pytorch</th></tr>
<tr><td rowspan="2">Input</td><td colspan="2">Images X → 4D np.ndarray / tensor</td><td rowspan="4"></td></tr>
<tr><td></td><td>Thread Per Block TPB → 16 x 16</td></tr>
<tr><td>Output</td><td colspan="2">out→ 4D np.ndarray / tensor</td></tr>
<tr><td>Description</td><td>• Use np.where() to to find keep cells’ positive values</td><td>• 1 thread per ouput cell, read directly from global memory, coalesced</td></tr>
<tr><td>Time</td><td>0.05819</td><td>0.00584
(x9.957)</td><td>0.00095
(x61.142)</td></tr>
</table>

Softmax

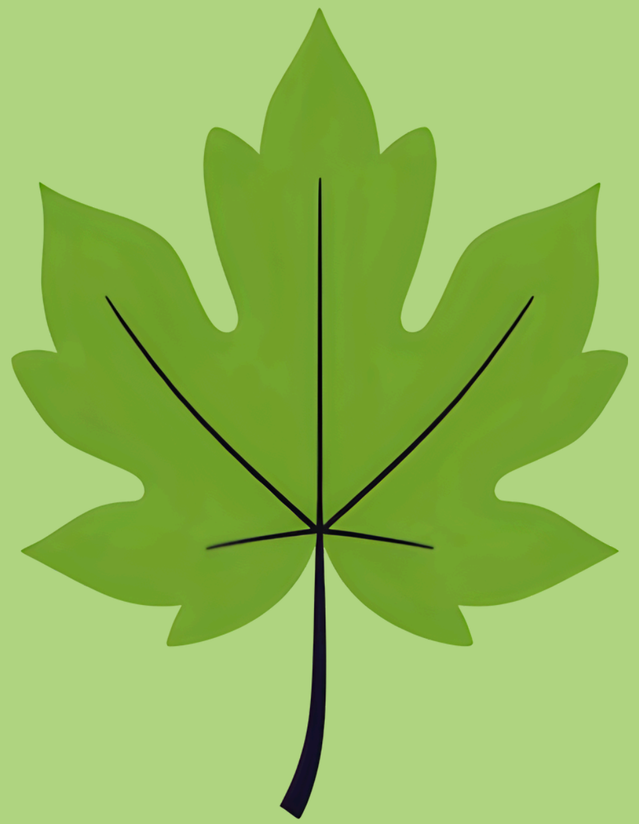
<table>
<tr><th></th><th>CPU-based</th><th>CUDA</th><th>Pytorch</th></tr>
<tr><td rowspan="2">Input</td><td colspan="2">Images X → 4D np.ndarray / tensor</td><td rowspan="3"></td></tr>
<tr><td></td><td>Thread Per Block TPB → 16 x 16</td></tr>
<tr><td>Output</td><td colspan="2">out→ 4D np.ndarray / tensor</td></tr>
<tr><td>Description</td><td>Use numpy methods</td><td>1 thread per ouput cell, read directly from global memory, coalesced</td></tr>
<tr><td>Time</td><td>0.00013</td><td>0.00365
(x0.036)</td><td>0.00094
(x0.141)</td></tr>
</table>

Concat

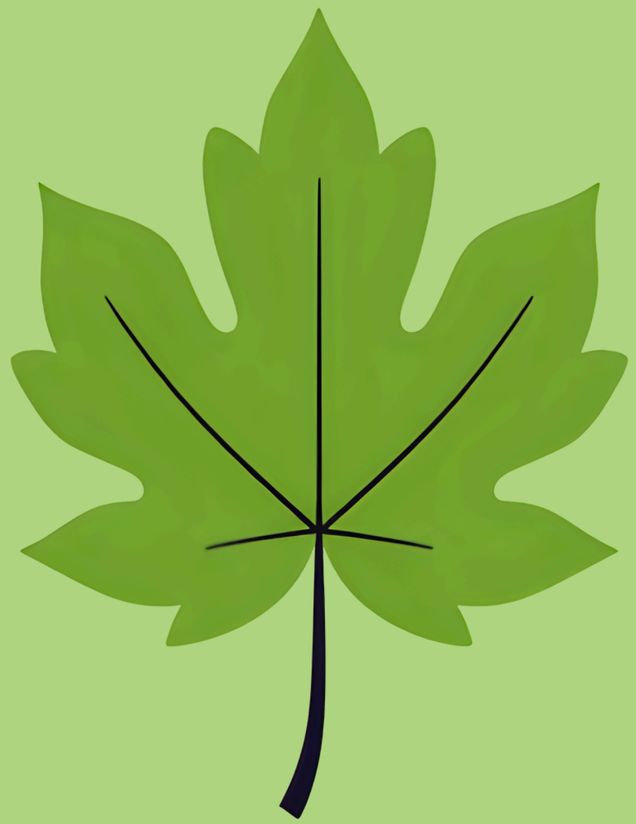
<table>
<tr><th></th><th>CPU-based</th><th>CUDA</th><th>Pytorch</th></tr>
<tr><td rowspan="2">Input</td><td colspan="2">Images X1 → 4D np.ndarray / tensor
Images X2 → 4D np.ndarray / tensor</td><td rowspan="3"></td></tr>
<tr><td></td><td>Thread Per Block TPB → 16 x 16</td></tr>
<tr><td>Output</td><td colspan="2">out→ 4D np.ndarray / tensor</td></tr>
<tr><td>Description</td><td>• Use numpy.concatenate() method</td><td>• 1 thread per ouput cell, read directly from global memory, coalesced</td></tr>
<tr><td>Time</td><td>0.00572</td><td>0.00459552
(x1.246)</td><td>0.00036
(x15.922)</td></tr>
</table>

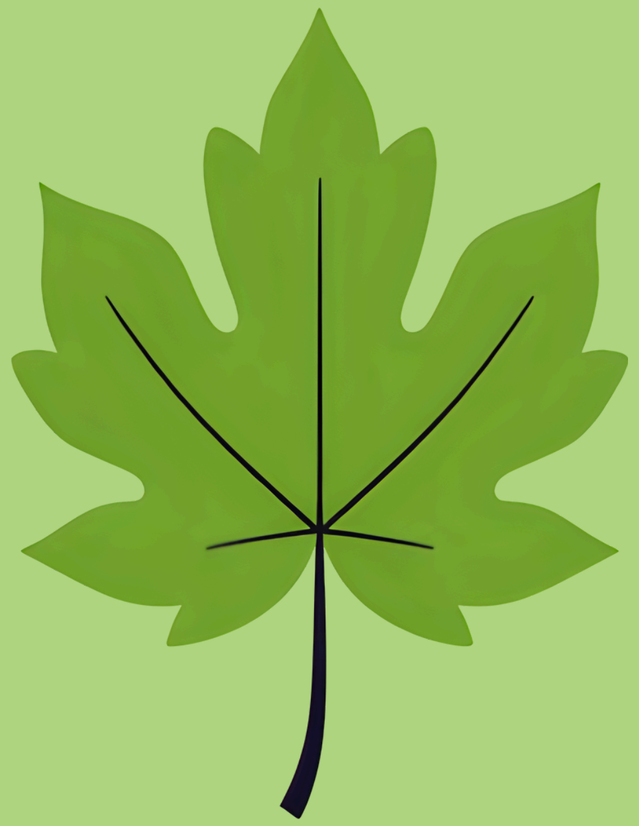
Fire Module

	CPU-based	CUDA	Pytorch
Input	**Images X** → 4D np.ndarray / tensor		
Output	**out** → 4D np.ndarray / tensor		
Time	**20.0657**	**0.01832 (x1095.27)**	**0.00142 (x14085.7)**

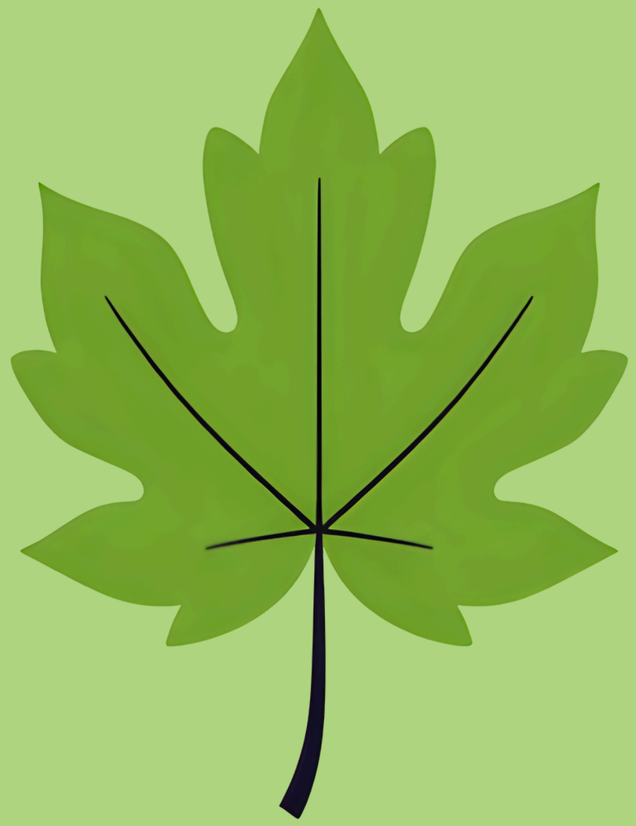


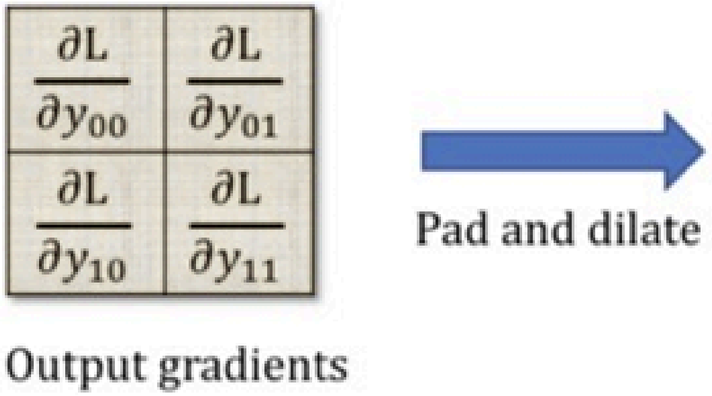
Gradient Calculation





Convolution Gradient w.r.t Input





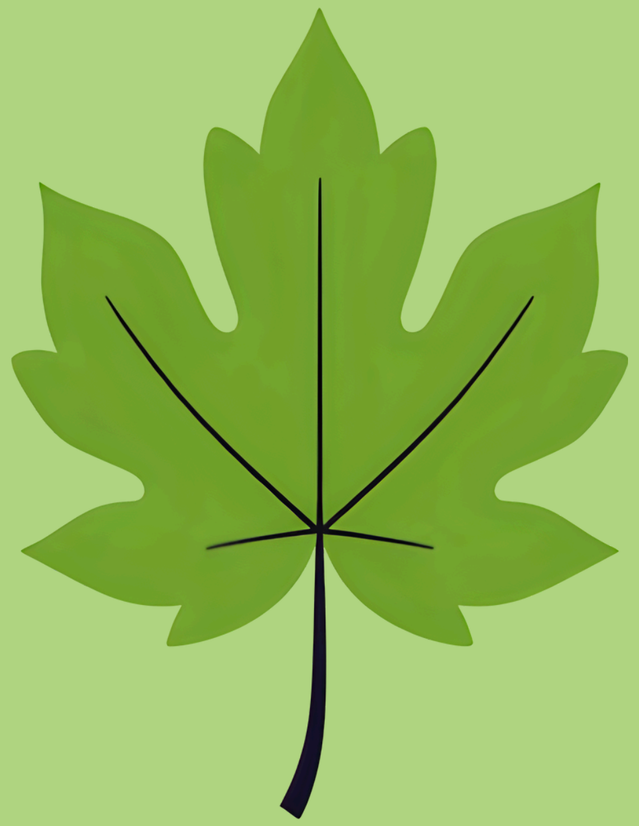
stride_S = stride_R= 2

$$\frac{\partial \mathrm{L}}{\partial x_{00}} = \frac{\partial L}{\partial y_{00}} f_{00}$$

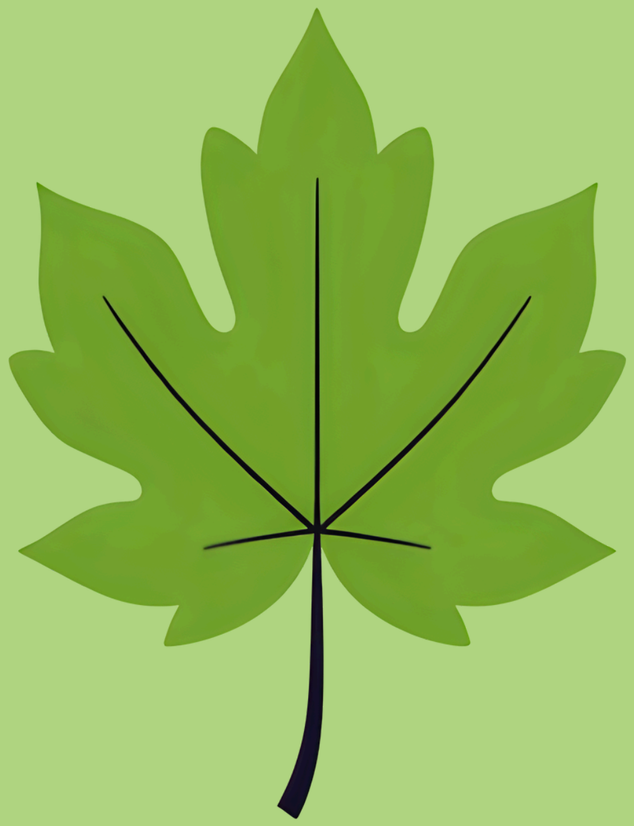
$\frac{\partial \mathrm{L}}{\partial x_{00}}$	$\frac{\partial \mathrm{L}}{\partial x_{01}}$	$\frac{\partial \mathrm{L}}{\partial x_{02}}$	$\frac{\partial \mathrm{L}}{\partial x_{03}}$	$\frac{\partial \mathrm{L}}{\partial x_{04}}$
$\frac{\partial \mathrm{L}}{\partial x_{10}}$	$\frac{\partial \mathrm{L}}{\partial x_{11}}$	$\frac{\partial \mathrm{L}}{\partial x_{12}}$	$\frac{\partial \mathrm{L}}{\partial x_{13}}$	$\frac{\partial \mathrm{L}}{\partial x_{14}}$
$\frac{\partial \mathrm{L}}{\partial x_{20}}$	$\frac{\partial \mathrm{L}}{\partial x_{21}}$	$\frac{\partial \mathrm{L}}{\partial x_{22}}$	$\frac{\partial \mathrm{L}}{\partial x_{23}}$	$\frac{\partial \mathrm{L}}{\partial x_{24}}$
$\frac{\partial \mathrm{L}}{\partial x_{30}}$	$\frac{\partial \mathrm{L}}{\partial x_{31}}$	$\frac{\partial \mathrm{L}}{\partial x_{32}}$	$\frac{\partial \mathrm{L}}{\partial x_{33}}$	$\frac{\partial \mathrm{L}}{\partial x_{34}}$
$\frac{\partial \mathrm{L}}{\partial x_{40}}$	$\frac{\partial \mathrm{L}}{\partial x_{41}}$	$\frac{\partial \mathrm{L}}{\partial x_{42}}$	$\frac{\partial \mathrm{L}}{\partial x_{43}}$	$\frac{\partial \mathrm{L}}{\partial x_{44}}$

=

$0 * f_{22}$	$0 * f_{21}$	$0 * f_{20}$	0	0	0	0
$0 * f_{12}$	$0 * f_{11}$	$0 * f_{10}$	0	0	0	0
$0 * f_{02}$	$0 * f_{01}$	$\frac{\partial \mathrm{L}}{\partial y_{00}} f_{00}$	0	$\frac{\partial \mathrm{L}}{\partial y_{01}}$	0	0
0	0	0	0	0	0	0
0	0	$\frac{\partial \mathrm{L}}{\partial y_{10}}$	0	$\frac{\partial \mathrm{L}}{\partial y_{11}}$	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0



Convolution Gradient w.r.t Filters



$$\frac{\partial \mathrm{L}}{\partial f_{00}} = \frac{\partial L}{\partial y_{00}} x_{00} + \frac{\partial L}{\partial y_{01}} x_{02} + \frac{\partial L}{\partial y_{10}} x_{20} + \frac{\partial L}{\partial y_{11}} x_{22}$$

$\frac{\partial \mathrm{L}}{\partial f_{00}}$	$\frac{\partial \mathrm{L}}{\partial f_{01}}$	$\frac{\partial \mathrm{L}}{\partial f_{02}}$
$\frac{\partial \mathrm{L}}{\partial f_{10}}$	$\frac{\partial \mathrm{L}}{\partial f_{11}}$	$\frac{\partial \mathrm{L}}{\partial f_{12}}$
$\frac{\partial \mathrm{L}}{\partial f_{20}}$	$\frac{\partial \mathrm{L}}{\partial f_{21}}$	$\frac{\partial \mathrm{L}}{\partial f_{22}}$

=

$\frac{\partial \mathrm{L}}{\partial y_{00}} x_{00}$	$0 * x_{01}$	$\frac{\partial \mathrm{L}}{\partial y_{01}} x_{02}$	x_{03}	x_{04}
$0 * x_{10}$	$0 * x_{11}$	$0 * x_{12}$	x_{13}	x_{14}
$\frac{\partial \mathrm{L}}{\partial y_{10}} x_{20}$	$0 * x_{21}$	$\frac{\partial \mathrm{L}}{\partial y_{11}} x_{22}$	x_{23}	x_{24}
x_{30}	x_{31}	x_{32}	x_{33}	x_{34}
x_{40}	x_{41}	x_{42}	x_{43}	x_{44}

Gradient Convolution

	CPU-based	CUDA
Input	**Images X** → 4D np.ndarray / tensor **Filters W** → 4D np.ndarray / tensor **Gradient pre-layer Output dY** → 4D np.ndarray / tensor **Stride S** → int **Padding P** → int	
		Thread Per Block TPB → 16 x 16
Output	**dX**→ 4D np.ndarray / tensor **dW**→ 4D np.ndarray / tensor **dB**→ 4D np.ndarray / tensor	
Description	2D sliding window algorithm with stride	1 thread per ouput cell, read directly from global memory, coalesced
	Treat dilation with indexing trick	
Time	**87.8563**	**0.11775** **(x746.131)**

Gradient ReLU

<table>
<tr><th></th><th>CPU-based</th><th>CUDA</th></tr>
<tr><td rowspan="2">Input</td><td colspan="2">Images X → 4D np.ndarray / tensor
Gradient pre-layer Output dY → 4D np.ndarray / tensor</td></tr>
<tr><td></td><td>Thread Per Block TPB → 16 x 16</td></tr>
<tr><td>Output</td><td colspan="2">dX→ 4D np.ndarray / tensor</td></tr>
<tr><td rowspan="2">Description</td><td>2D sliding window algorithm with stride</td><td>1 thread per ouput cell, read directly from global memory, coalesced</td></tr>
<tr><td colspan="2">Keep gradient cell if it is positive, else assign zero</td></tr>
<tr><td>Time</td><td>0.00358</td><td>0.00520
(x0.688)</td></tr>
</table>

Gradient Max Pooling

	CPU-based	CUDA
Input	**Images X** → 4D np.ndarray / tensor **Gradient pre-layer Output dY** → 4D np.ndarray / tensor	
		Thread Per Block TPB → 16 x 16
Output	**dX**→ 4D np.ndarray / tensor	
Description	2D sliding window algorithm with stride	1 thread per ouput cell, read directly from global memory, coalesced, using atomic add
	Find out all the positions of max value, pass gradient to these indice	
Time	**11.4671**	**0.00669** **(x1714.309)**

Gradient Global Average Pooling

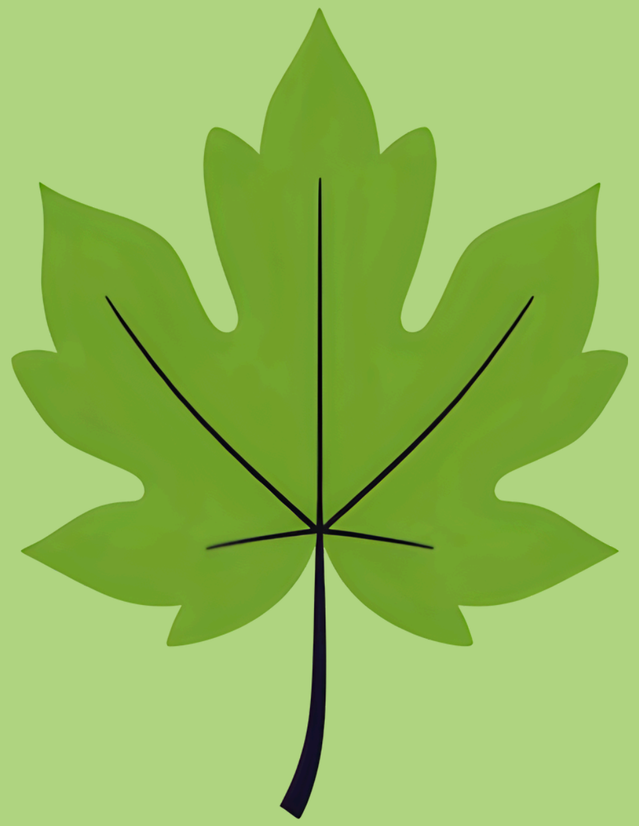
	CPU-based	CUDA
Input	**Gradient pre-layer Output dY** → 4D np.ndarray / tensor	
		Thread Per Block TPB → 16 x 16
Output	**dX**→ 4D np.ndarray / tensor	
Description	Use numpy.average() on all dimensions	1 thread per ouput cell, read directly from global memory, coalesced
Time	**0.00054**	**0.00401 (x0.134)**

Gradient Softmax

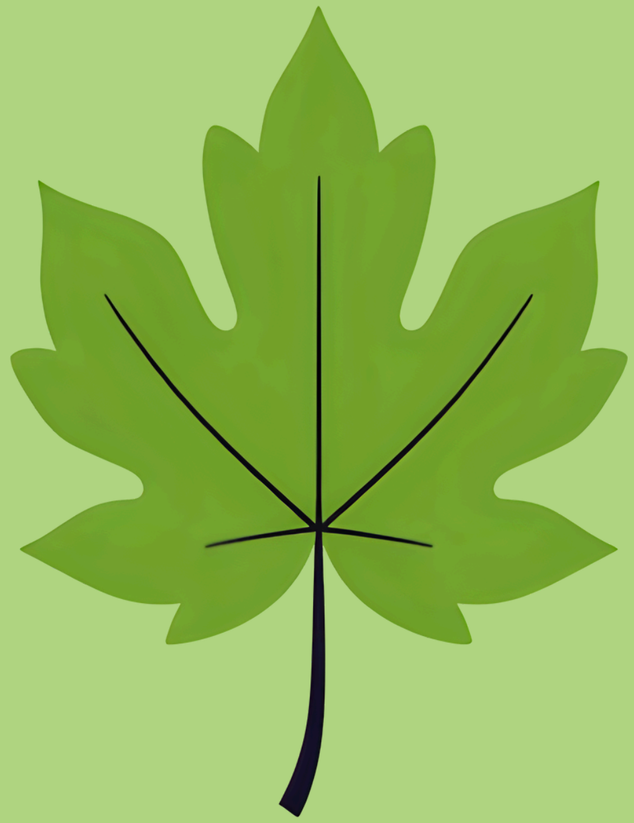
	CPU-based	CUDA
Input	**probs (B,N)** → 2D np.ndarray / tensor	**y_onehot** → 2D np.ndarray / tensor
		Thread Per Block TPB → 16 x 16
Output	**dLogits** → 4D np.ndarray / tensor	
Description	cross-entropy: dL/dz = (p - y)/B.	1 thread per ouput cell, read directly from global memory, coalesced
Time	**0.00014**	**0.00401** **(x0.035)**

Gradient Fire Module

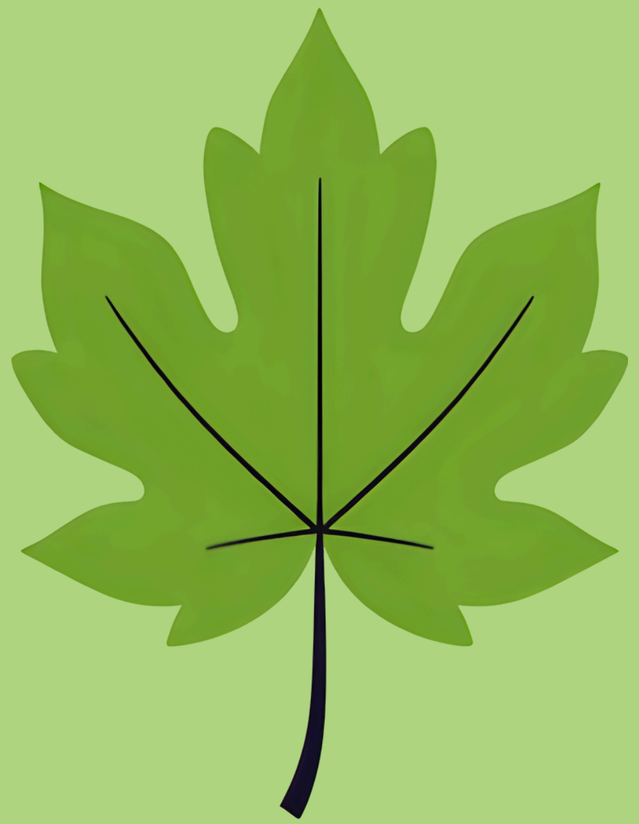
	CPU-based	CUDA
Input	**Images (X_prev)** → 4D np.ndarray / 4D tensor**,** Input activations from the previous layer. **Squeeze Weights (W_sq1x1)** → 4D np.ndarray / 4D tensor Parameters of the squeeze (1×1 conv). **Squeeze Bias (b_sq1x1)** → 1D np.ndarray / 1D tensor **Squeeze Output (X_sq)** → 4D np.ndarray / 4D tensor Cached outputs needed for gradient masking. **ReLU(Squeeze) Output (X_sq_relu)** → 4D np.ndarray / 4D tensor **Expand 1×1 Weights (W_ex1x1)** → 4D np.ndarray / 4D tensor **Expand 3×3 Weights (W_ex3x3)** → 4D np.ndarray / 4D tensor **Concat Output (X_concat)** → 4D np.ndarray / 4D tensor Forward concat of expand1×1 + expand3×3. **Expand 1×1 Bias (b_ex1x1)** → 1D np.ndarray / 1D tensor **Expand 3×3 Bias (b_ex3x3)** → 1D np.ndarray / 1D tensor **Gradient w.r.t Fire Output (dY)** → 4D np.ndarray / 4D tensor Gradient coming from the next layer.	
		Thread Per Block TPB → 16 x 16
Output	**dX_prev** → 4D np.ndarray / 4D tensor **dW_sq1x1** → 4D np.ndarray / 4D tensor **dW_ex1** → 4D np.ndarray / 4D tensor **dW_ex3** → 4D np.ndarray / 4D tensor	**db_sq1x1** → 1D np.ndarray / 1D tensor **db_ex1** → 1D np.ndarray / 1D tensor **db_ex3** → 1D np.ndarray / 1D tensor
Time	**31.0295**	**0.157624** **(x196.858)**



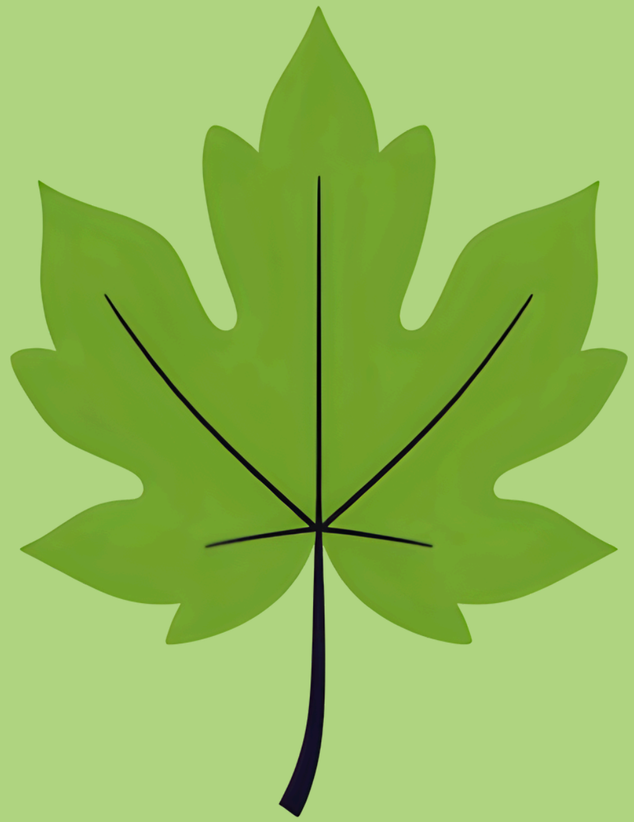
Forward
Backward



	CPU-based	CUDA
Input	**Images** → 4D np.ndarray / 4D tensor	
	Combine all module to model Squeezenet (both fordward and backward)	
Output forward	A dictionary of all layer in squeezenet	
Output backward	A gradient dictionary of all weight and bias in squeezenet	
Time forward	**227.427**	**0.195301 (x1164.495)**
Time backward	**350.383**	**1.32089 (x265.2628)**
Time train in 1 iteration	**577.814**	**1.51619 (x381.097)**



Training



Optimizer

Main Idea

- Use the Adam optimizer to adjust the learning rate, thereby updating gradients more efficiently.
- Since this is a custom optimization problem, instead of creating an update function like PyTorch's optimizer.step, we update directly during gradient computation to avoid slowing down the program

$t \leftarrow t + 1$
$g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ (Get gradients w.r.t. stochastic objective at timestep t)
$m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$ (Update biased first moment estimate)
$v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$ (Update biased second raw moment estimate)
$\widehat{m}_t \leftarrow m_t / (1 - \beta_1^t)$ (Compute bias-corrected first moment estimate)
$\widehat{v}_t \leftarrow v_t / (1 - \beta_2^t)$ (Compute bias-corrected second raw moment estimate)
$\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t / (\sqrt{\widehat{v}_t} + \epsilon)$ (Update parameters)

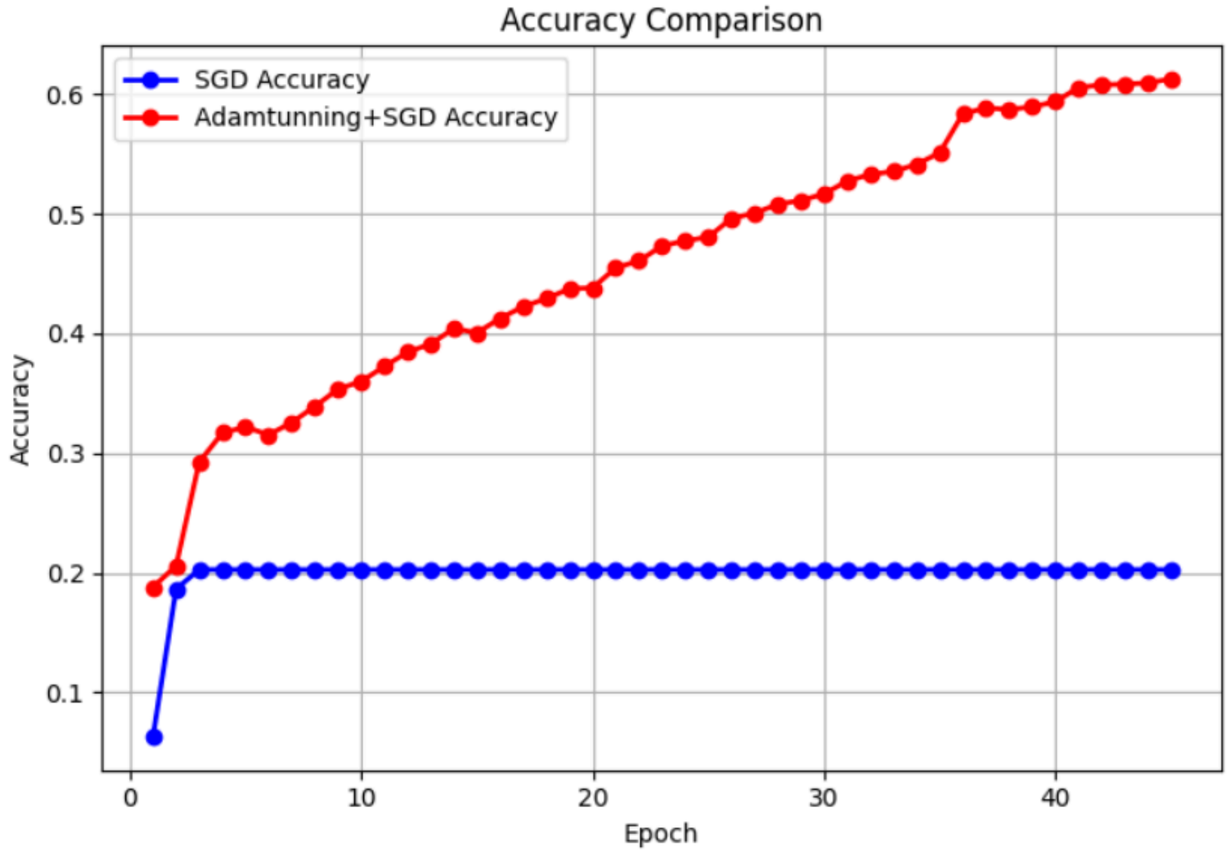
	CUDA+AdamTuning+SGD	Pytorch+SGD
Input	**Number of batch : 550** **Batch size: 32x3x224x224**	
Precision (45 epochs)	**61.3%**	**20.25%**

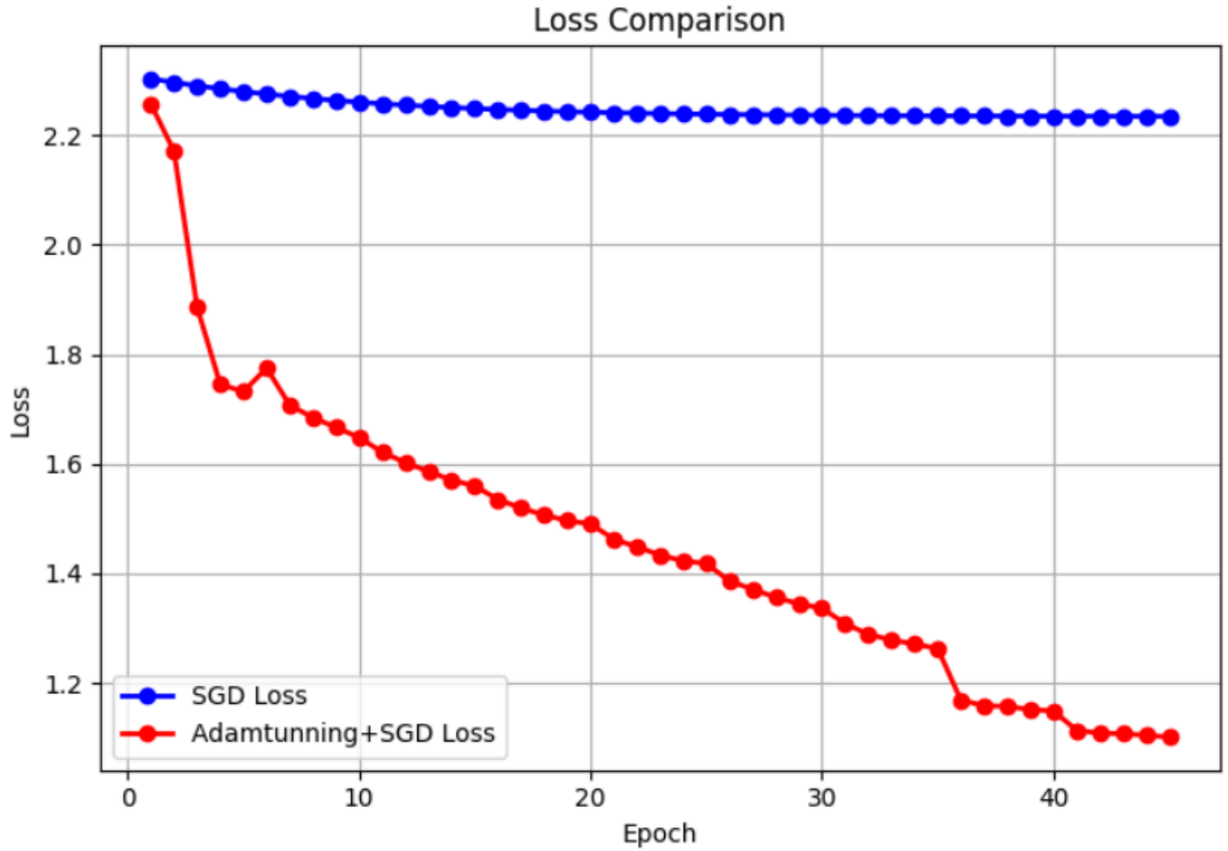
Cuda Memory Management

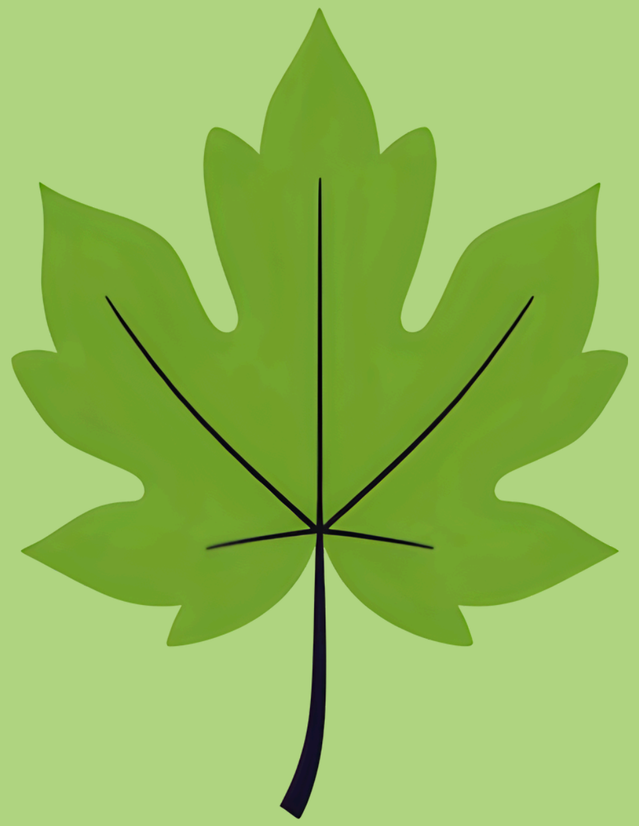
Main Idea

- The cuda.device(A) operation transfers array A to CUDA memory. Unlike regular arrays or PyTorch tensors on CPU, CUDA memory is not automatically released, requiring manual deallocation to free up space for model training.
- Our team uses cuda.get_current_device().reset() to release CUDA memory. However, before resetting, you must move the model's weights and optimizer state back to the CPU, as this function clears all data on the CUDA device.

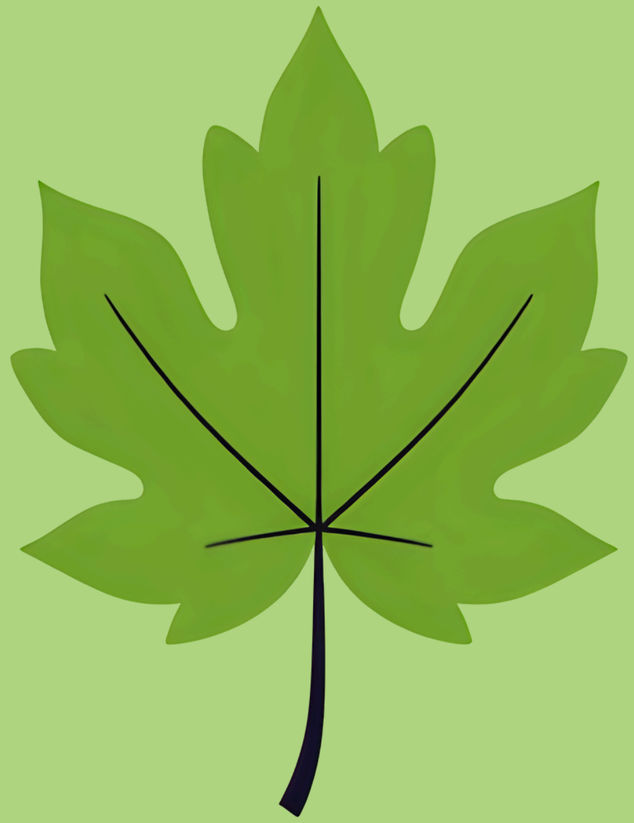
Cuda Squeenet Training







Final Results of CUDA



Forward

- ×1164 speedup
- 90% accuracy,
- 100% similar with Pytorch
- 0.017s inferent with image(3x224x224)

Backward

- GPU pass 256x speedup
- 100% similar with Pytorch
- Implement Adam optimizer

Training

- 381x speedup
- 0% → 63% accuracy in 45 epochs
- Implement Adam,SGD optimizer


THANK YOU