TWINRELECT

Cross-Layer Reliability Analysis of Slimmable Neural Networks under Permanent Faults

VTS 2026 – SPECIAL SESSION

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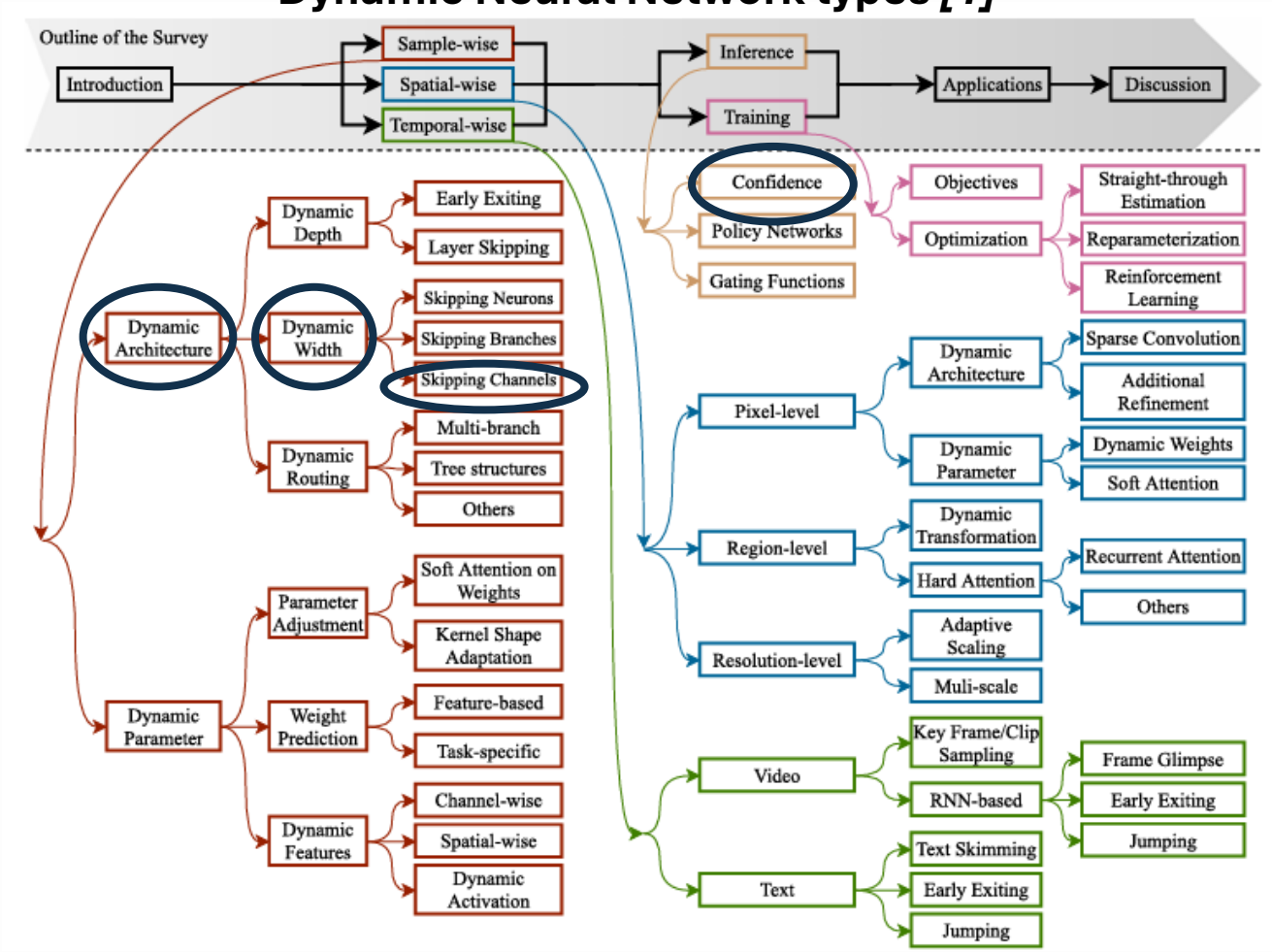
Dynamic Neural Networks

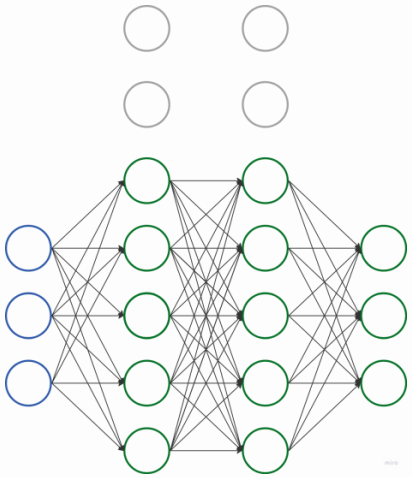
- **DyNNs** adjust their structures or parameters based on the specific input data *[1]*
- Many different flavors! *[1]*
- We focus on Skipping Channels Dynamic Width NN *[2]*
  - Known as **Slimmable NN**
- The width size is based on the **Confidence**

Dynamic Neural Network types *[1]*

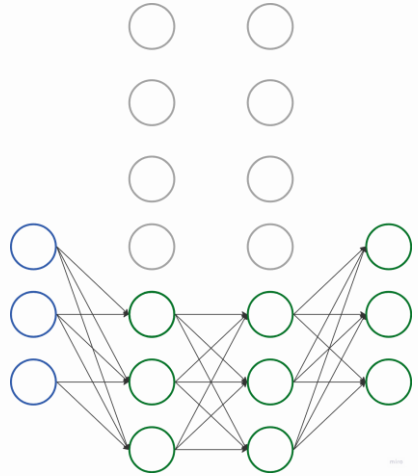


Slimmable Neural Network

- **Slimmable NN** adjust the output channels of the network based on the input
- Advantageous over other Dynamic NN types *[1, 3]*
  - ***Memory footprint***: One model is stored
  - ***Conditional Evaluation***: A simple criteria determines the width of the Network
  - ***Demonstrated Real-World Speedup*** on various hardware platforms



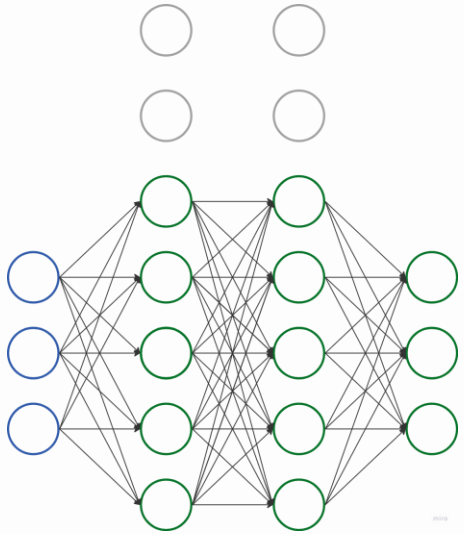
CAT



DOG

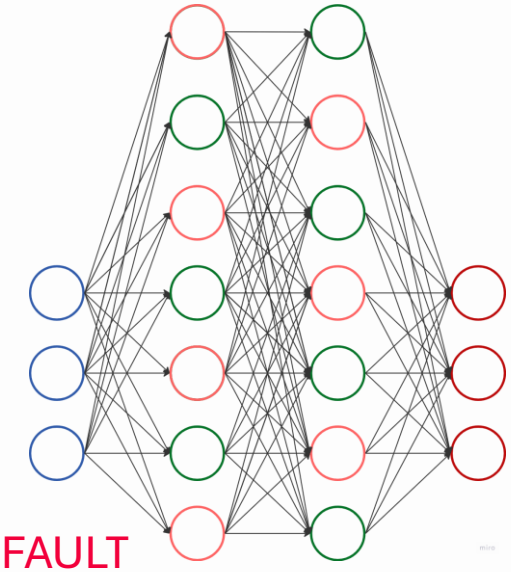
Reliability Analysis on Slimmable NN

- Reliability Analysis on Slimmable NNs is important!
  - **Accuracy Drop**: The predictive power worsens / Functional metric
    Common in Static NNs
  - **Increase in Inference Time**: The network may utilize more increments thar are needed meaning more **unnecessary** computations / Non-functional metric
    Not common in Static NNs
- We must be able to accurately estimate **both** metrics degradation!
  - *Can we quantify the accuracy loss?*
  - *Can we compensate by increasing the inference time?*



CAT

NO FAULT
EXPECTED OUTCOME & UTILISED NEURONS



DOG

HARDWARE FAULT
WRONG OUTPUT **AND / OR**
MORE UTILISED NEURONS

Fault Injection Setup

Test Reliability on NVDLA

- Open-source Architecture by NVDIA

Injecting Stuck-at 0 & 1

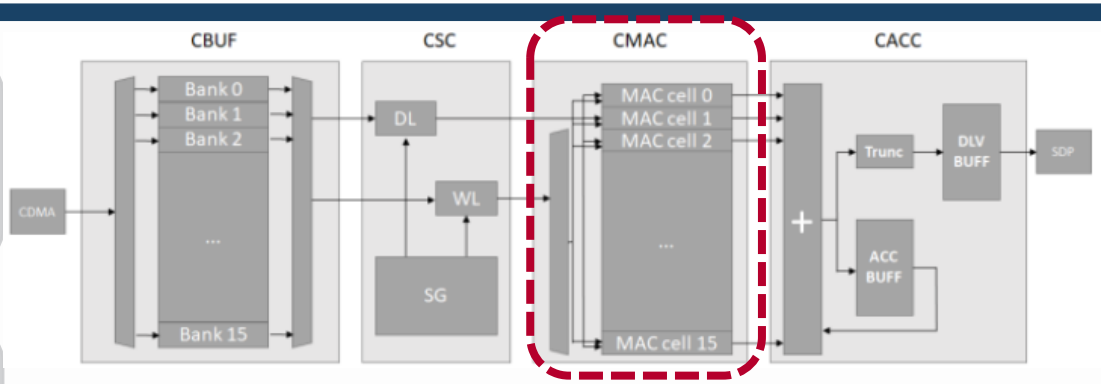
- Ware-out effects: caused by the EOL of the design

Targeting the MAC Array

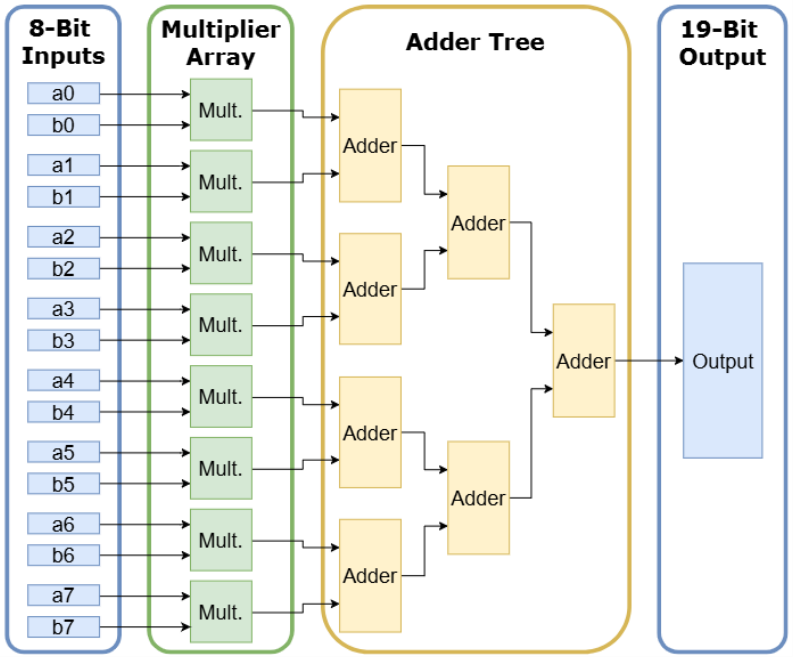
- Computing core of NVDLA

Hybrid Simulation-based FI

- Simulate fauly MAC units
- Utilize EMBER fault simulator
- Requires RTL only for MAC units
- Non faulty components are simulated with pytorch



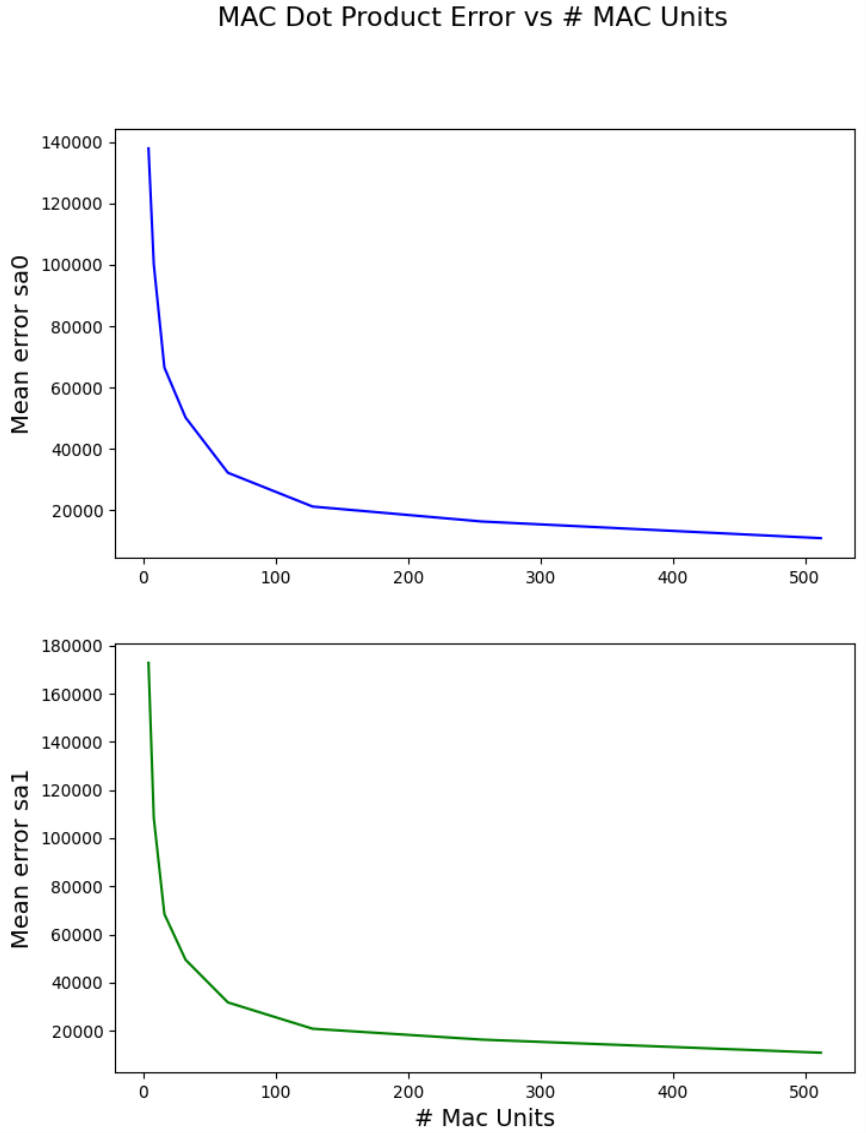
NVDLA MAC Pipeline *[10]*



NVDLA MAC Unit Architecture

Mapping MAC Units to NN Layers

- **N input** vectors -> **multiple MAC Units** are utilized
- **Matrix-Matrix** and **Matrix-Vector** multiplications are just **multiple dot product** operations
  - MAC Units are great at performing those!
  - NN operations are essentially matrix operations
- MAC Units are **NOT infinite** …
  - The available MAC Units must be mapped (tiling) to the needed operations / layers
  - Leads to **hardware reusage**!
  - Less MAC Units -> More reuse
  - A **single fault** in a **single MAC Unit** is present at
    - multiple layers
    - multiple operations in a single layer
  - **A single inference requires multiple RTL simulations**



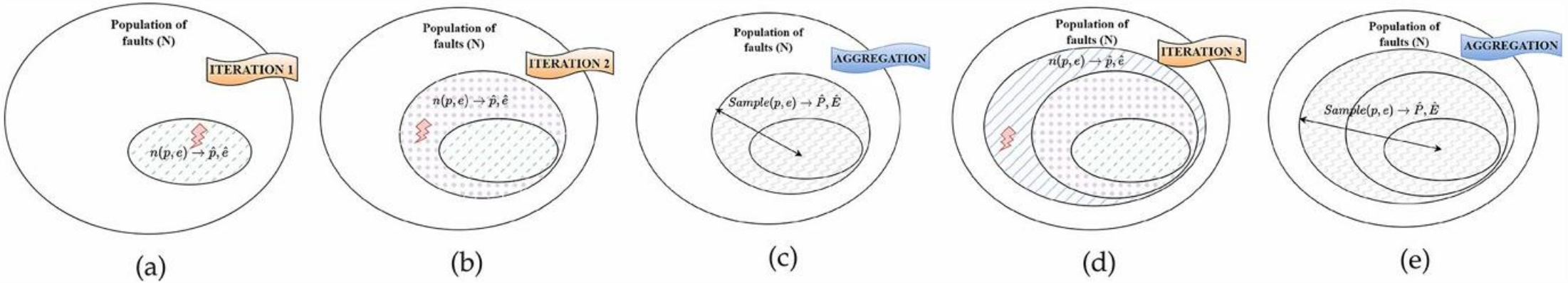
Statistical Fault Injection

MAC Unit has 1642 gates

Fault Injection Candidates: 1642 times the number of MAC units

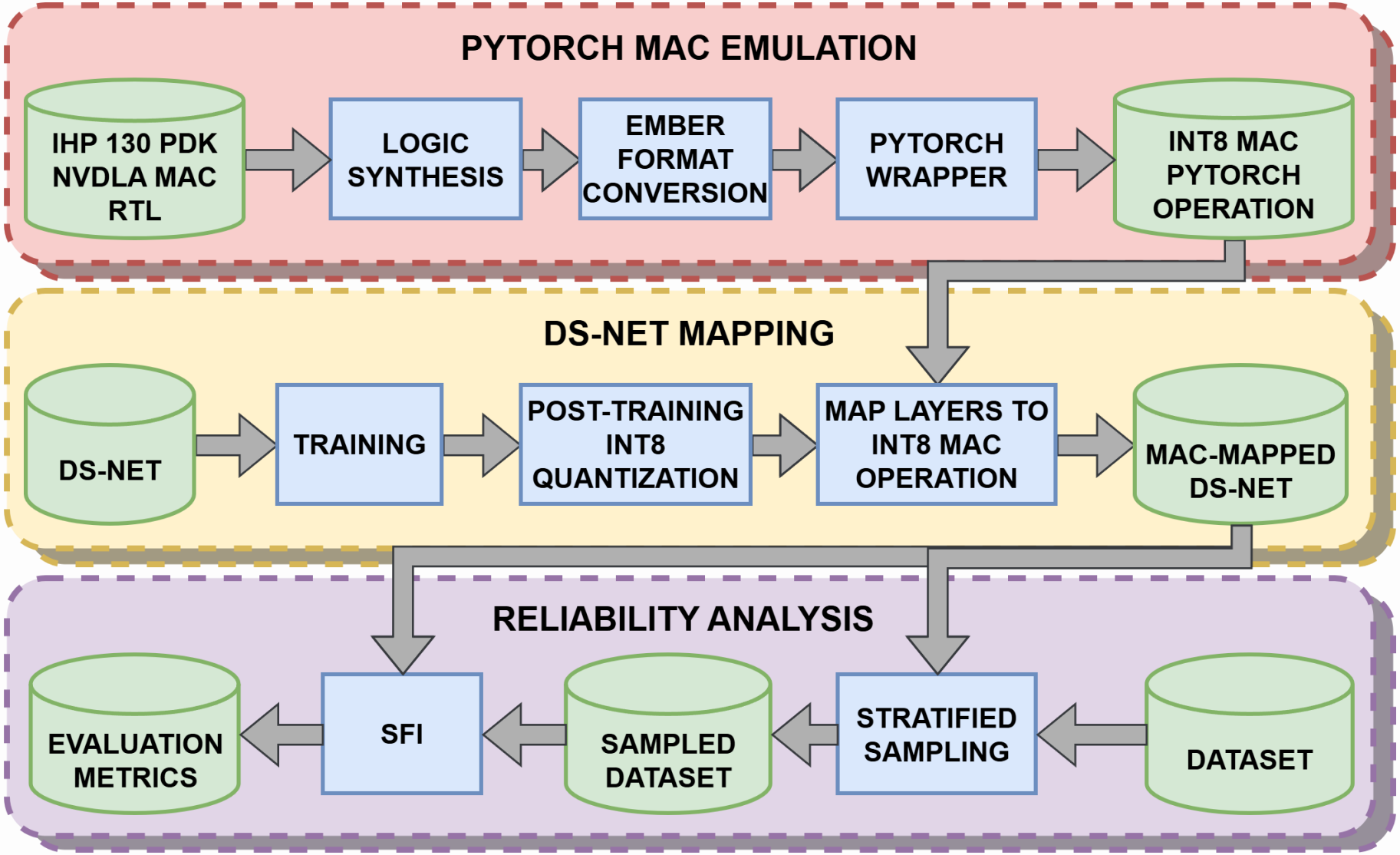
Impossible to inject fault at every candidate

Solution: Statistical Fault Injection *[12]*

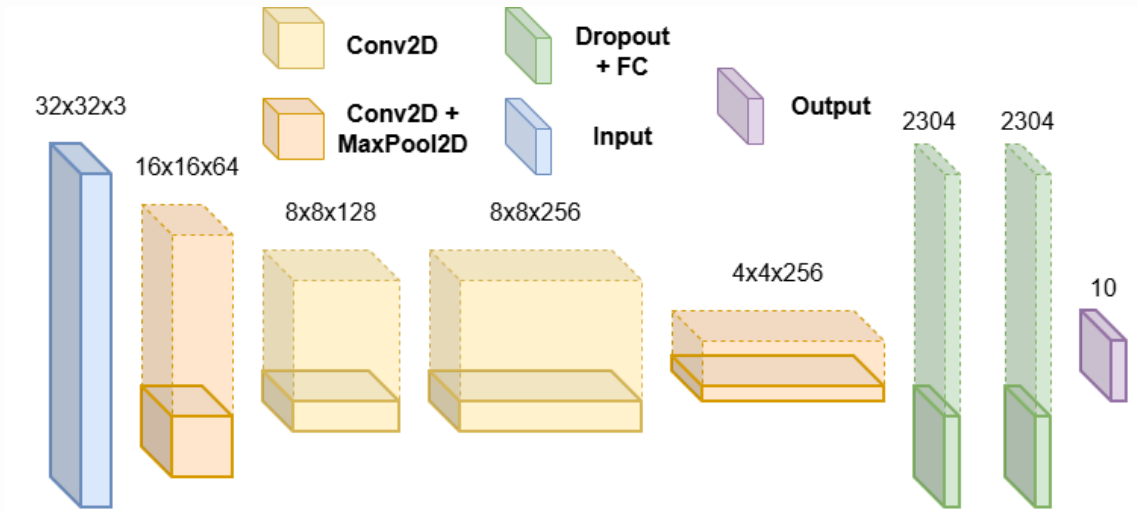


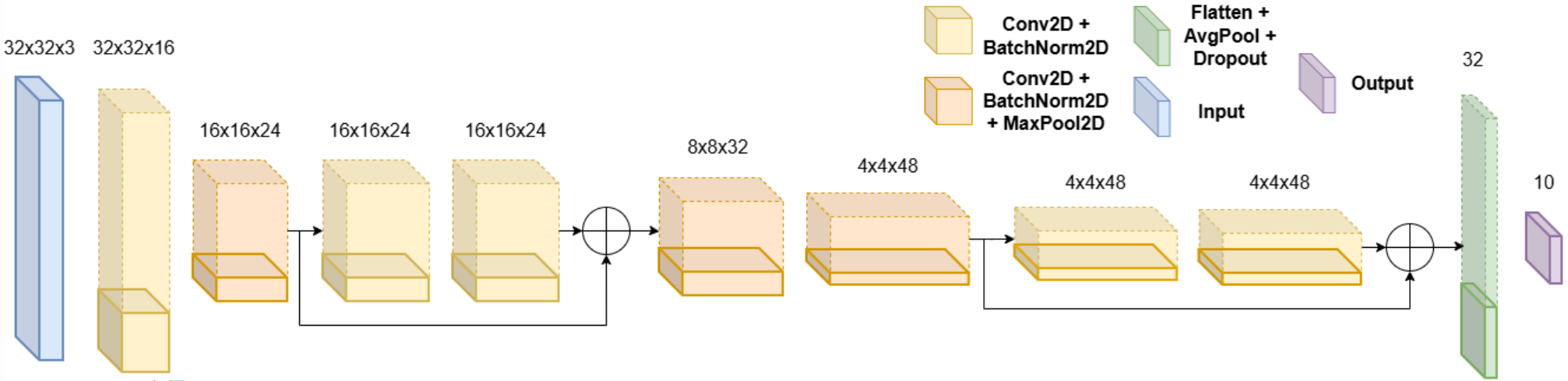
Source: Ruospo, Annachiara, et al. "An effective iterative statistical fault injection methodology for deep neural networks." IEEE Transactions on Computers (2025).

Methodology



Experimental Setup I



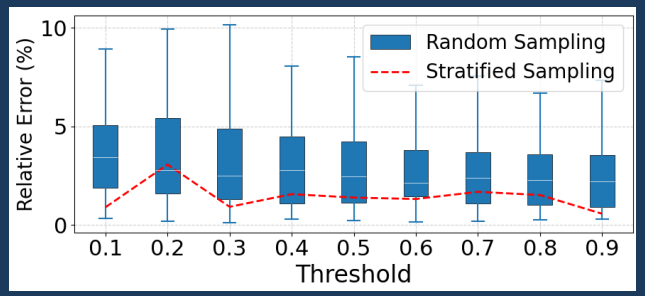


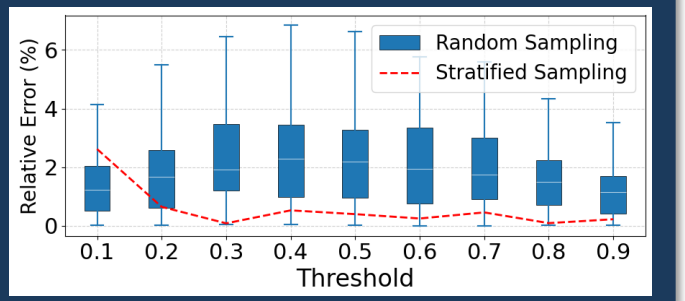
- **Smaller - pruned** version of **AlexNet & ResNet9**
  - DS-AlexNet
  - DS-ResNet
- Deployed **4** different **channels / increments**
  - **0.25x, 0.5x, 0.75x, 1x**
- Configured for **cifar10** dataset
  - 10000 test images
  - 32x32x3 size images
  - 10 output classes

Experimental Setup II

Stratified Dataset Sampling

Size 10000	Dataset Size
N 200	Number of samples
Deviation <5%	Deviation to original dataset





Statistical Fault Injection

Estart 5%	Initial error threshold
Egoal 2%	Target error threshold
Confidence 99%	Statistical confidence

Simulation Cost Reduction

131M → 124,800 inferences (8 MAC)
262M → 127,800 inferences (16 MAC)

≈ 99.9% reduction

Experimental Results I

SDC Rates exceeding 50% for most threshold values

- Much higher than hardware-agnostic approaches report

Different behavior for unique architectures

- DS-Alexnet SDC spikes at T=0.2 and exhibits a plateu for T > 0.2
- DS-Resnet9 SDC spikes at T=0.7 and exhibits a ringing effect across all T values

Similar behavior between fault models

- SA0 and SA1 exhibit almost identical SDC values for a given architecture

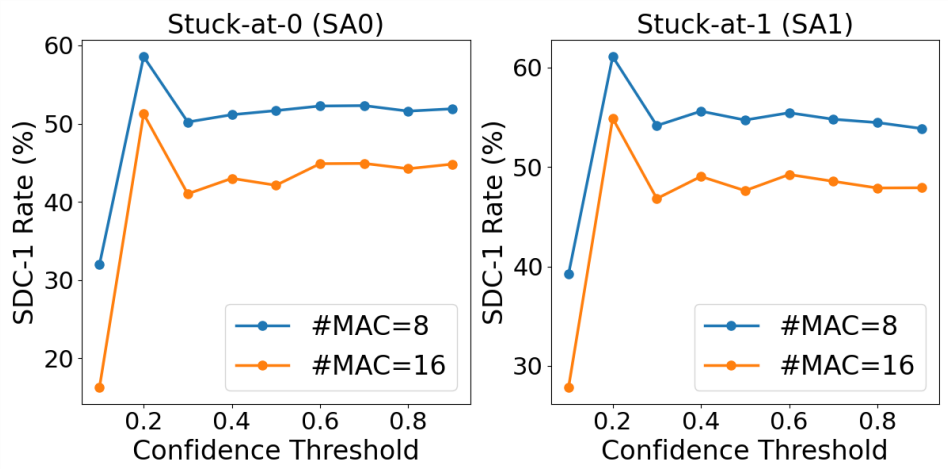
Significantly lower SDC at Threshold == 0.1

- Less utilized neurons
- Less faulty hardware reuse

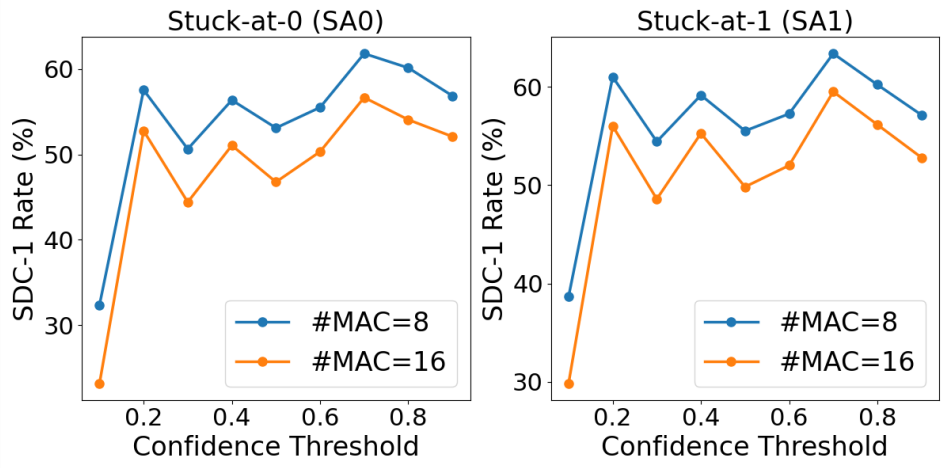
16 MAC Unit configuration is less error prone

- Similar behavior with 8 MAC Unit configuration but at lower level

DS-Alexnet

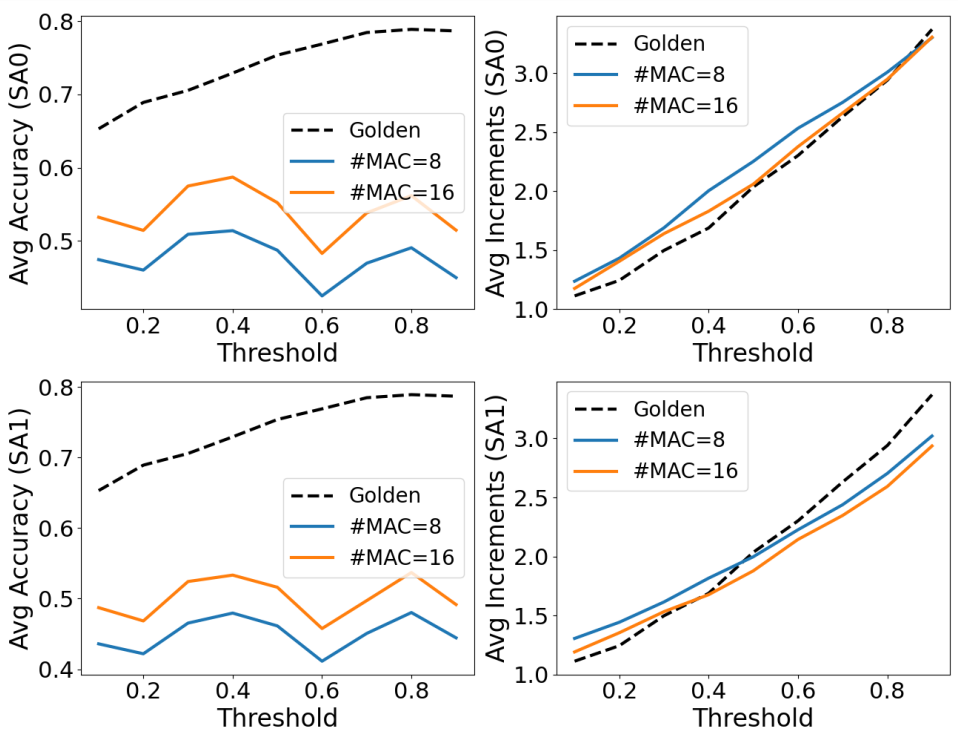


DS-Resnet9

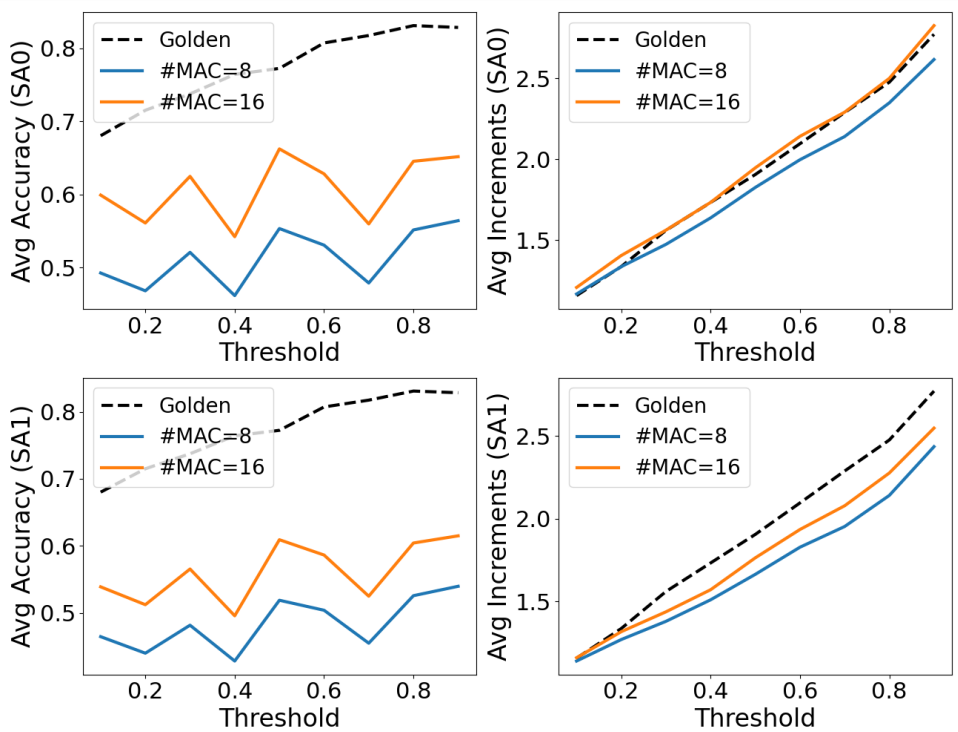


Experimental Results II

DS-Alexnet



DS-Resnet9



Significant Accuracy Drop

Accuracy is not a monotonic function of Threshold

Faulty MAC can both under- and overestimate the utilized neurons

Utilized Increments is a monotonic function of Threshold

More MAC Units lead metrics closer to Golden

Key Takeaways

Hardware Abstraction is Dangerous

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Thank you!

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SCAN ME

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