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High Performance SqueezeNext for CIFAR-10

Jayan Kant Duggal and Mohamed El-Sharkawy
jduggal@purdue.edu, melshark@iupui.edu

IoT Collaboratory IUPUI, Department of Electrical and Computer Engineering,
Purdue School of Engineering and Technology, Indianapolis

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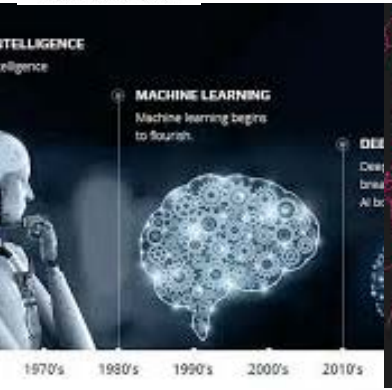
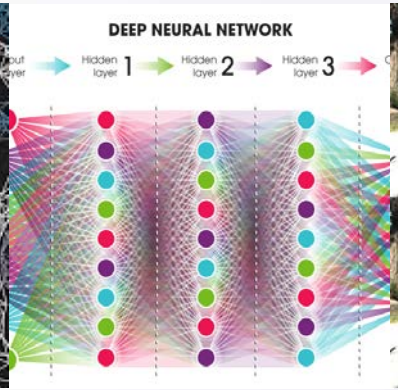
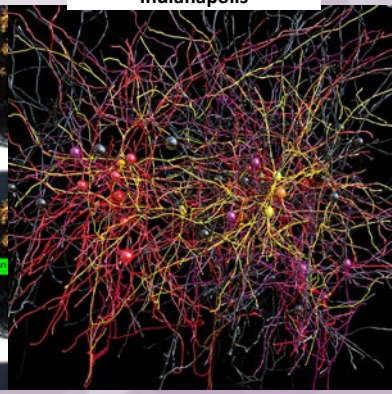
Outline

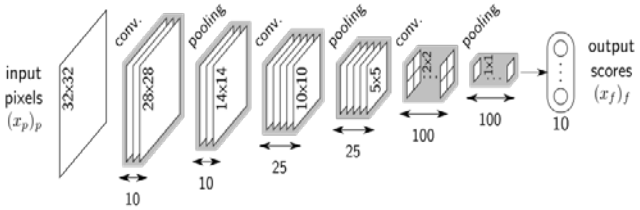






- *Problem Statement*
- *Background*
- *Proposed Architecture*
- *Results*
- *Conclusion*

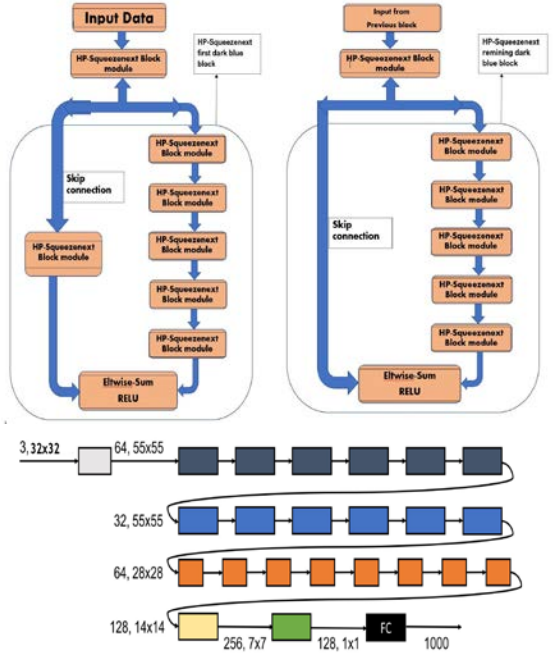
Problem Statement



CNN Requires HIGH COMPUTATION.
CNN Needs LARGE MEMORY.

- **DSE**
- **Arch. Modification.**
- **CIFAR-10 dataset specific training.**

Proposed High Performance SqueezeNext



- Computationally intensive models are not feasible for embedded or autonomous systems.
- Require:
  - **Good model size (less parameters).**
  - **Decent model accuracy.**
  - **Flexible CNN model(tradeoffs with less penalty).**

*DSE- Design Space Exploration, CNNs- Convolutional Neural Networks , DNNs- Deep Neural Networks

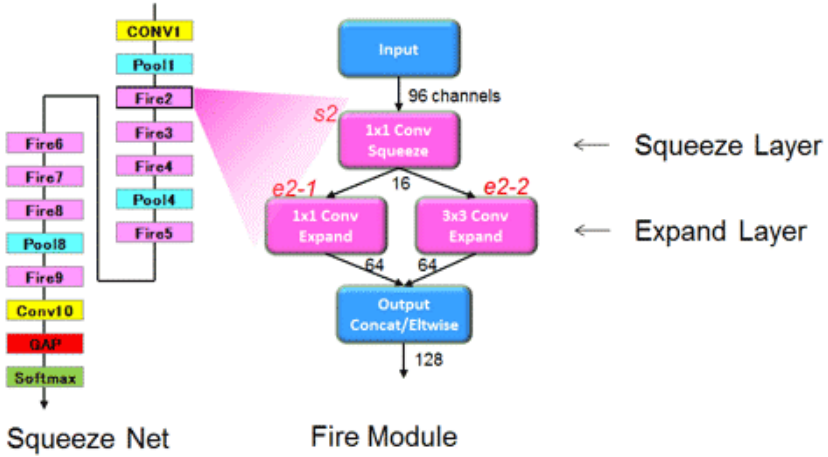
Abstract

- CNN is a memory and computationally and memory intensive.
- Need an efficient & small sized architecture with competitive accuracy.
- Perform Design Space Exploration (DSE) of CNN/ DNN.
- Methods to improve CNN performance.
- Proposed High Performance SqueezeNext for CIFAR-10.
- Results comparison between the proposed arch. and the baseline SqueezeNext arch.

Background

- *SqueezeNet*
- *SqueezeNext*
- *Methods to improve CNN architecture*

SqueezeNet Architecture



- Initial and final Convolution layers.
- 8 fire modules.
- 1 x 1 Squeeze layer.
- 1 x 1 & 3 x 3 Expand layer.
- Lack of FCC layer.
- Optimizer used: SGD

Model accuracy : 78.1%

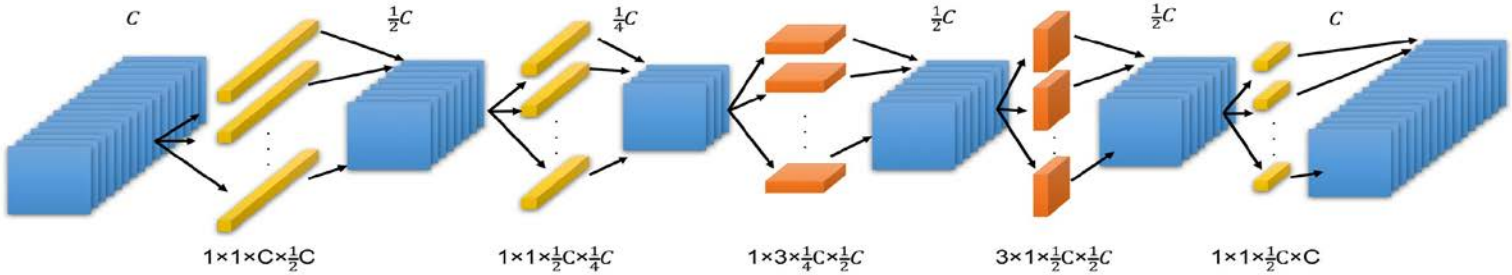
Original Model size : 4.80 MB

Modified Model size : 2.75 MB

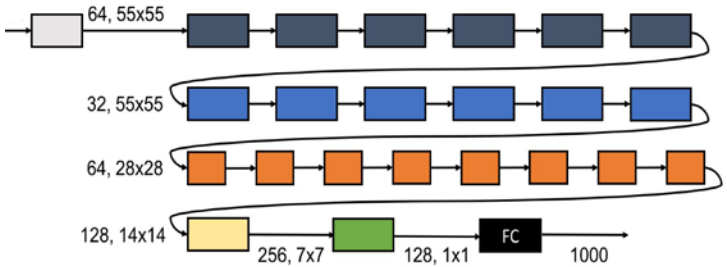
Model Speed : 7 sec / epoch

SqNet baseline model tweaked (improved) for fair comparison.

SqueezeNext Architecture



Bottle Neck Module



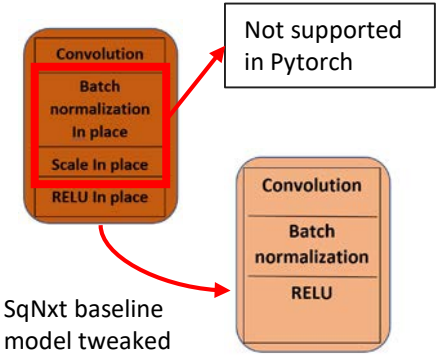
SqueezeNext 23_1x_v1 Arch.

CIFAR-10 Model accuracy : 87.56%

CIFAR-10 Model size : 2.59 MB

CIFAR-10 Model speed : 23 sec / epoch

SqueezeNext Baseline → Pytorch Modified SqueezeNext



SqNxt baseline model tweaked (improved) for fair comparison.

- 23 layer depth and 1.0 width.
- Use bottle neck modules.
- Element-wise addition skip connection.
- Four stage configuration implementation.
- Optimizer used: SGD+ momentum+ nestrov.
- 4 LR time step decay with exponential update.

Hardware and Software framework

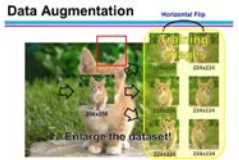
Hardware & Software used:

- Intel i7 8th generation processor with 32 GB RAM.
- Required memory for dataset and results: 4GB.
- NVIDIA GTX 1080 GPU.
- Spyder version 3.6.
- Pytorch version 1.1.
- Livelossplot (Loss and accuracy visualization).

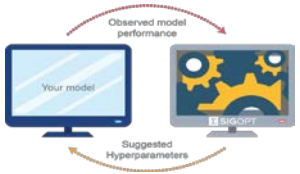
Livelossplot package : Package for live model loss and model accuracy, CNN model visualization tool .

Method to improve CNN Architecture

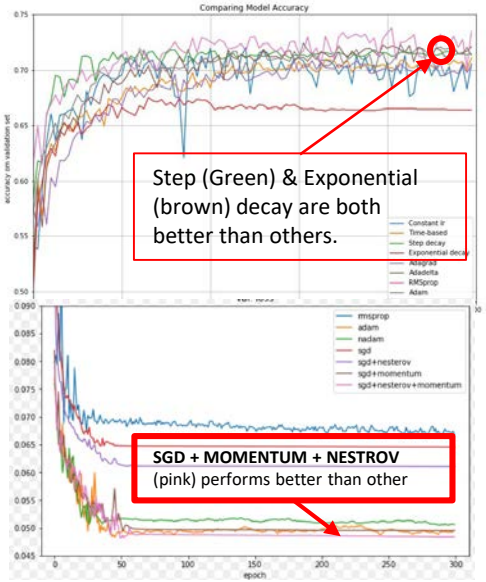
- **More Data or** (data augmentation)



- **Architecture Tuning**

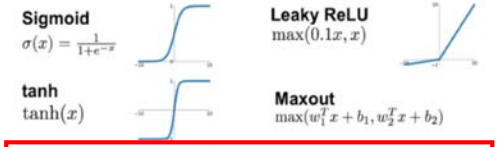


  - Learning Rate Schedule methods.
  - Different optimizers.
  - Different activation functions.
  - Save and Load checkpoint method (Model state dictionary method).

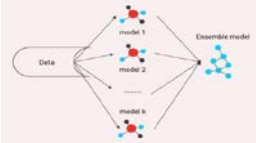


- **Architecture modification**

  (Proposing a new arch.)



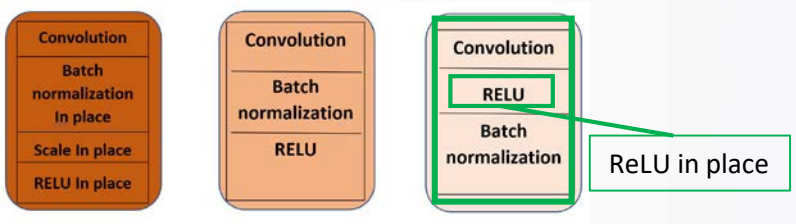
- **Model Ensembles**

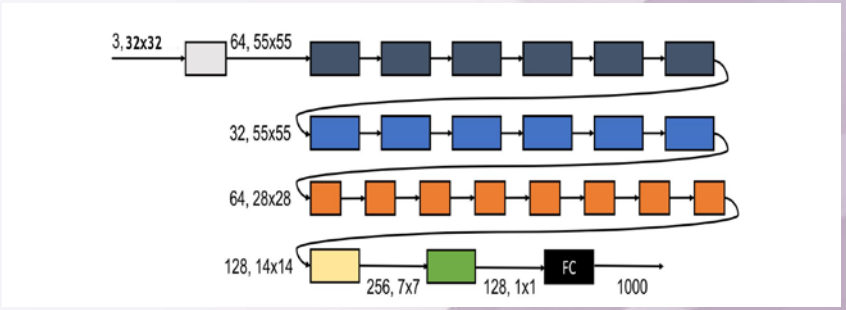


Proposed High Performance SqueezeNext Architecture

Proposed High Performance SqueezeNext for CIFAR-10

Proposed High Performance SqueezeNext Basic Block



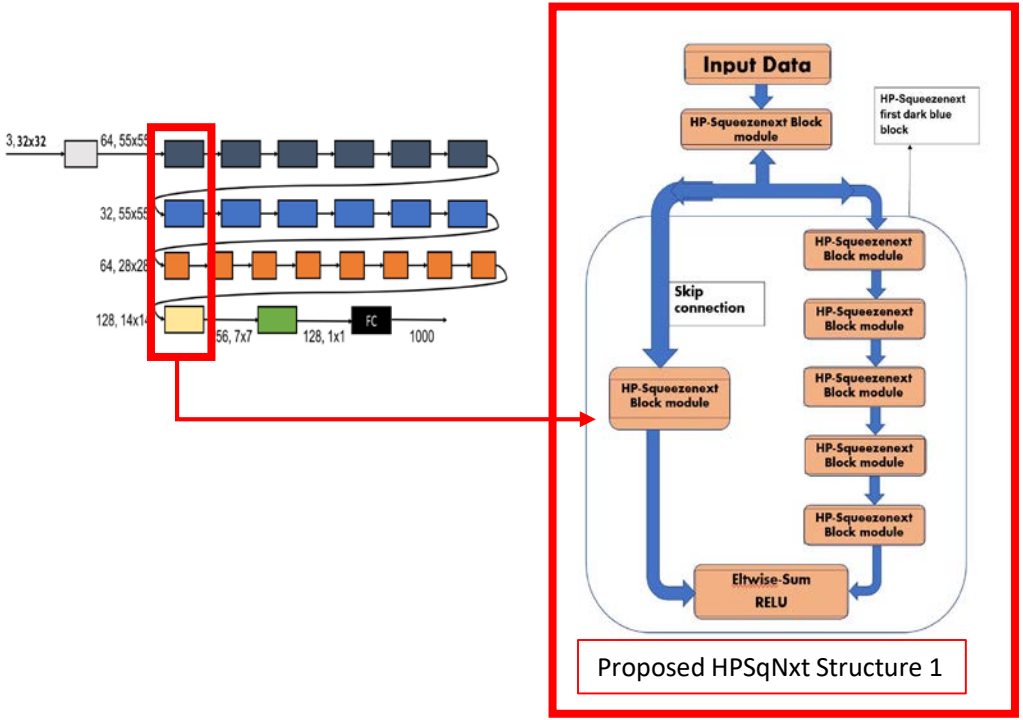


Proposed High Performance SqueezeNext Architecture [6,6,8,1] four stage implementation.

- *RELU sandwiched b/w conv & batch normalization performs better.*
- ***ReLU in place performs better than ReLU, signmoid, tanh and leakyRelu.***
- ***No need to reintroduce non- linearity or activation function after the basic block.***
- *Converges to good accuracy.*

Proposed High Performance SqueezeNext for CIFAR-10

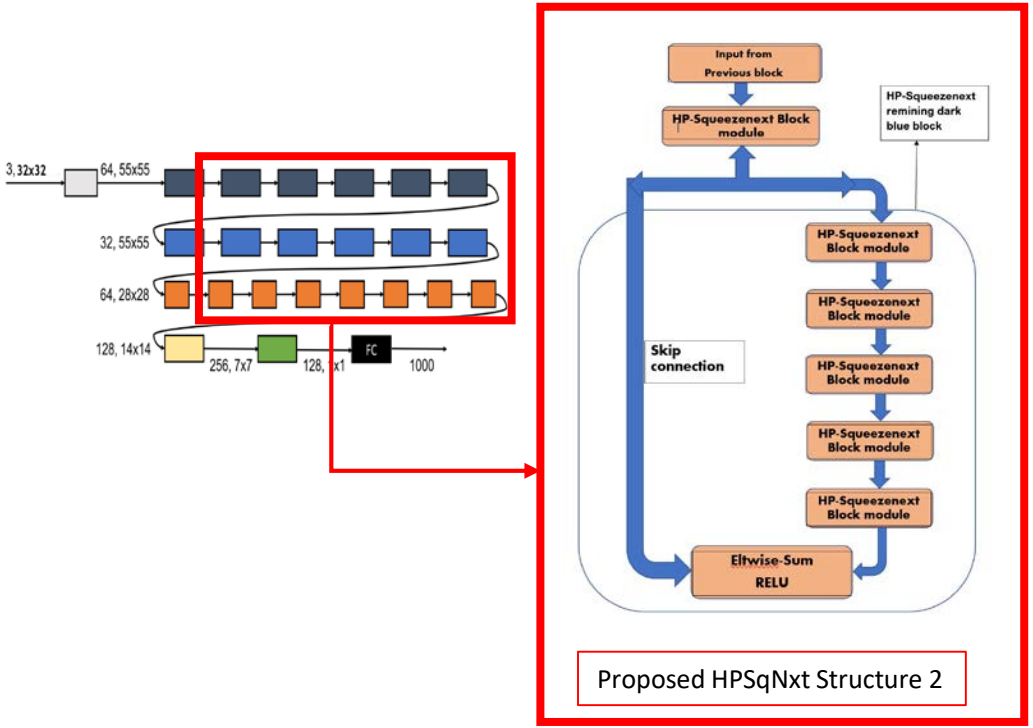
- ***Forms the 1st block of each stage in 4 stage implementation.***
- ***Four different colors** that are dark blue, blue, orange and yellow represent **4 stage implementation.***
- *Consists of Skip connection and one separate HPSqnxt basic block on the left, **preserves the important feature maps** in the initial stages.*
- *Initially **does not consist of max pooling** in the beginning.*



Proposed HPSqNxt Structure 1

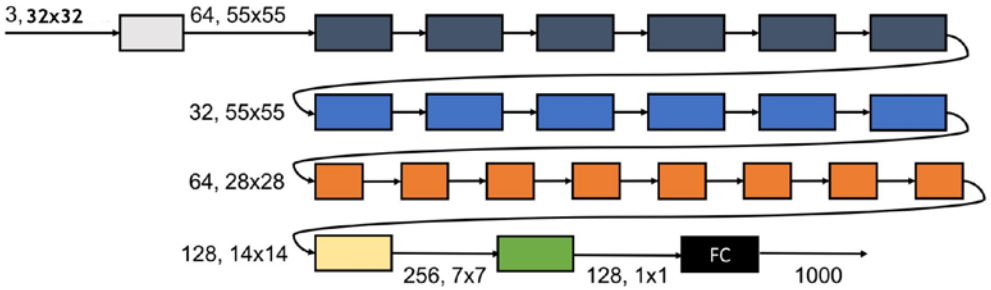
Proposed High Performance SqueezeNext for CIFAR-10

- **Forms the remaining blocks** of the four stage implementation.
- Consists of Skip connection only on the left.
- In the end consists of a average pooling.
- Due to **absence of extra basic block** module on the left in the remains blocks **attains a better model size & speed** without affecting accuracy.



Proposed HPSqNxt Structure 2

Proposed High Performance SqueezeNext for CIFAR-10



Proposed High Performance SqueezeNext 4-stage Implementation (6, 6, 8, 1)

- First block of each color is High Performance SqueezeNext Structure 1.
- Remaining blocks of each color is High Performance SqueezeNext Structure 2.
- **No max pooling layer used**.
- **Xavier- uniform initialization.**
- **One spatial and one FC layer.**
- **SGD+ momentum +nestrov is used**.
- **4 LRs with step decay and exponential update is used.**

Results

Proposed High Performance SqueezeNext for CIFAR-10

Model	Accuracy%	Model Size(MB)	Model speed (sec)
SqueezeNet-v1-0(baseline)	**78.1**	2.75	7
SqueezeNext-23-1x-v1(baseline)	**87.56**	2.59	23
Proposed modified implementation of SqueezeNext-23-1x-v1	**92.25**	**5.14**	48
Proposed HP-SqueezeNext-21-1x-v2	**92.05**	**2.60**	18
Proposed HP-SqueezeNext-06-0.50x-v1	82.44	0.370	7
Proposed HP-SqueezeNext-06-1x-v1	86.82	1.24	8
Proposed HP-SqueezeNext-06-0.75x-v1	82.86	1.24	8

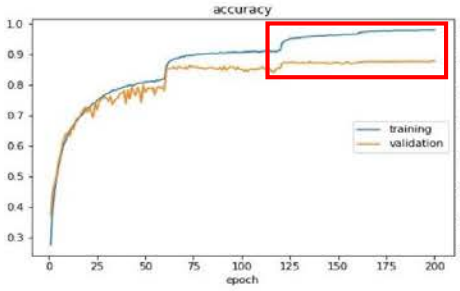
*All results are 3 average runs with SGD, LR is 0.1

Best model size & speed

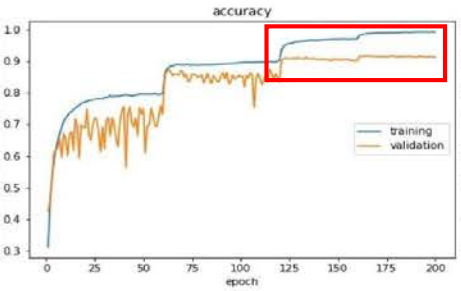
Best model accuracy

Results

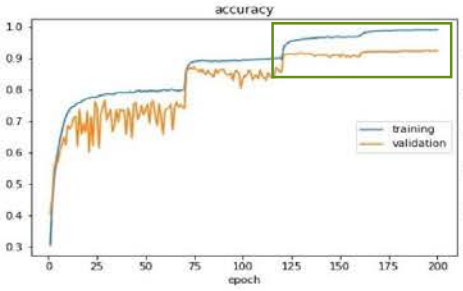
High Performance SqueezeNext for CIFAR-10



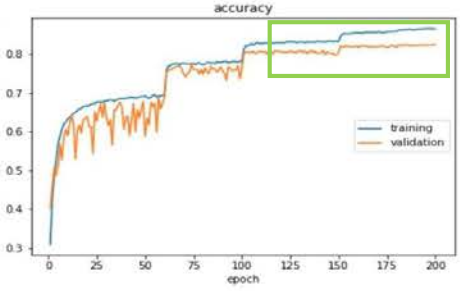
1) Baseline SqueezeNext



2) Pytorch SqueezeNext



3) Proposed Modified Implementation of SqueezeNext



4) High Performance SqueezeNext

4 Step decay with exponential update **LR schedule**.

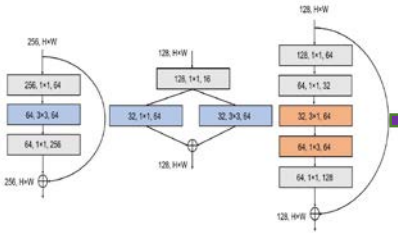
More dynamic and reaches a late accuracy **saturation point**.

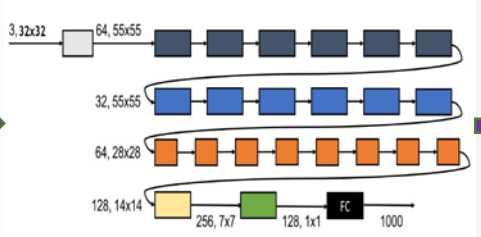
All architectures are trained with same hyperparameters for **fair comparison**.

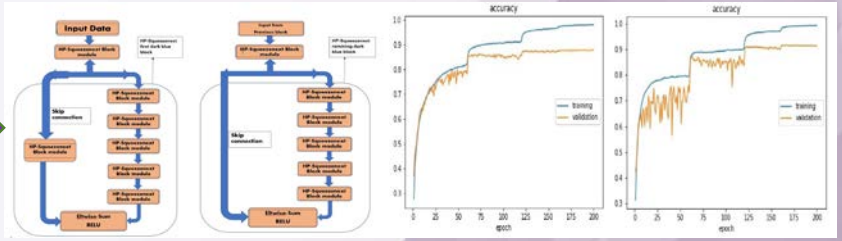
Less over fitting between training and testing accuracy.

Conclusion

Proposed High Performance SqueezeNext for CIFAR-10







- Propose HIGH PERFORMANCE SQUEEZENEXT architecture.
- CIFAR-10 specific dataset based training and testing improves DNN performance.
- *Livelossplot package* assists in rapid training of small sized CNN/ DNN models.
- **Prefer SAVE AND LOAD** model checkpoint with model state dictionary method.
- High Performance SqueezeNext attained a best model size and model speed with a **minimum tradeoff (less penalty)**.
- BEST MODEL ACCCURACY: **92.05%** (**14 %** better than SqNet (Baseline) & **4.5 %** better than SqNxt (Baseline)).
- BEST MODEL SIZE: **0.370 MB**
- BEST MODEL SPEED: **7 secs/ epoch** (**16 secs** better than SqNxt baseline and equivalent to SqNet baseline).

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Questions ??