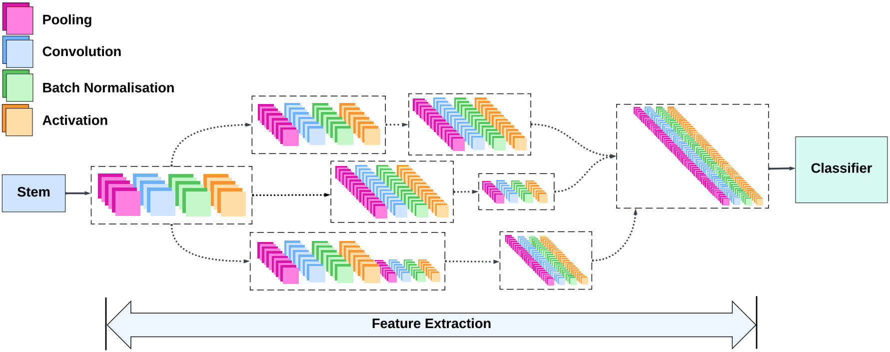
XC-NAS: A New Cellular Encoding Approach for Neural Architecture Search of Multi-Path Convolutional Neural Networks

Trevor Londt, Xiaoying Gao, Peter Andreae, Yi Mei

Victoria University of Wellington, Centre for Data Science and Artificial Intelligence &
School of Engineering and Computer Science

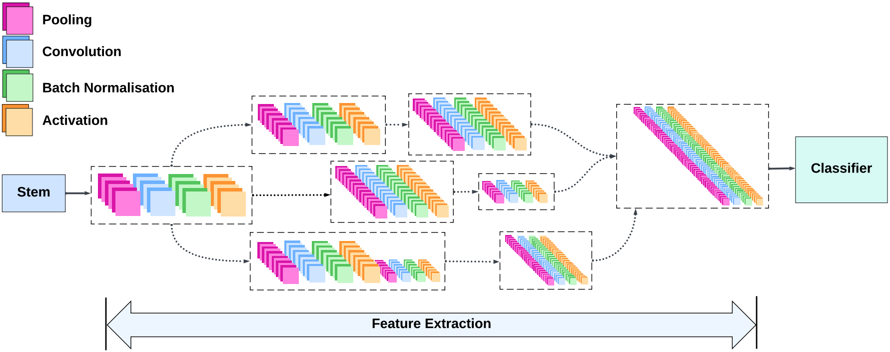
December 2023

Multipath CNNs



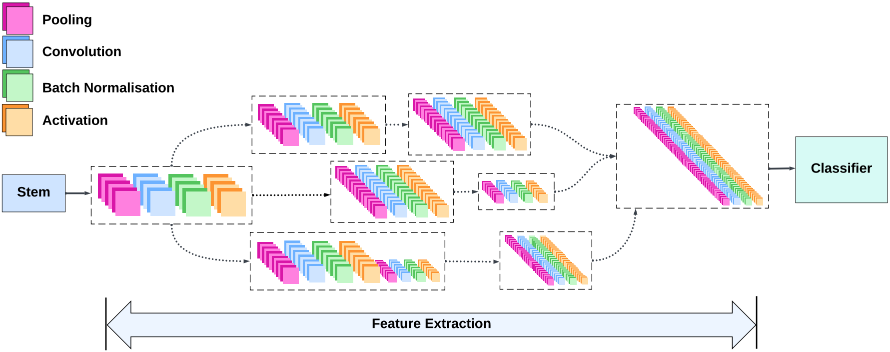
- Feature reuse and exploits both local and global context features
- Topologies can get complex - not practical to design it manually

Multipath CNNs



- Feature reuse and exploits both local and global context features
- Topologies can get complex - not practical to design it manually
- Need a representation that can capture the main idea of multi-path topologies (branching and joining)

Multipath CNNs



- Feature reuse and exploits both local and global context features
- Topologies can get complex - not practical to design it manually
- Need a representation that can capture the main idea of multi-path topologies (branching and joining)
- Need ability to represent heterogeneous blocks (micro-architectures)

Cellular Encoding

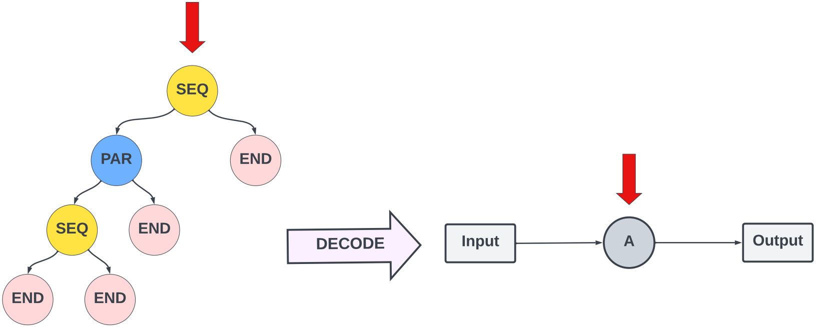
- Cellular Encoding (CE) a method to encode a family of artificial neural networks into a population of labelled trees. Uses Genetic Algorithm (GA) to facilitate evolution. Inspired by biological cell division

Cellular Encoding

- Cellular Encoding (CE) a method to encode a family of artificial neural networks into a population of labelled trees. Uses Genetic Algorithm (GA) to facilitate evolution. Inspired by biological cell division
- CE is concerned with generating topology between **neurons**

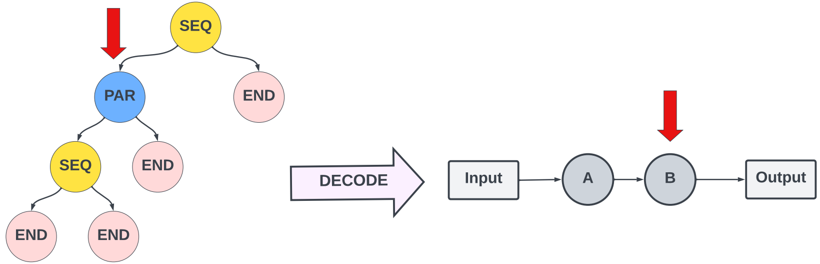
Cellular Encoding

- Cellular Encoding (CE) a method to encode a family of artificial neural networks into a population of labelled trees. Uses Genetic Algorithm (GA) to facilitate evolution. Inspired by biological cell division
- CE is concerned with generating topology between **neurons**



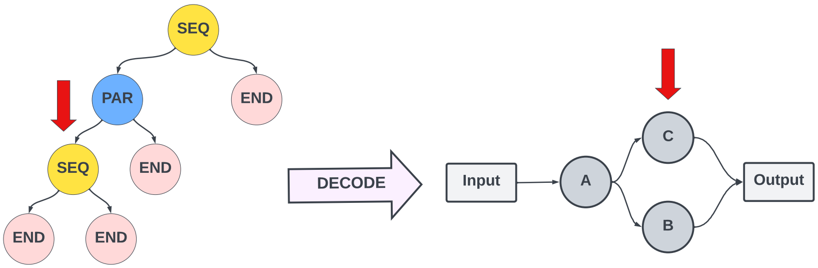
Cellular Encoding

- Cellular Encoding (CE) a method to encode a family of artificial neural networks into a population of labelled trees. Uses Genetic Algorithm (GA) to facilitate evolution. Inspired by biological cell division
- CE is concerned with generating topology between **neurons**



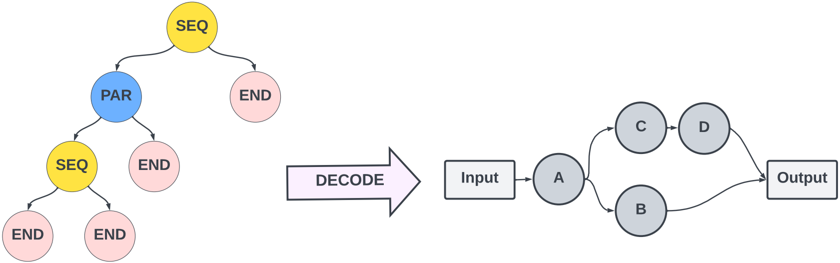
Cellular Encoding

- Cellular Encoding (CE) a method to encode a family of artificial neural networks into a population of labelled trees. Uses Genetic Algorithm (GA) to facilitate evolution. Inspired by biological cell division
- CE is concerned with generating topology between **neurons**

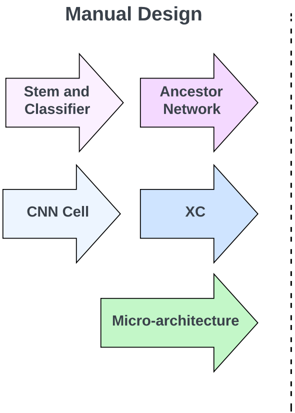


Cellular Encoding

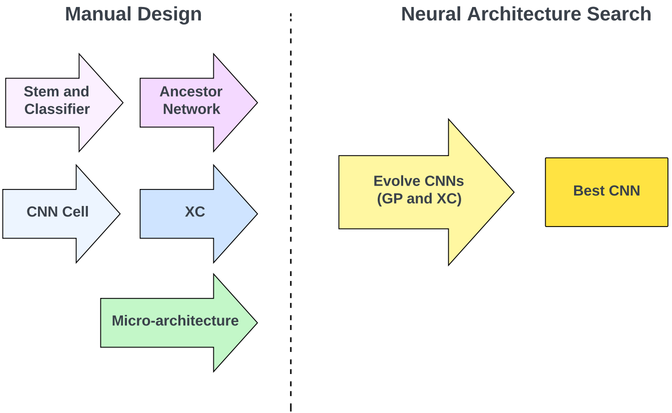
- Cellular Encoding (CE) a method to encode a family of artificial neural networks into a population of labelled trees. Uses Genetic Algorithm (GA) to facilitate evolution. Inspired by biological cell division
- CE is concerned with generating topology between **neurons**



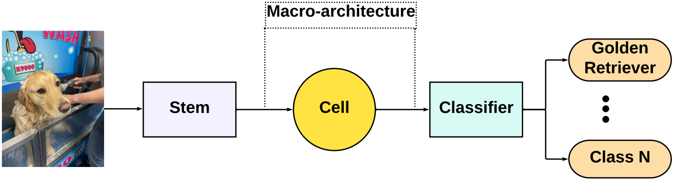
Our Approach



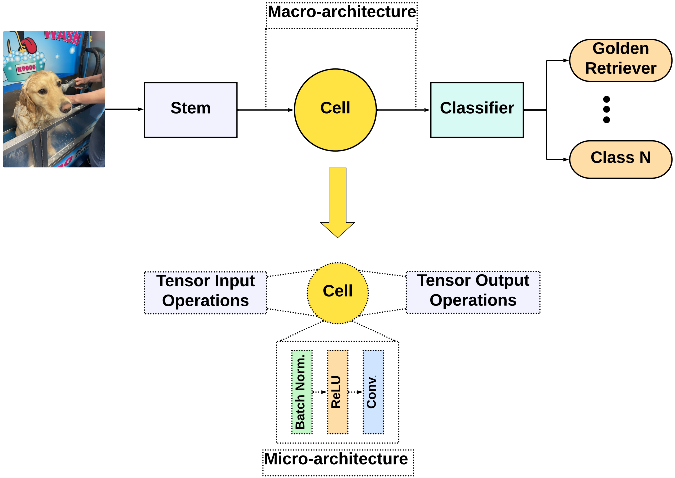
Our Approach



XC: Ancestor Network and CNN Network Cell



XC: Ancestor Network and CNN Network Cell



- Original CE: Cell → Neuron
- XC: Cell → Convolution Block (Micro-architecture)

Defined Operations

- Implement two CE operations that affects macro-architecture topology):

Operation	Effect
S	Duplicate cell and connect in series
P	Duplicate cell and connect in parallel

Defined Operations

- Implement two CE operations that affects macro-architecture topology):

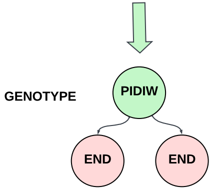
Operation	Effect
S	Duplicate cell and connect in series
P	Duplicate cell and connect in parallel

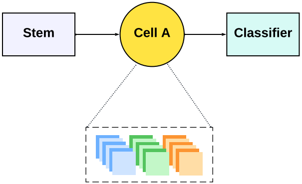
- Define **configurable modifiers** to manipulate the width and/or depth of a **micro-architecture** contained in a cell:

Modifier	Effect
ID	2 * number of layers in cell
DD	1/2 * number of layers in cell
IW	2 * number of filters in cell
DW	1/2 * number of filters in cell

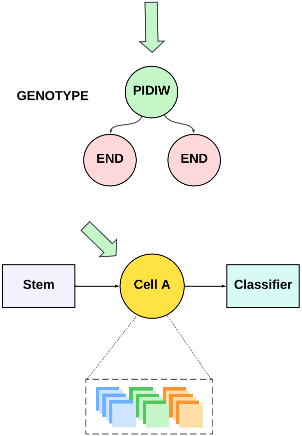
- Modifiers are combined with the defined CE operations to create **new CE operations**, eg: **SID**, **SIDIW**, **PID**, **PDD**, etc (18 combinations)

Operation Example

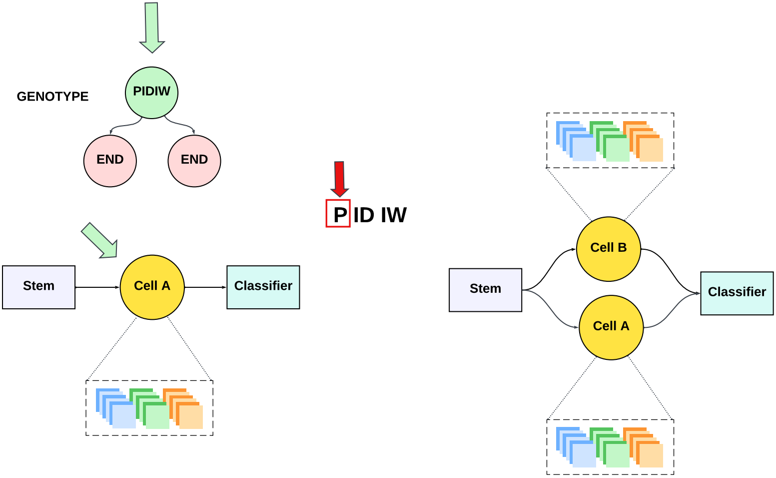




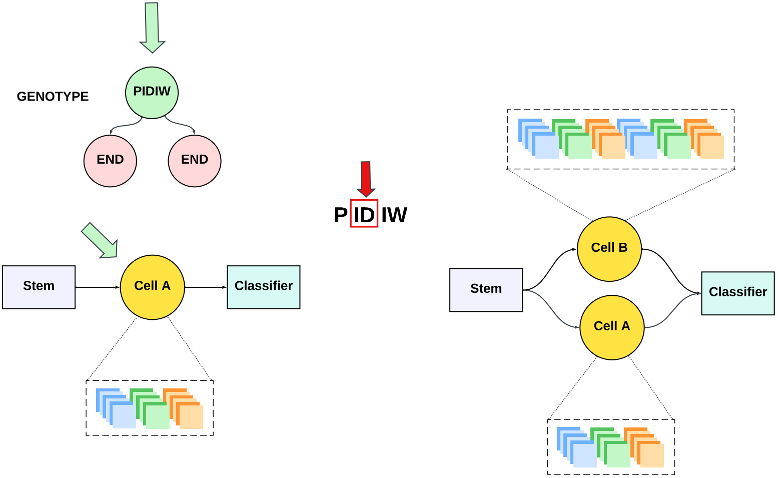
Operation Example



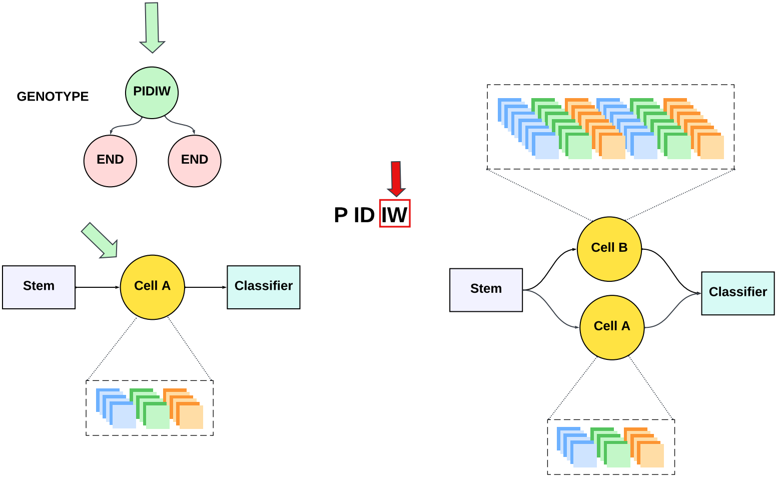
Operation Example



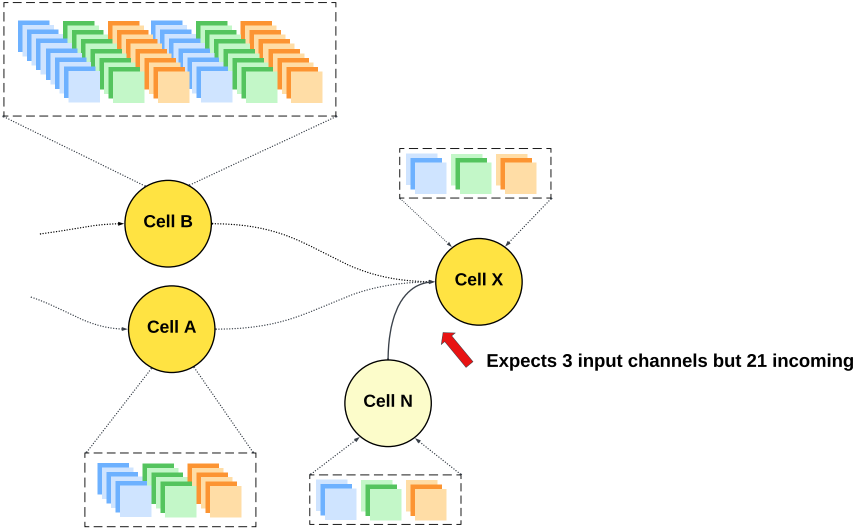
Operation Example



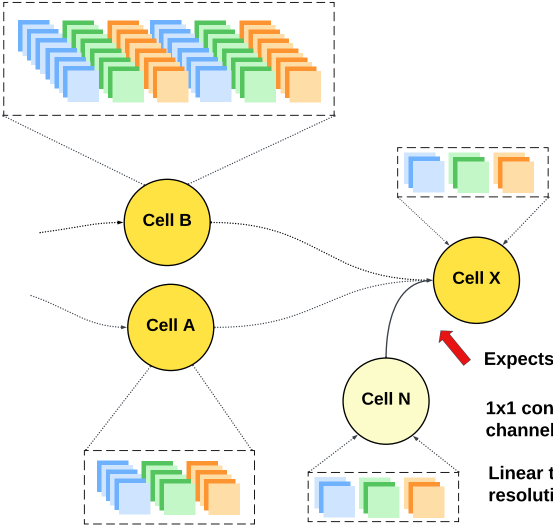
Operation Example



Cell Input/Output Operations Revisited



Cell Input/Output Operations Revisited



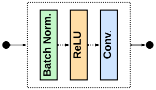
Expects 3 input channels but 21 incoming

1x1 convolutions to increase / decrease channel count

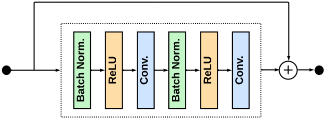
Linear transformation to increase/decrease resolution / temporal length

Chosen Micro-architectures

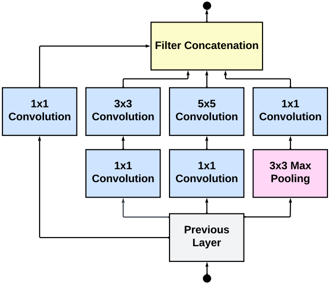
Simple Block

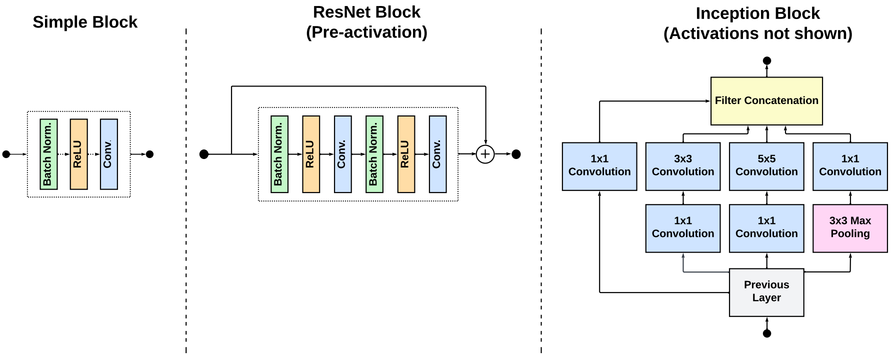


ResNet Block
(Pre-activation)



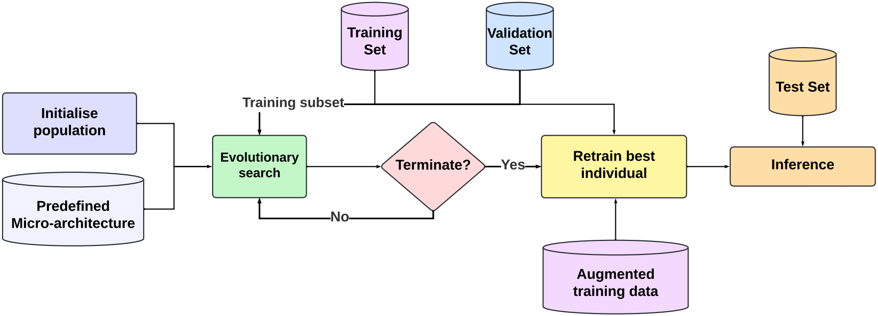
Inception Block
(Activations not shown)



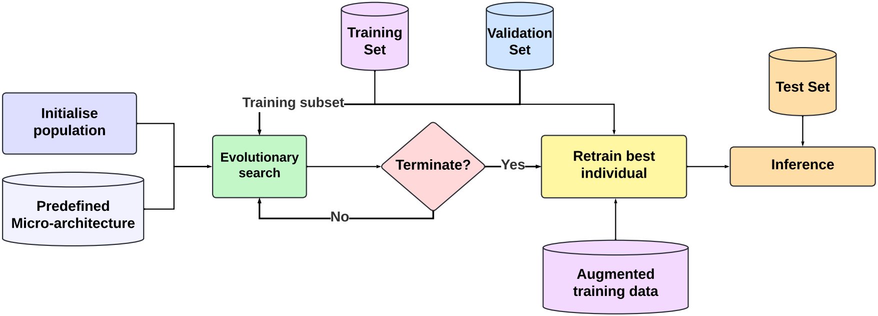


- Spatial operations for image data
- Temporal operations for text/audio data

Algorithm Flow



Algorithm Flow



- Data augmentation performed at end of evolutionary process

Some Important Settings and Limitations

- Subset of training data (25%) during evolutionary process $\rightarrow$ **reduced CNN training times**
- ...but potential for evolved networks to be **biased to smaller capacities**
- Therefore: **trade-off between faster training times and potential overfitting**

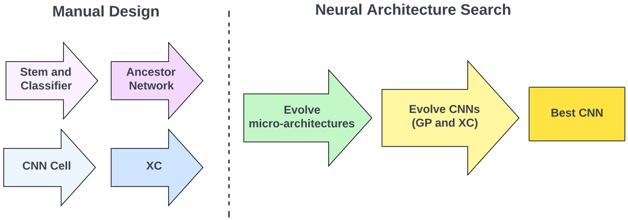
Classification Results: Test Accuracy (%)

Algorithm	Type	AG's News	Yelp Reviews Full	KMNIST	Fashion-MNIST	CIFAR-10
XC-NAS Simple (**ours**)	NAS	90.71	60.92	98.42	94.31	93.24
XC-NAS ResNet (**ours**)	NAS	89.94	61.26	**98.68**	94.72	93.74
XC-NAS Inception (**ours**)	NAS	**91.15**	61.01	**99.13**	**95.39**	**94.85**
Zhang et al. Lg. Full Conv.[1]	Manual	90.15	**61.60**	n/a	n/a	n/a
VDCNN-Convolution [2]	Manual	**91.27**	**64.72**	n/a	n/a	n/a
GP-Dense [3]	NAS	89.58	61.05	n/a	n/a	n/a
ResNet-110. [4]	Manual	n/a	n/a	97.82	93.40	93.57
InceptionNet (GoogLeNet) [5]	Manual	n/a	n/a	97.95	92.74	93.64
EvoCNN [6]	NAS	n/a	n/a	-	94.53	-
FPSO [7]	NAS	n/a	n/a	-	**95.07**	93.72
CGP-CNN-ConvSet [8]	NAS	n/a	n/a	-	-	93.25
EIGEN [9]	NAS	n/a	n/a	-	-	94.60
CE-GeneExpr [10]	NAS	n/a	n/a	-	-	**96.26**

- **Second highest** test accuracy on text datasets and CIFAR-10
- **Highest** test accuracy on KMNIST, Fashion-MNIST
- $<$ **1 GPU day** to evolve best model

Conclusions & Future Work

- XC-NAS can build competitive CNNs for classification tasks (verified on image and text)



- Evolve micro- and macro-architecture
- Challenge in evaluating a micro-architecture's fitness. (Which macro-architecture to use?)
- REC operator causes parameter count explosion - explore alternative

Thank You

- X. Zhang, J. Zhao, and Y. LeCun, "Character-Level Convolutional Networks for Text Classification," in *Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 1*, NIPS'15, (Cambridge, MA, USA), p. 649–657, MIT Press, 2015.
- A. Conneau, H. Schwenk, Y. L. Cun, and L. Barrault, "Very deep convolutional networks for text classification," in *15th Conference of the European Chapter of the Association for Computational Linguistics, EACL 2017 - Proceedings of Conference*, vol. 2, pp. 1107–1116, Association for Computational Linguistics (ACL), 2017.
- T. Londt, X. Gao, and P. Andreae, "Evolving Character-Level DenseNet Architectures Using Genetic Programming," *Lecture Notes in Computer Science*, pp. 665–680, 2021.
- K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 770–778, 12 2016.
- C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 1–9, 10 2015.
- Y. Sun, B. Xue, M. Zhang, and G. G. Yen, "Evolving Deep Convolutional Neural Networks for Image Classification," *IEEE Transactions on Evolutionary Computation*, pp. 394–407, 4 2020.
- J. Huang, B. Xue, Y. Sun, and M. Zhang, "A Flexible Variable-length Particle Swarm Optimization Approach to Convolutional Neural Network Architecture Design," *2021 IEEE Congress on Evolutionary Computation, CEC 2021 - Proceedings*, pp. 934–941, 2021.
- M. Suganuma, S. Shirakawa, and T. Nagao, "A Genetic Programming Approach to Designing Convolutional Neural Network Architectures," in *Proceedings of the Genetic and Evolutionary Computation Conference*, GECCO '17, pp. 497–504, 2017.
- J. Ren, Z. Li, J. Yang, N. Xu, T. Yang, and D. J. Foran, "Eigen: Ecologically-inspired genetic approach for neural network structure searching from scratch," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 9051–9060, 6 2019.
- C. Broni-Bediako, Y. Murata, L. H. B. Mormille, and M. Atsumi, "Evolutionary NAS with Gene Expression Programming of Cellular Encoding," in *2020 IEEE Symposium Series on Computational Intelligence (SSCI)*, pp. 2670–2676, 2020.