

# A Methodology to Generate Efficient Neural Networks for Classification of Scientific Datasets

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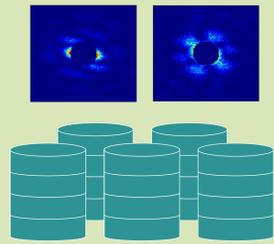
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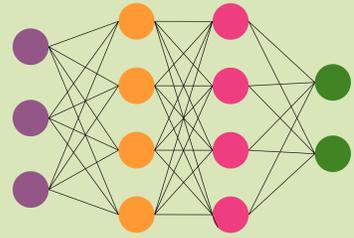
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## Using Neural Networks (NNs) for Scientific Discovery

Scientific Datasets



Neural Networks



Scientific Discoveries

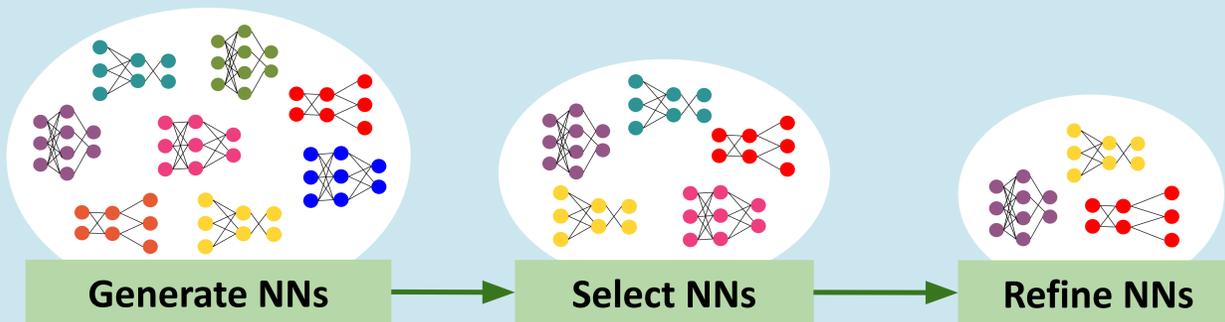


Achieving high accuracy and efficient performance is a challenge, so:

- We **define** a domain-agnostic methodology to find an efficient NN using a neural architecture search (NAS)
- We **optimize** for accuracy (minimize error) and for efficiency (minimize inference FLOPS).

## Domain Agnostic Methodology for NNs Search

Our methodology efficiently utilizes a NAS to find a NN architecture optimized to classifying scientific datasets based on accuracy and performance.



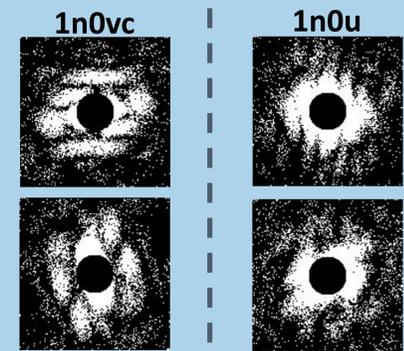
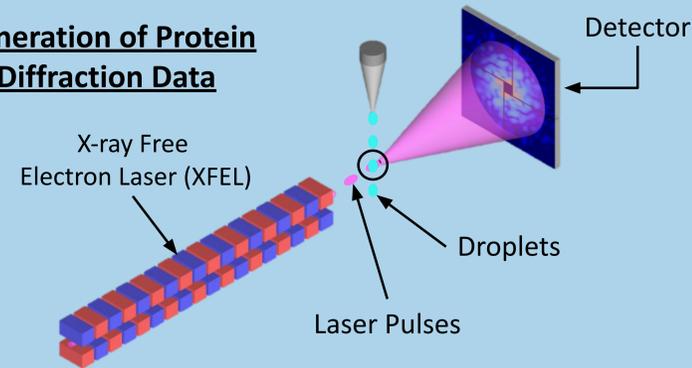
**Generate NNs**  
Generate and train several generations of NNs on a dataset using a NAS of desired choice

**Select NNs**  
Select Pareto-optimal sets of NNs for *each generation* based on:  
• high accuracy  
• low FLOPS usage

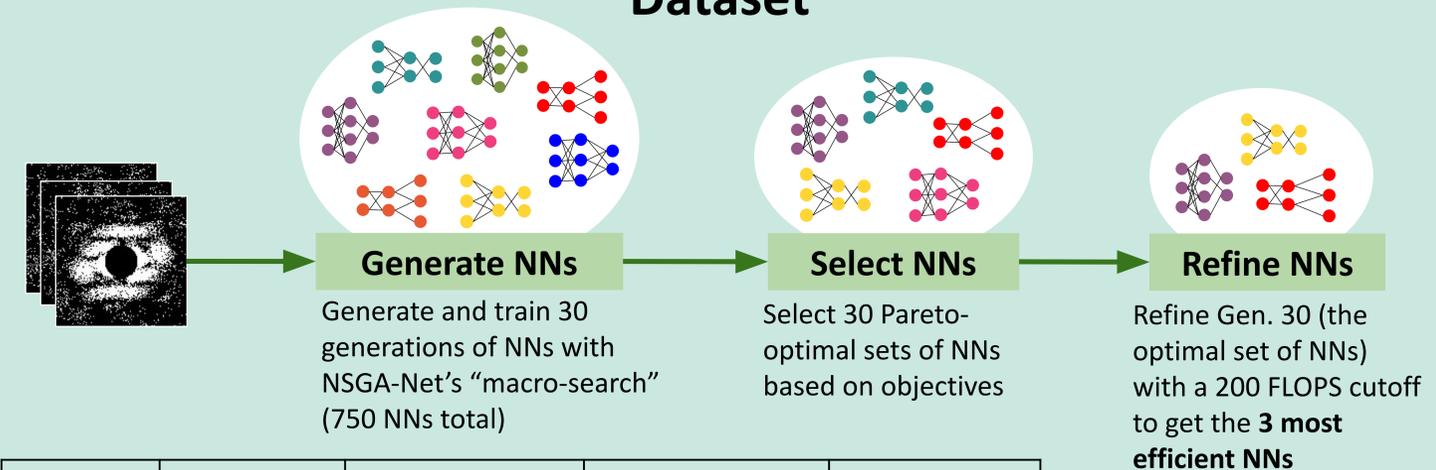
**Refine NNs**  
Refine by:  
• choosing the optimal set of NNs  
• establishing FLOPS cutoff  
• long targeted training (more epochs)

## Case Study: Protein Diffraction Dataset

Generation of Protein Diffraction Data

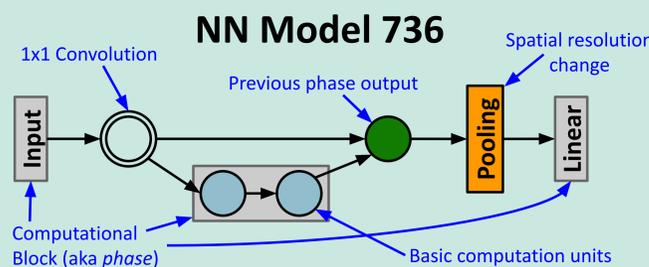


## Applying our Methodology to Classify Protein Diffraction Dataset



NN Model	FLOPS	Accuracy before refinement	Accuracy after refinement	Inference Time (s)
740	0.016	57.1	57.1	0.407
729	169.125	92.4	97.7	1.161
736	187.125	94.6	98.1	1.250

Best 2 NNs due to >97% accuracy and <200 FLOPS usage



Our methodology leverages NAS to find accurate and efficient NN architectures tailored to any scientific dataset.

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