DistHD: A Learner-Aware Dynamic Encoding Method for Hyperdimensional Classification

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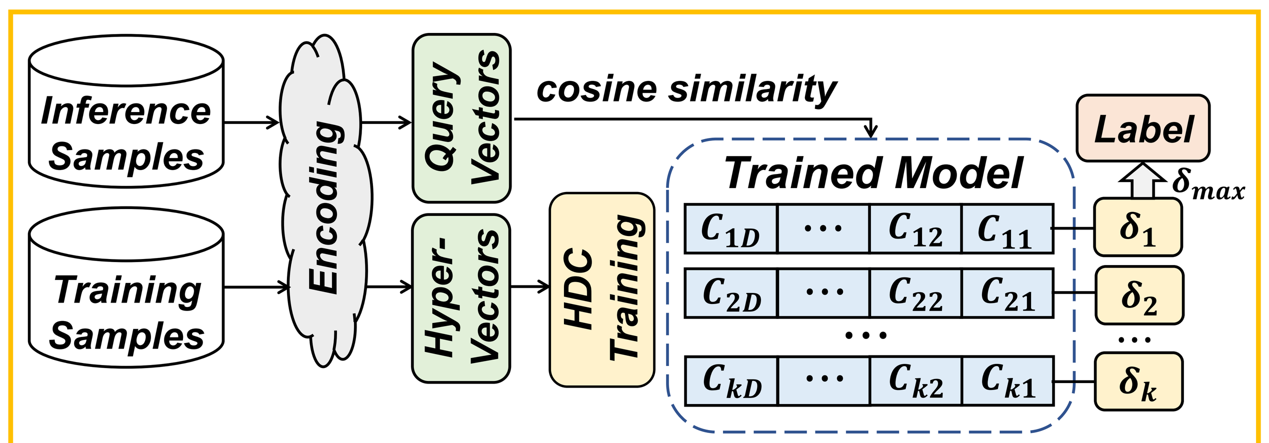
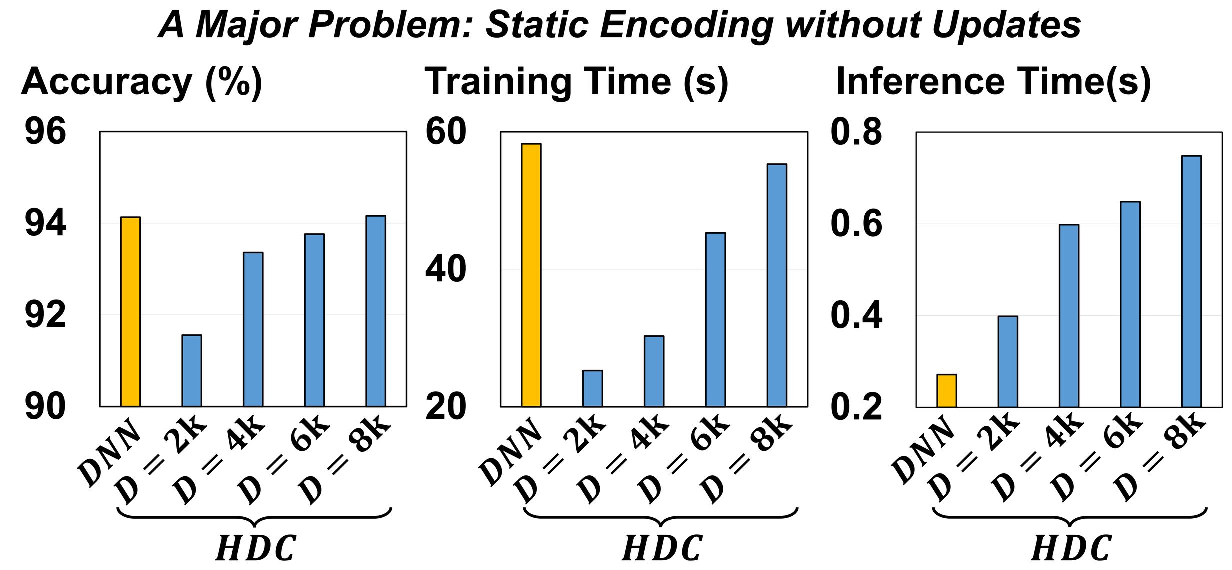
Hyperdimensional Computing



An Overview of Hyperdimensional Computing



Comparing State-of-the-art HDC with DNNs

Why Edge Computing?

Relieve Efficiency loss of sending data to the cloud

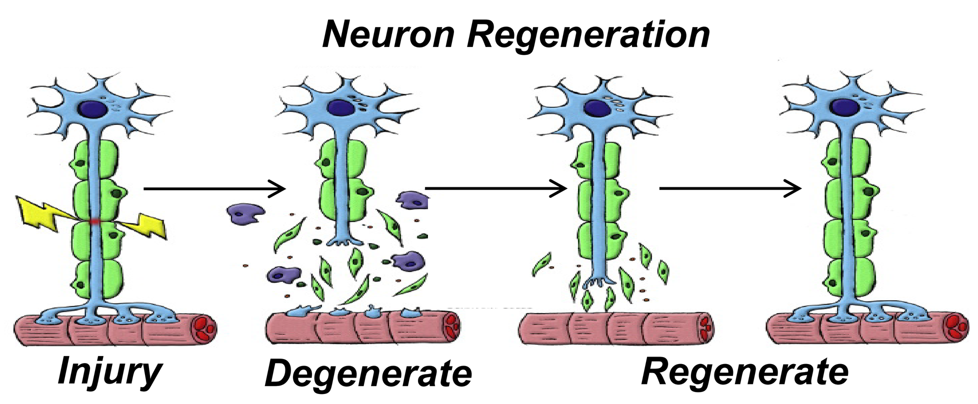
- Reduce Scalability Issues
- Eliminate Safety/Privacy Concerns

Accommodating high resource requisite of popular ML&DL on resource-constrained platforms can be extremely challenging!

A potential Solution: Hyperdimensional Computing (HDC)!

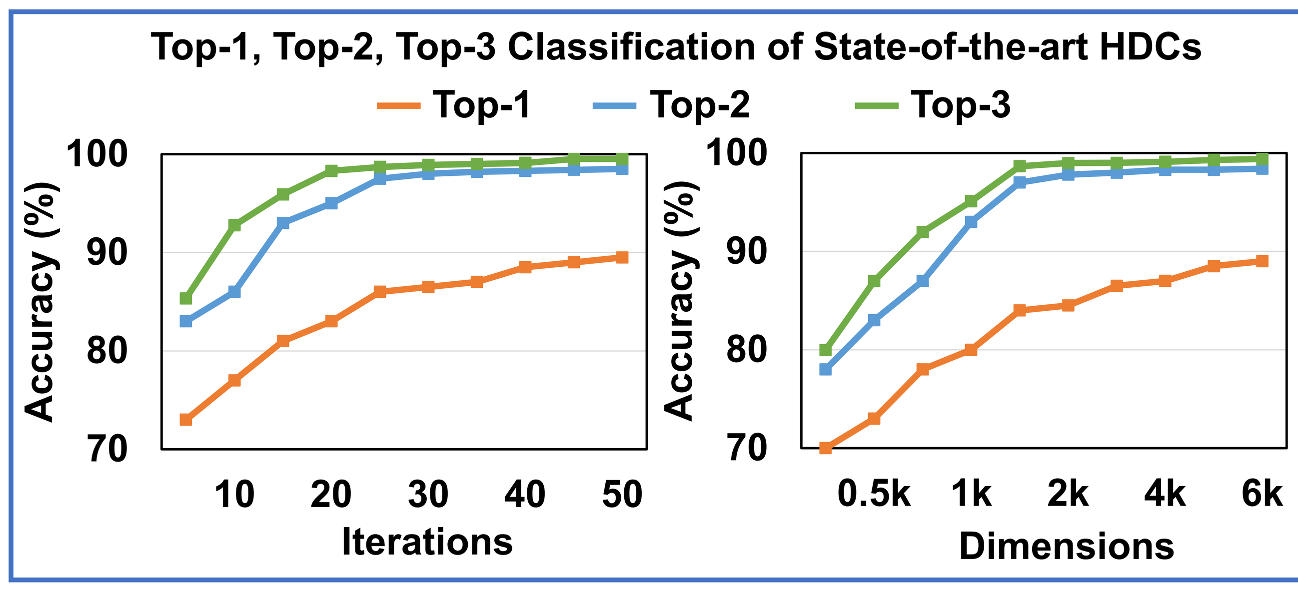
- ✓ High-computational efficiency ensuring real-time learning
- ✓ Strong robustness against noise – a key strength for IoT systems
- ✓ Lightweight Hardware Implementation for efficient execution on edge

Motivation



- Neurons in human brains dynamically change and regenerate all the time!
- Neurons provide new useful functionalities whenever they get access to new information!

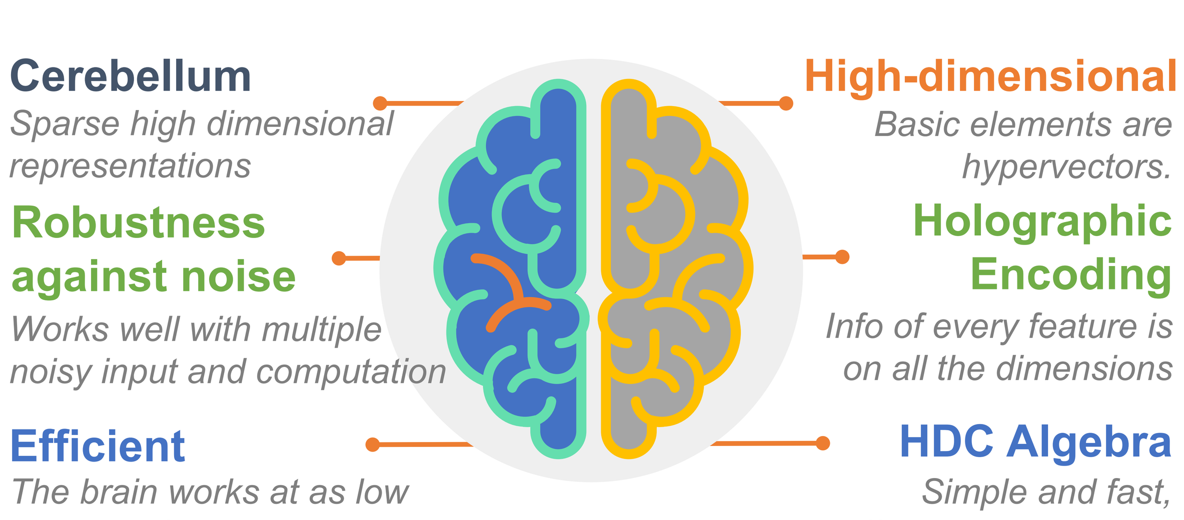
It remains challenging for existing HDCs to support a similar behavior as brain neural regeneration.



An interesting Observation:

- Define a top k-classification for a given data point as correct if the true label is one of the k most similar classes selected.
- *Accuracy(top-2) ≫ Accuracy(top-1)*
- *Accuracy (top-3)– Accuracy(top-2) ≫ Accuracy(top-2) – Accuracy(top-1)*

HDC Introduction



- **Binding (+):** Element-wise addition
  $\mathcal{H}_{bundle} = \mathcal{H}_1 + \mathcal{H}_2$
  $\delta(\mathcal{H}_{bundle}, \mathcal{H}_1) \gg 0, \delta(\mathcal{H}_{bundle}, \mathcal{H}_3) \approx 0$
- **Bundling:** Element-wise multiplication
  $\mathcal{H}_{bind} = \mathcal{H}_1 * \mathcal{H}_2$
  $\delta(\mathcal{H}_{bind}, \mathcal{H}_1) \approx 0, \delta(\mathcal{H}_{bind}, \mathcal{H}_2) \approx 0$
- **Reasoning:** measuring the similarity of hypervectors, e.g., cosine similarity is calculated as $\delta(\mathcal{H}_1, \mathcal{H}_2) = \frac{\mathcal{H}_1 \cdot \mathcal{H}_2}{\|\mathcal{H}_1\| \cdot \|\mathcal{H}_2\|}$

Conclusion & Future Works

Our Work:

- We propose DistHD, an accurate, efficient, and robust dynamic HDC learning framework
- With a powerful dynamic encoding module, DistHD identifies and regenerates dimensions that mislead the classification and reduce the learning accuracy
- DistHD is the first attempt utilizing dynamic encoding technique to improve learning accuracy

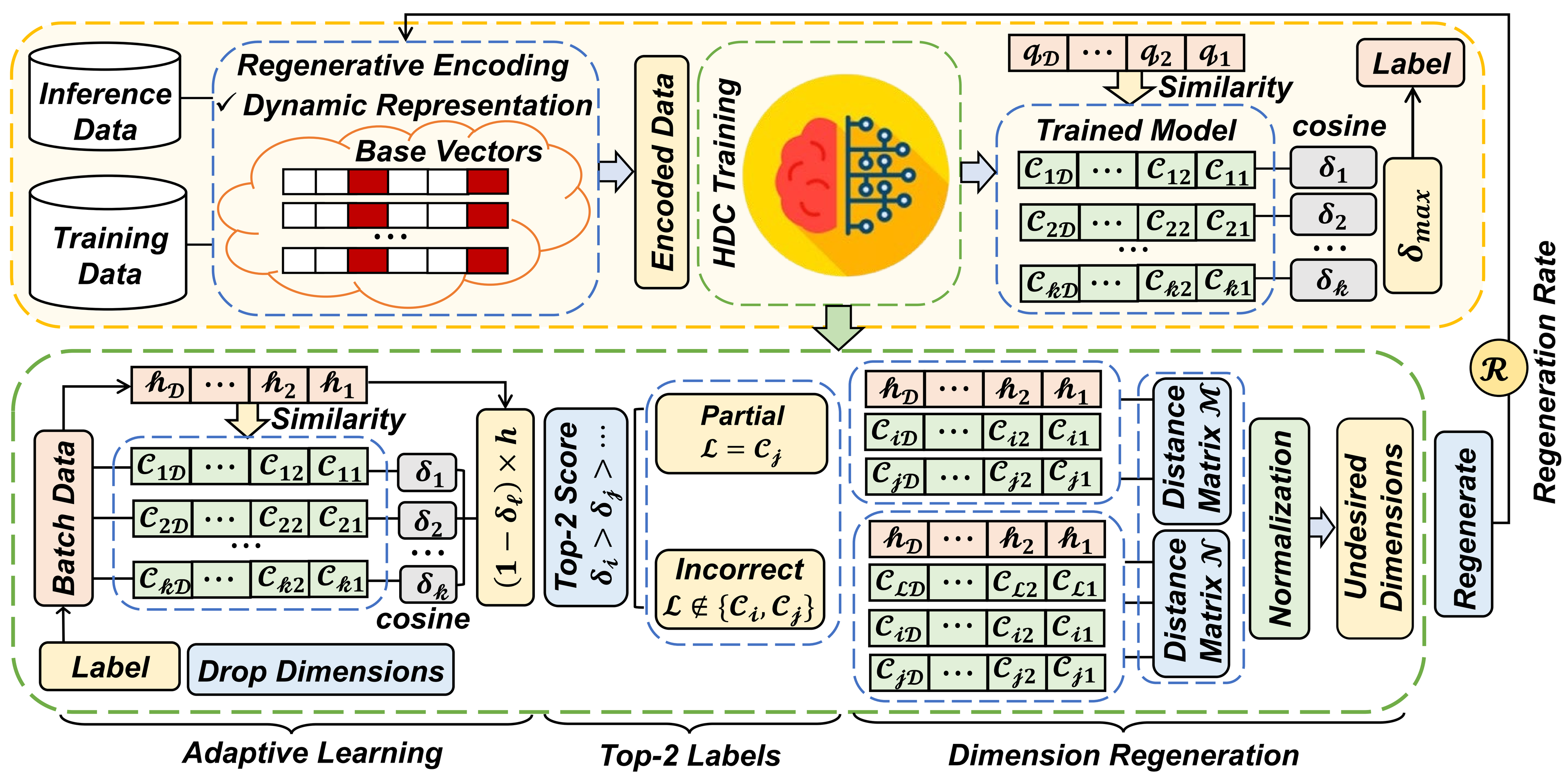
Future Work:

- Better dynamic encoding technique
- Broader Applications & More complicated datasets
- Customized hardware acceleration for HDC on resource-constrained computing platforms

DistHD is open-sourced for future research at: https://github.com/jwang235/DistHD

Our Paper is available at: https://sites.uci.edu/junyaowang/

DistHD: A Learner-Aware Encoding Method



Step 1: Top-2 Classification

- Adaptive learning
- Selecting top-2 labels

Step 2: Dimension Regeneration

- Identifying undesired dimensions
- Regenerate undesired dimensions for enhanced learning quality

Our strategy is simple: searching for dimensions that farthest away from the correct class hypervectors and closest to the incorrect class hypervectors

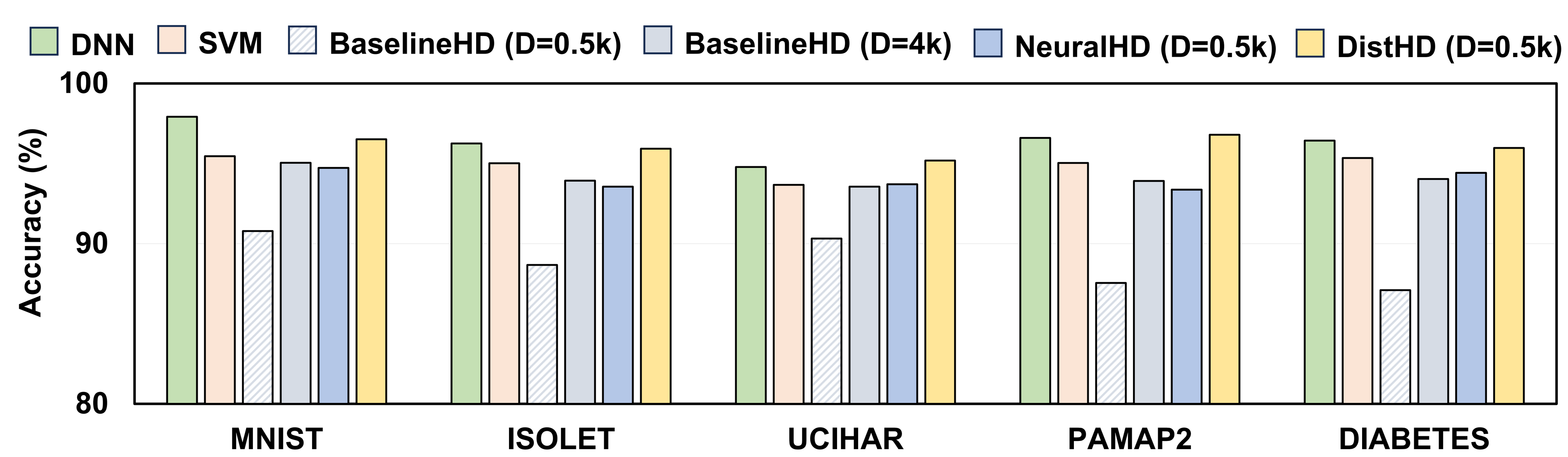
Evaluations *(Selected)*

❖ ***We compare DistHD with the following learning algorithms:***

- SOTA DNN with similar runtime
- SVM
- SOTA HDC without dynamic encoding (BaselineHD)
- NeuralHD *(the first dynamic HDC primarily aims to improve learning efficiency)*

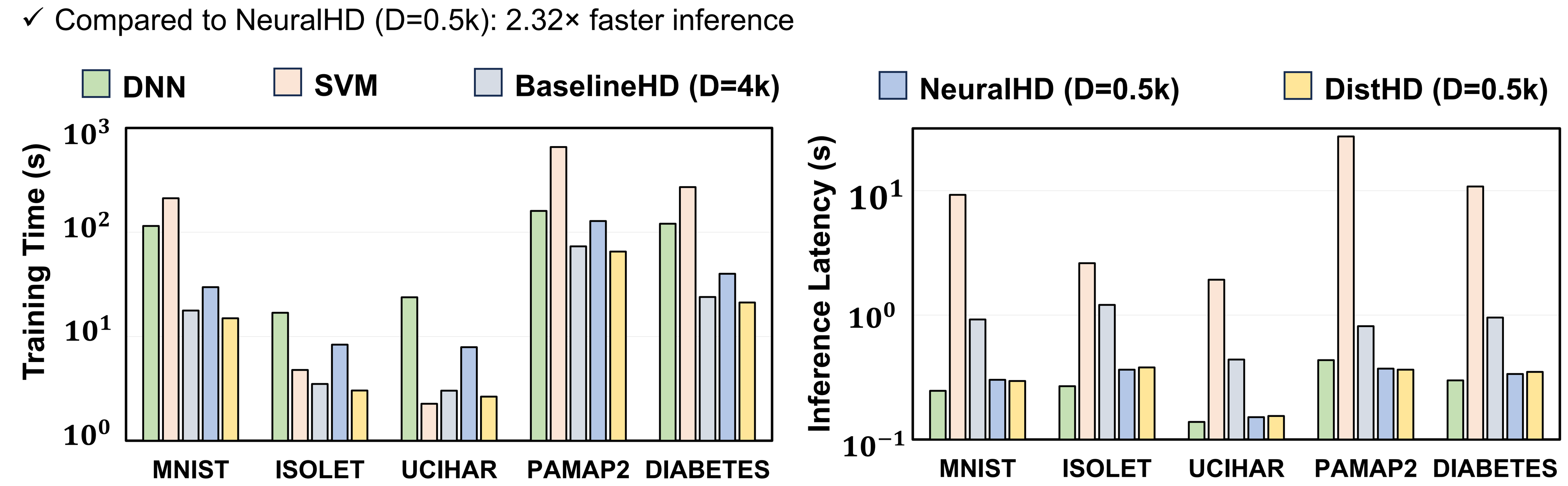
❖ ***Accuracy:***

- ✓ Comparable accuracy to DNN with similar runtime, 1.17% higher accuracy than SVM
- ✓ 6.96 % and 1.82% higher accuracy than BaselineHD (D=0.5k) and BaselineHD (D*=4k), respectively
- ✓ 1.89% higher accuracy than NeuralHD (D=0.5k)



❖ ***Efficiency:***

- ✓ Compared to SOTA DNN: 5.92× faster training, comparable inference latency
- ✓ Compared to BaselineHD (D*=4k): 1.15× faster training, 8.09× faster inference
- ✓ Compared to NeuralHD (D=0.5k): 2.32× faster inference



Selected References

1. Zhuowen Zou et al, “Scalable edge-based hyperdimensional learning system with brain-inspired neural adaptation”, The International Conference for High Performance Computing, Networking, Storage, and Analysis (SC), 2021
2. Alejandro Hernández-Cano, et al, "OnlineHD: Robust, Efficient, and Single-Pass Online Learning Using Hyperdimensional System", IEEE/ACM Design Automation and Test in Europe Conference (DATE), 2021.