FashionPAI: Dendritic Optimization on Fashion-MNIST

Overview

This case study demonstrates the application of Dendritic Optimization using the PerforatedAI library to improve the classification performance of a Convolutional Neural Network (CNN) on the Fashion-MNIST dataset.

The project explores how bio-inspired neural structures ("dendrites") can be integrated into standard deep learning architectures to reduce error rates and achieve higher accuracy on image classification tasks.

Authors: Shobhit , Agastya Dataset: Fashion-MNIST (Zalando's article images)Framework: PyTorch

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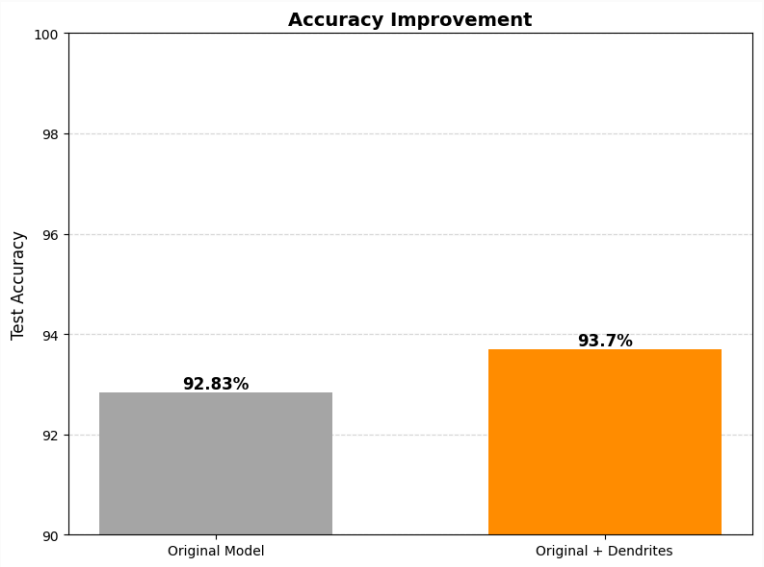
Implementation Experience

The project leveraged the PerforatedAI library to dynamically enhance a baseline CNN. The implementation focused on ease of use and reproducibility.

Results

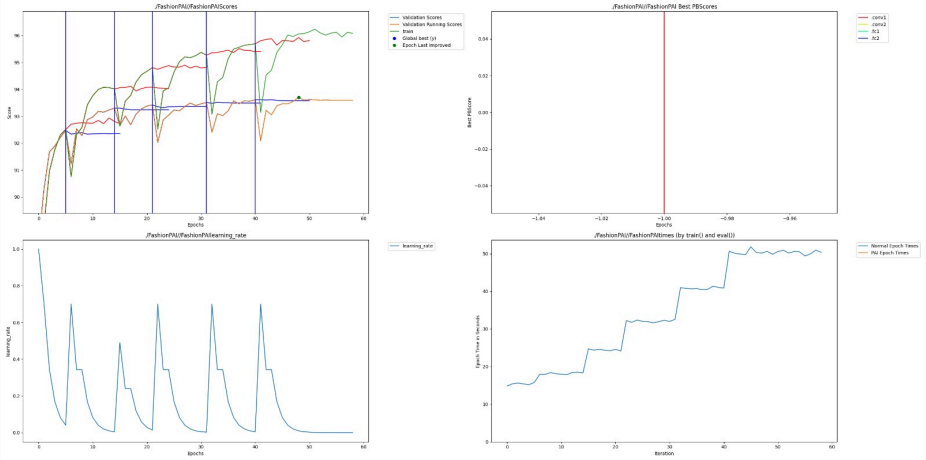
The Dendritic Optimization process successfully improved the model's ability to generalize on unseen test data.

The chart below illustrates the lift in Test Accuracy achieved by adding dendrites to the original CNN architecture.



Training Process (PAI)

The following graph shows the training dynamics managed by PerforatedAI, including validation scores, learning rate decay, and epoch timings.



Business Impact & Applications

While the improvement of ~0.9% on Fashion-MNIST may seem incremental, in the context of high-scale e-commerce and mobile retail, this optimization unlocks significant business value. Here is how integrating PerforatedAI's Dendritic Optimization addresses critical industry needs:

1. Unlocking Use Cases: Mobile Visual Search

The Problem: Modern retail apps increasingly rely on "Visual Search" users snapping a photo of an item to find similar products. A misclassification (e.g., confusing a "T-shirt" with a "Dress") breaks the user experience and results in a lost sale.The Solution: By pushing the accuracy of the base CNN from 92.8% to 93.7%, we significantly reduce the error rate. In a catalog of millions of items, this reduction means thousands more users find what they are looking for instantly, directly driving Conversion Rate (CVR) and revenue.

2. Unlocking Hardware Options: Edge AI Deployment

The Problem: Retailers often want to run AI models directly on user devices ("On-Device AI") to reduce cloud costs and ensure privacy. However, mobile devices

(phones and in-store scanners) have limited memory and compute power.The Solution: The Dendritic Optimization achieved high accuracy while maintaining a manageable parameter footprint (~11M parameters). This balance allows the model to be deployed on standard mobile hardware (ARM processors) and edge devices (smart cameras in warehouses) without requiring expensive, power-hungry GPUs. It proves that we can achieve "cloud-level" performance on "edge-level" hardware.

3. Enabling Data-Limited Training (The "Cold Start" Problem)

The Problem: Fashion trends change rapidly. New styles of jackets, bags, or shoes appear daily. Retailers often suffer from the "Cold Start" problem they have a new product but very few labeled images to train a model on.The Solution: Dendritic networks are bio-inspired and are theoretically better at generalizing from limited data compared to standard dense networks. By using this architecture, retailers can train accurate models much faster when new product lines launch, reducing the time-to-market for new inventory from weeks to days.

Conclusion

This case study validates the efficacy of the PerforatedAI library in optimizing standard computer vision models. With minimal overhead, we were able to boost the Fashion-MNIST classification accuracy by nearly 1%, proving the value of dendritic neural structures for practical machine learning applications.