Volumetric Neural Execution and Sovereign Edge Adaptation: A Comprehensive Evaluation of the Welvet 1.0.3 Training Topology Matrix

The transition of artificial intelligence from centralized, high-compute cloud environments to constrained, sovereign edge hardware necessitates a fundamental reevaluation of neural network training paradigms. Historically, deep learning models deployed to edge sensors suffer from the "frozen brain" phenomenon: learning ceases the moment the model leaves the laboratory environment due to the prohibitive computational and memory overhead associated with classical optimization algorithms[1]. The introduction of the Welvet engine—a Deterministic Neural Virtual Machine (DNVM) written entirely in Go—presents a radical departure from this limitation[2]. By operating on a volumetric 3D grid architecture (z, y, x, l) and enforcing bit-exact reproducibility across disparate hardware backends (CPU Tiled, Plan 9 SIMD, and WebGPU), Welvet facilitates continuous, on-device adaptation[3].

This report provides an exhaustive evaluation of the 29 distinct training modes integrated into the latest AllModes matrix, associated with the test53 and tide test suites, operating on the Welvet 1.0.3 engine architecture. The analysis specifically focuses on evaluating these learning topologies across a comprehensive spectrum of learning rates (LR) applied to continuous data streams originating from dual environmental edge sensors, denoted as Cam 1 (high-resolution spatial capture) and Cam 3 (high-framerate temporal/sequential capture)[6]. All empirical benchmarking context is derived from native execution on highly constrained edge hardware, explicitly mirroring the 1GB RAM constraints of a Raspberry Pi 3B, ensuring that memory bandwidth thrashing, VRAM exhaustion, and execution thread locking are strictly quantified[6].

Central to this evaluation is the Lucy Score, a composite metric defining the efficacy of continuous edge learning. It is calculated as the product of Throughput, Availability (duty cycle), and Accuracy[6]. Because classical backpropagation locks the global execution thread and requires massive activation caching, it inherently yields low Availability, driving down the Lucy Score. Conversely, target propagation algorithms (denoted in Welvet as "Tween") and their decoupled proxy variants allow simultaneous inference and training, fundamentally altering the calculus of edge adaptation[6].

The Welvet 1.0.3 Engine and the Dense MatVec Microkernel

To contextualize the performance of the 29 training modes, it is first necessary to dissect the underlying engine architecture introduced in the Welvet 1.0.3 update. The engine abandons the

industry-standard reliance on Python, C-bindings, and massive external libraries like CUDA or cuDNN, instead leveraging a pure Go core that compiles to a single binary or WebAssembly (WASM) payload[2]. The framework has achieved a 100-point scorecard on its internal validation suite, passing 227,194 test cells and 456 suite cases with zero unlogged arithmetic drift (MAE < 1e-8) across platforms[2].

At the heart of the Welvet 1.0.3 engine is the layers/dense microkernel, which underpins the vast majority of floating-point operations across the network, including composite projections for Multi-Head Attention (MHA), SwiGLU, and Convolutional structures[5]. The dense execution stack strictly defines storage truth. Unlike traditional Quantization-Aware Training (QAT) frameworks that maintain a hidden, high-precision Float32 master weight tensor in parallel with quantized weights, Welvet explicitly forbids retained Float32 masters[5]. A network morphed into an 8-bit integer state (INT8) or a packed block quantization (e.g., Q4_0) stores only those bits[4]. This microkernel supports 34 distinct native data types (FormatNone×34) and 20 specific packed quantization formats, routed through three primary execution backends: CPU Tiled (Single-Core and Multi-Core), Plan 9 SIMD for localized fused dot products, and WebGPU for device-level acceleration[5]. When any of the 29 training modes initiates a weight update via Stochastic Gradient Descent (SGD) or Hebbian target gap correction, the engine unpacks the specific quantized block into a short-lived scratch buffer, applies the arithmetic update directly in that reduced precision space, and immediately re-packs the block[5]. This mechanism dramatically reduces memory pressure, an absolute necessity for 1GB RAM edge devices, but it dictates highly non-linear responses to learning rate scaling. The interplay between the dense microkernel's rigid storage formats and the continuous flow of data from Cam 1 and Cam 3 forms the mechanical foundation for the diverging efficacy of the tested topologies.

Architectural Taxonomy of the 29 Training Modes

The AllModes suite encompasses 29 discrete training permutations. These can be categorized into overarching algorithmic families based on their approach to gradient calculation, temporal unfolding, spatial distribution, and target proxy generation. The naming conventions follow a specific legend where [T]=Tween, [S]=Split, [FP]=FastProxy, [L]=Linear, and [HP]=HeadProxy.

The Classical Gradient Descent (BP) Family

The baseline configurations rely on classical automatic differentiation, calculating exact mathematical gradients via the chain rule.

- **NormalBP (sgd)**: The traditional SGD mechanism. It utilizes global execution locks and requires a maximal activation cache footprint. For an objective function, the weight update forces the entire forward inference pipeline to halt while gradients are calculated and propagated backward[6].
- **StepBP (step_sgd)**: Designed for recurrent or sequential architectures, this mode temporally unrolls the SGD operations within the step mesh, executing Backpropagation Through Time (BPTT). It is highly prone to exponential VRAM explosion on constrained devices due to the necessity of storing activations across all time steps[6].

- **MeshBP (MeshBP)**: Gradient backpropagation is routed through 3D spatial hops across the volumetric grid. While spatializing the gradient calculation, it remains prone to pipeline stalling as nodes must wait for exact upstream derivative signals to arrive[6].

Core Target Propagation (Tween)

Target propagation replaces the continuous mathematical gradient with localized, gap-based Hebbian learning. Instead of passing derivatives backward, the network propagates desired *target* activation values. The weight update is determined by the error between the current output and the target, effectively turning the update into an informed, localized bit-flip mechanism on quantized weights[6].

- **Tween ([T] / tween)**: The foundational target propagation mode. It eliminates global gradient locks entirely and demonstrates exceptional synergy with tight quantizations (e.g., Q4_0, INT2, Binary)[6].
- **TweenChain ([T]Chain / tween_chain)**: Combines standard target propagation with localized, adjacent-layer gradient refinements, bridging the gap between pure Hebbian updates and exact chain-rule derivations[6].
- **MeshTween (Mesh[T])**: Transposes target propagation into an asynchronous, 3D spatial mesh. Optimized heavily for parallel WebGPU/SIMD workloads, it allows distant grid cells to process targets independently of the global state[6].
- **MeshTweenChain (Mesh[T]Chain)**: Enhances the spatial target propagation with neighbor-informed boundary corrections, smoothing the target vectors as they traverse the spatial axes of the grid[6].

Temporal Target Propagation (Step)

These modes address the processing of sequential data streams without incurring the prohibitive memory costs of unrolled BPTT.

- **StepTween (Step[T] / step_tween)**: Delivers clock-cycle accurate targeting for recurrent architectures. It calculates target vectors per time step without requiring recurrent VRAM overhead, effectively mitigating the memory explosion seen in StepBP[6].
- **StepTweenChain (Step[T]Chain / step_tween_chain)**: Integrates clock-cycle targeting with localized adjacent-step gradient refinements, preserving temporal context across longer sequences without massive caching[6].

Decoupled Splits and Alternating Topologies

These topologies physically or temporally isolate the forward inference pass from the backward update pass to maximize the edge sensor's availability.

- **TweenSplit ([T][S])**: Bisects the neural network into autonomous zones. Each zone optimizes to local boundary targets independently, preventing latency in deep layers from stalling early layers[6].
- **StepTweenSplit (Step[T][S])**: The temporal equivalent of TweenSplit, applying zone bisection to clock-cycle recurrent streams[6].

- **TweenAlt ([T]Alt)**: Alternates between target generation and target application phases. By separating these phases, it minimizes memory bandwidth thrashing on shared-memory architectures[6].
- **StepTweenAlt (Step[T]Alt)**: Applies the alternating phase methodology to sequential/recurrent data streams[6].
- **MeshTweenSplit (Mesh[T][S])**: Bisects the 3D spatial mesh into autonomous zones, creating highly localized target optimization within specific volumetric coordinates[6].
- **MeshTweenAlt (Mesh[T]Alt)**: Implements phase alternation across the 3D spatial mesh[6].

Proxy-Accelerated Generators

To achieve zero-latency target propagation, the Welvet engine supports grafting micro-networks or lookup mechanisms onto the primary execution graph. These proxies instantly predict optimal targets for early structural splits, allowing deep layers to update in the background while shallow layers continue live inference[6].

- **TweenSplitHeadProxy ([T][S][HP])**: Grafted micro-networks that instantaneously predict targets for early structural splits[6].
- **TweenSplitLinear ([T][S][L])**: Utilizes extremely fast, linear affine approximations of target generation. This mode is explicitly engineered for compatibility with low-bit integer ALUs[6].
- **TweenSplitFastProxy ([T][S][FP])**: Deploys sparse lookup tables and 2-bit quantized proxy weights to achieve maximum edge throughput[6].
- **TweenSplitLinearCache ([T][S][L]Cache)**: Caches target predictions and applies momentum smoothing to stabilize Hebbian weight shifts over time[6].
- **TweenSplitHeadProxyAsync ([T][S][HP]Async)**: Asynchronous target generation runs completely on off-threads, enabling true background learning during live user inference[6].
- **MeshTweenSplitFastProxy (Mesh[T][S][FP])**: Applies the 2-bit quantized lookup tables to the 3D spatial mesh[6].
- **StepTweenSplitHeadProxy (Step[T][S][HP])**: Applies grafted micro-network target generation to temporal recurrent splits[6].
- **StepTweenSplitLinear (Step[T][S][L])**: Linear affine target approximation for recurrent architectures[6].
- **StepTweenSplitFastProxy (Step[T][S][FP])**: Temporal application of 2-bit sparse lookup proxies[6].
- **StepTweenSplitLinearCache (Step[T][S][L]Cache)**: Temporal prediction caching with momentum smoothing[6].
- **StepTweenSplitHeadProxyAsync (Step[T][S][HP]Async)**: Asynchronous, off-thread recurrent target generation[6].

Budgeted Sparsity

On edge devices, memory write cycles are often the physical hardware bottleneck. Sparse

modes introduce dynamic thresholds that block weight modifications unless the error gap exceeds a defined ϵ boundary[6].

- **TweenSplitSparse ([T][S]Sparse)**: Applies update thresholds to standard target propagation splits[6].
- **MeshTweenSplitSparse (Mesh[T][S]Sparse)**: Combines 3D spatial zones, localized proxies, and sparse update budgets. This is noted in engine documentation as the apex edge configuration[6].
- **StepTweenSplitSparse (Step[T][S]Sparse)**: Ensures that recurrent models only execute memory writes when sequential drift becomes statistically significant[6].

Learning Rate Dynamics and Quantization Synergy

The experimental framework dictates evaluating all 29 modes across a spectrum of learning rates. Classical deep learning literature generally confines the learning rate (η) to a narrow band, typically bounded between 10^{-5} and 10^{-2}. If η is scaled too high in a standard SGD configuration, the continuous exact derivative causes the optimizer to wildly overshoot the loss landscape minima, leading to catastrophic weight explosion and model collapse.
However, the Welvet 1.0.3 architecture, utilizing FormatNone×34 storage and avoiding QAT float32 masters, alters this mathematical reality[5]. Under target propagation (Tween modes), the error is calculated as the finite gap between the network output and the generated target vector. The maximum weight update is therefore inherently physically bounded by the activation space. Furthermore, target propagation on deeply quantized networks behaves fundamentally as an informed, localized bit-flip mechanism[6].
Consequently, three distinct learning rate regimes produce wildly divergent behaviors across the 29 modes:

1. **Low Regime ($\eta \in [10^{-5}, 10^{-4}]$)**: Classical SGD operates cleanly here, assuming infinite memory and time. However, target propagation on 4-bit or 2-bit integer weights often stalls entirely in this regime, as the fractional update magnitude is insufficient to trigger a discrete jump to the next integer bin.
2. **Mid Regime ($\eta \in [10^{-3}, 10^{-2}]$)**: Serves as a transitional boundary where localized gradient chains (TweenChain variants) perform optimally, balancing discrete stepping with spatial continuity[6].
3. **High Regime ($\eta \in [10^{-1}, 1.0]$)**: Historically destructive for BP, this regime is essential for Split, Proxy, and Mesh Tween modes. A high learning rate ensures that when a target proxy identifies a structural feature gap, the integer weights flip states immediately, inducing rapid behavioral adaptation to the live data stream without causing overflow[6].

Exhaustive Comparison on Cam 1: Dense Spatial

Execution

The Cam 1 profile represents high-resolution spatial data ingress. In edge AI applications, such as unsupervised domain adaptive person re-identification or static visual classification, the neural network acts as a frame-by-frame spatial feature extractor[7]. Evaluating Cam 1 stresses the Welvet Dense and Convolutional execution stack, measuring how rapidly the system can project matrices and whether the backward update pass interrupts the live inference feed.
When analyzing classical SGD (NormalBP and MeshBP) on Cam 1, the data reveals a fundamental incompatibility with edge sovereignty. Operating on a single gigabyte of RAM, the Pi 3B hardware is choked by the global execution lock required to traverse the chain rule back through the dense spatial layers. The network must cache millions of intermediate activation floats. While a Low LR produces theoretical convergence over a period of days, the Lucy Score is destroyed because the system's Availability drops below 15%. Frame processing stalls continuously as the main thread pauses inference to calculate exact gradients[6]. Attempting to increase the learning rate to accelerate adaptation immediately triggers quantization collapse; the exact mathematical gradients amplified by High LR exceed the boundaries of the Q4_0 packed matrices, resulting in immediate catastrophic divergence.
The transition to Target Propagation completely inverts the performance metrics on the Cam 1 feed. Tween calculates target activations locally. When paired with High LR, the discrete nature of the dense weights acts as a biological regulator. Instead of overshooting, the high LR simply forces the quantized state to flip instantly if the gap between the camera feed output and the local target is wide enough[6].
The introduction of Split and Proxy topologies unlocks continuous spatial learning. TweenSplit bisects the spatial network into autonomous zones. For Cam 1, this means deep classification layers can optimize against targets from a previous frame while the shallow feature extractors simultaneously ingest the current live frame. This concurrent operation pushes Availability toward 100%, dominating the Lucy Score[6].
The absolute peak performance for spatial processing is achieved via TweenSplitHeadProxyAsync and MeshTweenSplitSparse. The asynchronous head proxy utilizes an off-thread micro-network to guess the structural target instantly[6]. The edge device devotes its primary thread exclusively to processing the Cam 1 video feed, while the secondary thread calculates targets and pushes background bit-flips to the spatial weights. Furthermore, because Cam 1 feeds often contain static spatial backgrounds (e.g., walls, stationary objects), the Sparse modes introduce a dynamic ϵ threshold[6]. The dense microkernel bypasses millions of redundant matrix write operations where the spatial data has not drifted, preserving the physical flash memory of the edge hardware and drastically reducing thermal load[6].

#	Training Mode (Short)	LR Response (Low)	LR Response (Mid)	LR Response (High)	Cam 1 Performance Dynamics

					& Constraints
1	sgd	Slow convergence	Unstable on quants	Catastrophic	Global lock destroys Availability; massive activation cache overhead.
7	MeshBP	Moderate stalls	Gradient spikes	Catastrophic	Spatial routing improves throughput slightly but pipeline stalls remain.
3	[T]	Stalled updates	Optimal learning	Stable bit-flips	Eliminates global locks; highly synergistic with Q4_0 and INT2 formats.
4	[T]Chain	Weak updates	Optimal learning	Spatial jitter	Neighboring gradient refinements smooth spatial targets.
8	Mesh[T]	Stalled updates	Rapid adaptation	Maximum speed	Asynchronous 3D targeting excels on parallel

					WebGPU backends.
10	[T][S]	Stalled updates	High Lucy Score	Peak throughput	Autonomous zone bisection allows simultaneous inference and training.
12	[T]Alt	Low thrashing	Low thrashing	Moderate jitter	Alternating target generation reduces shared-memory bandwidth contention.
14	[T][S][HP]	Sub-optimal	Instant targeting	Instant targeting	Grafted micro-networks provide zero-latency targets for early layers.
16	[T][S][FP]	Ineffective	Highly efficient	Maximum throughput	2-bit sparse lookups fit entirely in L1 cache, circumventing RAM speed.
18	[T][S][HP]As	Background	Background	True simultaneo	Off-thread target

	ync	processing	processing	us	generation yields the highest theoretical Lucy Score.
19	[T][S]Sparse	Bypasses writes	Optimal filtering	Optimal filtering	ϵ thresholds block redundant writes for static background regions.
23	Mesh[T][S]Sparse	Extremely efficient	Apex configuration	Apex configuration	3D zones + localized proxies + update budgets = optimal Cam 1 execution.

Table 1: Exhaustive Evaluation of Spatial/Dense Execution Topologies on Cam 1 Across Learning Rate Regimes.

Exhaustive Comparison on Cam 3: Temporal Sequential Execution

Cam 3 represents a fundamentally distinct computational challenge: high-framerate temporal reasoning and sequential state tracking. In environments requiring the neural execution to maintain track graphs across time—such as dynamic object permanence or continuous predictive modeling—the engine relies on recurrent components (e.g., RNN, LSTM) embedded within the volumetric architecture[7]. The temporal unrolling of these recurrent loops places massive strain on memory retention.

Classical gradient optimization collapses almost instantaneously on the Cam 3 temporal feed. StepBP (step_sgd) executes Backpropagation Through Time. For the engine to calculate exact gradients across a sequence of incoming frames from Cam 3, it must cache the intermediate

float activations for every single time step[6]. On a 1GB Raspberry Pi 3B, attempting to unroll a modest temporal window of a few seconds immediately results in an Out-Of-Memory (OOM) halt[6]. Even at the lowest learning rates, StepBP is entirely unviable for continuous edge processing due to exponential VRAM explosion.

The introduction of the Temporal Target Propagation (Step) family elegantly bypasses the BPTT limitation. StepTween calculates target vectors for the recurrent layers at exactly the current clock cycle[6]. By analyzing the gap between the expected temporal output and the current temporal state, it applies a Hebbian correction to the recurrent matrix instantly. Crucially, the VRAM footprint becomes $O(1)$ constant time, as historical activations are discarded immediately after the target is generated[6].

Temporal streams are inherently noisy; a sudden occlusion, a lighting glitch, or a rapidly moving entity on Cam 3 can generate erratic target vectors. If the learning rate is High, pure StepTween might aggressively unlearn valid historical track graphs to fit a single noisy frame. This physiological reality necessitates the Proxy and Cache topologies specifically designed for the Step family.

StepTweenSplitLinearCache emerges as a dominant topology for Cam 3. By utilizing linear affine target generation[6] and applying a momentum smoothing cache, the system mathematically dampens erratic temporal targets. If Cam 3 experiences a visual glitch, the momentum cache ensures the Hebbian target does not immediately corrupt the recurrent memory matrix. This stabilization allows the topology to utilize a High LR for rapid adaptation to genuine environmental shifts without falling victim to catastrophic forgetting during momentary noise spikes[6].

Similarly, StepTweenSplitSparse applies strict write budgets to the recurrent loop. The LSTM or RNN structures will absolutely not modify their internal hidden states via memory writes unless the Cam 3 sequential drift exceeds a statistically significant boundary[6]. Because reading from VRAM is cheap but writing is slow and power-intensive, this mode ensures that stable temporal tracks consume zero training power until the targeted object deviates from its predicted trajectory.

#	Training Mode (Short)	LR Response (Low)	LR Response (Mid)	LR Response (High)	Cam 3 Performance Dynamics & Constraints
2	step_sgd	Exponential OOM	Exponential OOM	Exponential OOM	BPTT activation caching immediately

					exhausts 1GB edge memory bounds.
5	Step[T]	Stalled temporal learning	Stable targeting	Prone to noise jitter	Clock-cycle accuracy prevents VRAM explosion; targets are applied instantly.
6	Step[T]Chain	Weak sequential link	Optimal track graphs	Recurrent instability	Localized adjacent-step gradients preserve context across sequential frames.
11	Step[T][S]	Stalled updates	High Lucy Score	Peak throughput	Temporal zone bisection prevents late-sequence lag from blocking intake.
13	Step[T]Alt	Low memory thrashing	Low memory thrashing	Moderate jitter	Phase separation protects the temporal input stream from write

					collisions.
24	Step[T][S][HP]	Sub-optimal	Instant prediction	Instant prediction	Micro-networks predict optimal future states for recurrent structures.
25	Step[T][S][L]	Weak approximations	Efficient ALUs	Rapid but coarse	Linear affine approximations maximize low-bit integer math efficiency.
26	Step[T][S][FP]	Ineffective	Highly efficient	Maximum throughput	2-bit lookup proxies provide ultra-fast sequential target guesses.
27	Step[T][S][L]Cache	Over-smoothed	Optimal dampening	Critical for high LR	Momentum smoothing stabilizes temporal shifts, preventing catastrophic forgetting.
28	Step[T][S][HP]Async	Background unrolling	Background unrolling	True simultaneo	Off-thread recurrent targets

				us	allow uninterrupted tracking of Cam 3 streams.
29	Step[T][S]Sparse	Bypasses writes	Optimal filtering	Optimal filtering	Preserves recurrent memory; updates only trigger upon sequence divergence.

Table 2: Exhaustive Evaluation of Temporal/Recurrent Execution Topologies on Cam 3 Across Learning Rate Regimes.

Second and Third-Order Implications for Edge Sovereign Learning

The exhaustive evaluation of these 29 modes yields implications that fundamentally shift the theoretical framework of distributed machine intelligence, extending far beyond the immediate numerical outputs of the Welvet DNVM.

The Eradication of the Frozen Brain Architecture

The prevailing industry standard assumes that edge sensors are essentially dumb terminals executing fixed computational graphs. A model is trained in a cloud data center, aggressively pruned, quantized to INT4 or INT8, and flashed to the edge device. When the operational environment inevitably drifts—for example, when the physical lens of Cam 1 accrues micro-scratches, or the seasonal lighting dynamics fundamentally alter the contrast ratios fed into Cam 3—the static model's accuracy permanently degrades, necessitating an expensive, centralized retraining and redeployment cycle[1].

The integration of MeshTweenSplitSparse and TweenSplitHeadProxyAsync proves conclusively that continuous, real-time edge learning is computationally trivial, even on hardware as constrained as a Raspberry Pi 3B[6]. By utilizing off-thread proxies and sparse update budgets, an edge sensor can continuously fine-tune its heavily quantized weight matrices against live environmental stimuli[6]. The network autonomously adapts to the physical lens scratch or the seasonal lighting shift without executing a single API call to a centralized server. This eradicates the frozen brain problem, ensuring that the model's accuracy asymptotically improves over its

deployment lifespan rather than degrading[1].

The Redefinition of Quantization Synergy

Historically, the deep learning community has viewed quantization strictly as a necessary compromise—a post-training compression technique required to accelerate inference at the expense of learning capacity and representational granularity. Under classical Backpropagation, this is largely true; exact gradients cannot be cleanly applied to extreme discrete states without complex QAT simulations and Float32 master tensors[5].
However, the behavioral data from the Welvet Target Propagation sweeps indicates a paradigm shift. Extreme discretization (e.g., Binary, Ternary, INT2, Q4_0) is not a compromise but a *feature* when paired with localized Hebbian updates[6]. The discrete integer states act as a natural, physical regularization mechanism against the inherently noisy targets generated by high-speed proxies on Cam 1 and Cam 3. A high learning rate in a Tween setup does not cause mathematical overflow; it simply guarantees that the activation gap is sufficient to trigger a single, definitive bit-flip in the dense microkernel[6]. This structural reality implies that future sovereign edge architectures should be designed from inception as discrete, localized state machines optimized for target propagation, rather than attempting to force continuous floating-point mathematics into constrained integer spaces.

Autonomous Network Self-Distillation and Biological Mimicry

The architectural behavior of the Proxy-Accelerated modes, specifically TweenSplitHeadProxy and its asynchronous variants, induces an effect analogous to continuous network self-distillation[6]. By grafting micro-networks to early structural splits in the 3D grid, the engine isolates the learning process into discrete localized zones[6]. The head proxy acts as a localized teacher, instantaneously providing target vectors to the early feature extractors based on the continuous feed from Cam 1 or Cam 3.
Over time, these shallow layers become hyper-optimized to the precise data distributions of the localized edge environment. As the early layers increasingly extract near-perfect representations, the computational burden on the deeper layers of the mesh is drastically reduced. This localized offloading mirrors the development of reflex arcs in biological nervous systems, where repetitive stimuli are processed entirely within the spinal cord (shallow layers) rather than requiring transmission to the cerebral cortex (deep layers). This biological mimicry allows the Welvet engine to route complex processing exclusively to deep layers only when novel or highly ambiguous anomalies are detected by the edge sensors.

Absolute Sovereign Privacy and Determinism

By executing continuous adaptation entirely via target propagation without cloud reliance, the system guarantees 100% data sovereignty. Because the Welvet engine enforces bit-level cross-platform determinism (MAE < 1e-8) across CPU, SIMD, and WebGPU backends[2], the adapted weight matrices from a sensor in the field can be extracted and shared peer-to-peer with other edge devices without drift[1]. A fleet of sensors processing distinct Cam 1 and Cam 3 environments can independently adapt, share their localized INT4 matrices, and achieve a

hive-mind intelligence that is entirely disconnected from centralized surveillance or cloud API latency[2].

Strategic Conclusions and Future Outlook

The empirical evaluation of the 29 Welvet 1.0.3 training topologies across the Cam 1 (dense spatial) and Cam 3 (temporal sequential) data streams definitively establishes that classical gradient backpropagation (NormalBP, StepBP, MeshBP) is functionally obsolete for continuous, sovereign edge adaptation. Its inherent requirements for global execution locks, massive activation caching, and continuous exact mathematics render it fatally incompatible with constrained physical hardware and discrete quantized weight storage.

Target propagation algorithms—specifically the decoupled, proxy-accelerated, and sparse Split topologies—represent the definitive path forward for edge intelligence. They achieve vastly superior Lucy Scores by maintaining near-perfect availability duty cycles, allowing simultaneous, uninterrupted inference and background training.

The structural recommendations are unequivocal:

1. **For Static/Spatial Edge Deployments (Cam 1 profiles)**: Utilize MeshTweenSplitSparse[6]. The synthesis of 3D autonomous zones, fast proxies, and budgeted sparsity ensures that physical VRAM writes are minimized, preserving edge hardware lifespan while allowing the model to adapt to spatial environmental drift instantly.
2. **For High-Framerate/Temporal Deployments (Cam 3 profiles)**: Deploy StepTweenSplitLinearCache or StepTweenSplitHeadProxyAsync[6]. The integration of momentum smoothing and asynchronous off-thread generation is absolutely critical to preventing catastrophic forgetting in noisy, high-frequency temporal streams, enabling stable recurrent adaptation without triggering exponential VRAM exhaustion.
3. **Algorithmic Learning Rate Paradigms**: When operating on the discrete microkernel (FormatNone×34, Q4_0, etc.), engineering teams must abandon the classical avoidance of high learning rates. Target propagation structurally requires Mid to High LR regimes to effectively execute the localized bit-flip mechanisms necessary for updating integer storage formats in the absence of a Float32 master tensor[5].

The implementation of the Welvet DNVM proves that immensely complex, adaptive neural architectures can be continuously trained on hardware as constrained as a 1GB edge processor. By pivoting away from global mathematical derivatives and embracing localized, proxy-driven, sparse target propagation, the field unlocks the capacity to deploy truly sovereign, perpetually adapting artificial intelligence.

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