US Patent 12,242,946-B1 — MLiglon Corporation

23 August 2025. Comparative Analysis of IGL and Backpropagation in Machine Learning Performance. Prepared by MLiglon Corporation; Dr. Michael J. Pelosi.

Executive Summary

This study evaluates the performance of MLiglon's patented Integer Gate Logic (IGL) framework against traditional backpropagation (BP) across two distinct machine learning tasks: (1) handwritten digit recognition using MNIST/EMNIST datasets, and (2) RF modulation classification using the RML2018.01A dataset. Results demonstrate IGL's superior scalability, accuracy, and efficiency, particularly in high-dimensional, noisy environments. These findings position IGL as a transformative alternative to BP, with significant implications for resource-constrained and real-world applications.

1. Methodology

1.1 Datasets and Objectives

- **MNIST/EMNIST**: 28×28 pixel grayscale images of handwritten digits/characters (784 features).
- **RML2018.01A**: Radio frequency (RF) modulation recognition dataset with 24 modulation types across SNR levels (-20dB to +30dB). Focus on SNR+4dB (realistic noise conditions) and SNR+30dB (low-noise baseline).

1.2 Data Preprocessing

- **RF Data**: IQ (In-phase/Quadrature) samples converted to 200×200 pixel frequency histograms (40,000 features) followed by log-normalization to mitigate skewness.
- **ML Architectures**:
    - **BP**: PyTorch implementation with GPU acceleration (4 hidden layers, 35 nodes/layer).
    - **IGL**: Proprietary framework leveraging binary logic and integer-only operations.

1.3 Evaluation Metrics

- Model size (parameters and memory footprint).
- Test accuracy across multiple runs.
- Noise tolerance and pruning efficiency.

2. Results

2.1 MNIST/EMNIST Benchmarking

- **IGL Advantages**:
    - **Smaller Models**: Achieved comparable accuracy with 82% fewer parameters vs. BP.
    - **Higher Accuracy**: Marginal gains in test accuracy (e.g., 99.1% vs. 98.7% for BP).
    - **Noise Robustness**: Sustained performance at higher noise levels where BP degraded.

2.2 RML2018.01A RF Modulation Recognition

| **Framework** | **Parameters** | **Memory Footprint** | **Accuracy (24 Modulations)**

| Backpropagation (PyTorch) | 1,403,851 (4-byte floats) | 5.615 MB | 98.52% (avg. across 12 runs) |
| IGL (Proposed) | 120,825 (1-byte integers) | 0.121 MB | 99.39% (avg. across 6 runs) |

- **Pruning Efficiency**: IGL models reduced to 18% of original size with **no accuracy loss** (0.4% of BP's footprint).
- **Speedups**: Integer-only operations and lookup tables enabled faster inference/training cycles.

3. Discussion

3.1 Scalability and Compression

IGL demonstrates **exponential gains in parameter efficiency** as problem complexity scales:

- **MNIST (784 features)**: 1/5th the size of BP for marginal accuracy gains.
- **RML2018 (40,000 features)**: 1/255th the size of BP with **higher accuracy**.
  This suggests IGL's knowledge compression scales super-linearly, a phenomenon warranting further theoretical analysis (e.g., via computational complexity theory).

3.2 Technical Advantages

- **Noise Tolerance**: IGL's binary architecture inherently mitigates noise, critical for RF/sensor data.
- **Hardware Efficiency**: Integer-only operations reduce computational overhead, enabling deployment on edge devices.
- **Pruning Potential**: Minimal redundancy in IGL networks allows aggressive model compression.

3.3 Limitations and Future Work

- **Theoretical Foundations**: While empirical results are conclusive, formal proofs of scalability require collaboration with domain experts in mathematics and computational theory.
- **Generalization**: BP may remain optimal for small-scale or low-noise tasks; IGL's niche lies in high-dimensional, noisy domains.

4. Conclusion and Commercial Implications

IGL outperforms BP in scalability, accuracy, and efficiency for complex, real-world tasks such as RF signal analysis. These results validate its potential as a **drop-in replacement** for BP in resource-constrained applications (e.g., IoT, autonomous systems) and establish a foundation for broader adoption.

Key Takeaways for Stakeholders:

- **Cost Reduction**: Smaller models lower hardware, energy, and operational costs.
- **Competitive Edge**: Superior noise tolerance and speed enable deployment in challenging environments.

- **IP Positioning**: Patented IGL technology offers a defensible moat in the multi-billion ML acceleration market.

Appendices

- **Appendix A**: PyTorch implementation code for BP baseline.
- **Appendix B**: IGL architecture schematics and pruning methodology.
- **Appendix C**: Full accuracy metrics and SNR-specific performance breakdowns.
- **Appendix D**: IQ data visualization guide (see attached “Understanding IQ Data.pdf”).

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End of Report

This formalized benchmark study emphasizes empirical rigor, scalability benefits, and commercial viability while aligning with investor and partner expectations for technical depth and strategic clarity.