Storage Capacity Limitations

Severely limited capacity, theoretically around 0.15N (N = neuron count)
Generates spurious memories when pattern count exceeds limits
Linear capacity scaling with network size
Poor efficiency in memory utilization

Convergence Issues

No guarantee of convergence to local minima
Risk of oscillating between states
Energy function may miss global optimum
Unpredictable convergence time
Potential for infinite loops

Pattern Recognition Limitations

High sensitivity to input noise
Limited to binary/bipolar data
Struggles with complex/continuous patterns
Pattern completion heavily depends on initial state
Poor generalization capabilities

Training and Learning Issues

Oversimplified learning rules (Hebbian learning)
No online learning capability
Requires symmetric weight matrix
Learning interference problems
Limited adaptability

Architectural Constraints

Requires full connectivity, $O(N^2)$ complexity
Fixed neuron count
No hierarchical structure support
Difficult modularization
High interconnection overhead

Memory Issues

Requires orthogonal or near-orthogonal patterns
Prone to spurious memories
Unstable memory retrieval
Poor discrimination between similar patterns
Cross-talk between stored patterns

Performance Limitations

Computationally inefficient
Difficult parallel implementation
Suboptimal energy function optimization
Limited real-time applications
Poor scaling with problem size

Practical Implementation Challenges

Complex hardware implementation
High computational resource requirements
Significant power consumption
Scaling issues in real-world applications
Implementation complexity

Theoretical Limitations

Lack of theoretical guarantees
Difficult mathematical analysis
Unclear performance boundaries
Hard-to-control optimization process
Limited theoretical framework

Application Constraints

Limited practical use cases
Poor handling of sequential data
Unsuitable for temporal tasks
Weak competitiveness in modern ML tasks
Limited flexibility