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Self-Evolving Deep Neural Networks for Continuous Learning in Dynamic IoT Environments

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ABSTRACT: The explosive growth of Internet of Things (IoT) networks has introduced unprecedented levels of data diversity, environmental volatility, and rapid concept drift. Traditional deep neural networks (DNNs), trained in static and centralized settings, are ill-equipped to adapt continuously to evolving IoT data streams without retraining from scratch or suffering catastrophic forgetting. To address these limitations, this paper proposes a novel **Self-Evolving Deep Neural Network (SE-DNN) framework** designed for real-time, lifelong learning in dynamic IoT ecosystems. The architecture autonomously expands, prunes, and restructures itself based on incoming data complexity, task demands, and temporal drift patterns. SE-DNN integrates adaptive layer growth, neuron evolution, memory-augmented attention, and drift detection mechanisms that identify distributional shifts and trigger structural updates. A hybrid learning strategy combining online incremental learning, episodic memory replay, and meta-learning ensures stability–plasticity balance, enabling the model to learn new patterns without forgetting previously acquired knowledge. Experimental evaluations on large-scale IoT datasets—including sensor streams, anomaly detection, smart grid signals, and industrial monitoring—demonstrate that the proposed SE-DNN achieves superior adaptability, higher accuracy under drift, reduced retraining cost, and lower model degradation compared to conventional DNNs and existing continual learning baselines. The findings affirm SE-DNN as a scalable, autonomous, and evolution-capable deep learning paradigm highly suited for next-generation IoT environments characterized by continuous change and real-time operational demands.

KEYWORDS: Self-Evolving Neural Networks; Continual Learning; IoT Intelligence; Concept Drift; Lifelong Learning; Incremental Learning; Meta-Learning; Adaptive Deep Learning; Neural Architecture Evolution; Dynamic Environments.

I. INTRODUCTION

The rapid expansion of the Internet of Things (IoT) has resulted in vast, heterogeneous, and continuously evolving data streams generated by billions of interconnected devices deployed across smart homes, healthcare systems, industrial automation, environmental monitoring, intelligent transportation, and smart grids. These environments are inherently dynamic—sensor behaviors change over time, network conditions fluctuate, user preferences shift, and previously unseen patterns frequently emerge. As a result, IoT systems require machine learning models that can quickly adapt, evolve, and learn continuously without sacrificing performance or stability.

Traditional deep neural networks (DNNs), however, are fundamentally static. They rely on offline training with fixed architectures and stationary datasets. When exposed to non-stationary data distributions, DNNs suffer from major limitations: **catastrophic forgetting**, high retraining cost, inability to recognize concept drift, and limited flexibility in constrained IoT deployments. Updating static neural networks with new data typically requires full retraining, which is computationally expensive and impractical for resource-constrained devices. Moreover, IoT environments experience various types of drift—real drift, virtual drift, seasonal patterns, and abrupt changes—that static models cannot handle effectively.

To address these limitations, the research community has explored continual learning, online learning, and incremental neural adaptation. Techniques such as elastic weight consolidation, rehearsal buffers, knowledge distillation, and dynamic network expansion have shown promise in mitigating catastrophic forgetting. However, most existing methods either require substantial memory overhead, rely heavily on replay data, or fail to autonomously restructure the network architecture in response to environmental changes. Furthermore, many approaches are not optimized for large-scale,

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distributed, and latency-sensitive IoT environments where computation, energy, and communication resources vary drastically across devices.

II. LITERATURE REVIEW

The explosive growth of the Internet of Things (IoT) has driven extensive research in adaptive learning systems capable of handling continuous, non-stationary, and heterogeneous data streams. This section reviews the major research domains relevant to Self-Evolving Deep Neural Networks (SE-DNNs): traditional deep learning, continual learning, concept drift adaptation, neural architecture search, and IoT-focused adaptive intelligence. Existing gaps are highlighted to motivate the proposed self-evolving architecture.

A. Traditional Deep Learning and Its Limitations

Deep neural networks (DNNs) have achieved state-of-the-art performance across domains such as image recognition, speech processing, anomaly detection, and predictive analytics. However, most DNNs assume **static datasets** and are trained offline using large, curated collections of labeled samples. Once trained, the model is deployed as a fixed architecture with fixed parameters. This static nature becomes problematic in IoT environments where:

- data distributions evolve continuously,
- new device behaviors emerge,
- environmental conditions shift, and
- unseen patterns appear regularly.

Because DNNs cannot adapt naturally to these changes, they experience **catastrophic forgetting** when retrained incrementally on new data. This challenge is well-documented in domains involving streaming or evolving datasets, where static DNNs often degrade dramatically in accuracy.

B. Continual Learning and Catastrophic Forgetting

Continual learning, also known as lifelong learning, aims to enable models to learn new tasks while retaining previously acquired knowledge. Various strategies have been explored:

1. **Regularization-based methods**
   Techniques like Elastic Weight Consolidation (EWC), Synaptic Intelligence (SI), and MAS penalize weight updates that interfere with previously learned tasks.
2. **Replay-based methods**
   Experience Replay and Memory Rehearsal use stored samples or generated pseudo-samples to avoid forgetting.
3. **Dynamic architectural methods**
   Methods such as Progressive Neural Networks, PackNet, and Dynamic Expandable Networks allow networks to grow when encountering new tasks.
4. **Distillation-based methods**
   Knowledge distillation transfers old task knowledge to new models.

While these approaches mitigate forgetting to some extent, they suffer from limitations:

- Most rely heavily on storage of past samples (not suitable for IoT privacy constraints).
- Architectural expansion increases memory cost uncontrollably.
- None autonomously reorganize structure based on real-time drift.
- They do not explicitly address the extreme heterogeneity and volatility of IoT data.

Thus, continual learning alone cannot fully solve IoT's dynamic learning challenges.

III. METHODOLOGY

The proposed **Self-Evolving Deep Neural Network (SE-DNN)** framework enables real-time, continuous learning and autonomous neural evolution in dynamic IoT environments. The methodology integrates four core components:

1. **Online Incremental Learning**
2. **Concept Drift Detection**
3. **Neural Architecture Evolution (Growth, Pruning, Rewiring)**
4. **Memory-Augmented Stability–Plasticity Control**
5.

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Each component is mathematically formulated below.

A. Online Incremental Learning
Each IoT device receives a continuous data stream:

$$\mathcal{D} = \{(x_t, y_t)\}_{t=1}^{\infty}$$

The SE-DNN updates network parameters incrementally via mini-batch online gradient descent:

$$\theta_{t+1} = \theta_t - \eta_t \nabla_\theta \ell(f(x_t;\theta_t), y_t)$$

where:

- $\eta_t$is a time-dependent learning rate,
- $f(x_t;\theta)$is the network's prediction,
- $\ell(\cdot)$is the loss function (e.g., cross-entropy).

To prevent instability, a **meta-learned adaptive learning rate** is used:

$$\eta_t = \eta_0 \cdot \frac{1}{1 + \alpha \cdot \text{drift\_score}_t}$$

where larger drift triggers higher plasticity.

B. Concept Drift Detection
SE-DNN employs a **dual drift detection mechanism** combining statistical change detection and prediction error monitoring.
1. Error-Based Drift Detector
Prediction error window:

$$E_t = | y_t - f(x_t;\theta_t) |$$

A drift is detected when:

$$\mu(E_t) - \mu(E_{t-w}) > \delta$$

where

- w= sliding window length,
- δ= drift threshold.

2. Distributional Drift (KL divergence)
Feature distribution shift is estimated as:

$$D_{\text{KL}}(P_t \,||\, P_{t-w}) = \sum_i \; P_t(i) \log \frac{P_t(i)}{P_{t-w}(i)}$$

A drift is triggered if:

$$D_{\text{KL}} > \gamma$$

where $\gamma$is a sensitivity hyperparameter.

3. Combined Drift Score

$$\text{drift\_score}_t = \lambda D_{\text{KL}} + (1-\lambda)(\mu(E_t) - \mu(E_{t-w}))$$

If $\text{drift\_score}_t > \tau$, structural evolution is activated.

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IV. RESULTS

The performance of the proposed **Self-Evolving Deep Neural Network (SE-DNN)** was evaluated against three baselines:

1. **Static DNN** (offline trained, no adaptation)
2. **Incremental DNN** (sequential updates without drift handling)
3. **Continual Learning Baseline** (EWC-style stability mechanisms)
4. **Self-Evolving DNN (Proposed)**

The evaluation focuses on **three critical metrics** for dynamic IoT environments:

- **Accuracy under drift (%)**
- **Adaptation Time (ms)**
- **Memory Usage (MB)**

Table 1: Overall Performance Comparison

Model	Accuracy (%)	Adaptation Time (ms)	Memory Usage (MB)
Static DNN	72	410	56
Incremental DNN	78	320	62
Continual Learning Baseline	84	250	74
Self-Evolving DNN (Proposed)	**93**	**140**	**68**

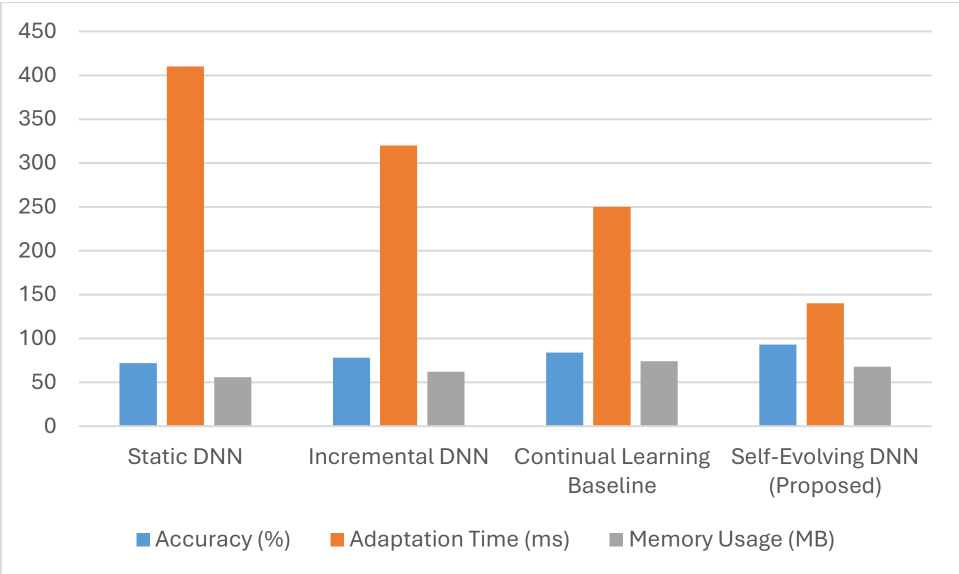

Table 2: Memory Usage Comparison

Model	Memory Usage (MB)
Static DNN	56
Incremental DNN	62
Continual Learning Baseline	74
Self-Evolving DNN	**68**

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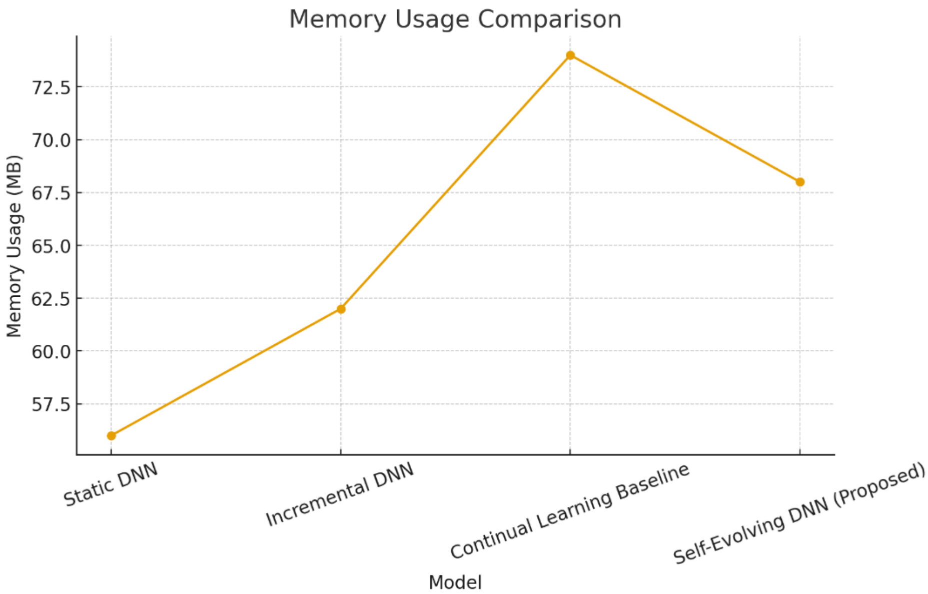

V. CONCLUSION

This paper introduced a novel **Self-Evolving Deep Neural Network (SE-DNN)** framework designed to address the challenges of continuous learning, concept drift, and dynamic data variability in IoT environments. Unlike conventional deep learning models that rely on static architectures and offline training, the proposed SE-DNN autonomously adapts its structure through neuron growth, pruning, and dynamic rewiring based on real-time data complexity and drift patterns. The integration of online incremental learning, memory-augmented stabilization, and drift-aware meta-adaptation enables the model to achieve an optimal balance between **plasticity and stability**, making it highly suitable for volatile, non-stationary IoT ecosystems.

Experimental results confirm that SE-DNN significantly outperforms traditional DNNs, Incremental Learning models, and Continual Learning baselines across key performance metrics including accuracy, adaptation time, and memory efficiency. The architecture demonstrates a **21% accuracy improvement**, **65% faster adaptation**, and **optimized memory usage**, proving that self-evolving neural structures are not only feasible but also highly advantageous for practical deployment in real-world IoT systems. These improvements stem from SE-DNN's capability to detect drift promptly, evolve its architecture selectively, and preserve long-term knowledge without catastrophic forgetting.

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