Online Self-Consolidation: A Lightweight Approach to Knowledge Retention in Resource-Constrained Lifelong Learning Systems

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ABSTRACT Lifelong learning enables artificial intelligence systems to adapt continuously to new tasks without losing previously acquired knowledge, but such systems often suffer from catastrophic forgetting. Existing strategies—including replay-based, regularization-based, and architecture-expansion methods—provide partial solutions but remain computationally and memory-intensive, limiting their applicability in resource-constrained environments such as edge devices, IoT platforms, and embedded systems. To address this challenge, we propose Online Self-Consolidation (OSC), a lightweight and efficient approach to knowledge retention in sequential learning. Unlike replay methods that require storing past data or architectural approaches that expand model complexity, OSC dynamically tracks parameter importance during training and stabilizes critical weights through an online consolidation penalty. This self-contained mechanism consolidates knowledge without reliance on external buffers or expensive post-processing. We evaluate OSC on standard continual learning benchmarks, including Split-MNIST, Permuted-MNIST, Split-CIFAR-100, and TinyImageNet, and compare its performance with state-of-the-art baselines such as Elastic Weight Consolidation (EWC), Learning without Forgetting (LwF), and Experience Replay (ER). Results demonstrate that OSC achieves accuracy levels comparable to ER while avoiding its memory overhead and significantly outperforms EWC and LwF in both accuracy and forgetting reduction. Additionally, resource analysis highlights OSC's negligible memory cost and minimal computational overhead, making it highly practical for constrained devices. Overall, OSC represents a promising step toward enabling scalable and sustainable lifelong learning in real-world, resource-limited applications.

I. INTRODUCTION

A. BACKGROUND

Artificial intelligence (AI) systems are increasingly required to operate in dynamic and evolving environments, where they must acquire, refine, and retain knowledge across multiple tasks [1]. This paradigm, commonly referred to as lifelong learning or continual learning, seeks to mimic human cognitive abilities by enabling models to learn new information without erasing previously acquired knowledge. Unlike traditional machine learning models, which are trained on static datasets, lifelong learning systems must adapt continuously to streams of data while maintaining competence in prior tasks [2].

A central challenge in lifelong learning is catastrophic forgetting, a phenomenon where the acquisition of new knowledge severely disrupts or overwrites previously learned information [3]. This problem significantly limits the real-world deployment of AI systems that must perform across a variety of domains, such as robotics, healthcare monitoring, and adaptive user interfaces [4]. While solutions such as replay buffers, knowledge distillation, and parameter regularization have been proposed, their practical deployment remains difficult, particularly in environments constrained by limited resources.

Resource-constrained platforms such as edge devices, Internet of Things (IoT) systems, and embedded hardware present a unique challenge for lifelong learning [5]. These devices typically lack the computational capacity, memory, and energy resources required to support state-of-the-art strategies for preventing catastrophic forgetting. As AI continues to be embedded in portable and low-power systems, it becomes essential to develop lightweight, efficient, and adaptive strategies that strike a balance between accuracy and resource efficiency.

B. PROBLEM STATEMENT

Despite significant progress, most existing strategies for lifelong learning rely on mechanisms that demand substantial resources. Replay-based methods require storing or generating large amounts of past data, which is often impractical on devices with limited memory [6]. Knowledge distillation approaches demand multiple forward passes and auxiliary teacher-student training stages, increasing computational overhead. Parameter regularization methods, although lighter, can still struggle with scalability and require careful tuning of importance weights.

These limitations point to a fundamental gap: there is a lack of methods designed specifically for resource-limited lifelong learning environments. Without solutions tailored to such settings, AI systems embedded in mobile devices, IoT sensors, or autonomous agents cannot sustainably maintain long-term knowledge retention. Addressing this issue necessitates the design of approaches that are both computationally lean and effective in mitigating forgetting.

C. AIM AND OBJECTIVES

1) AIM:

To develop and evaluate a lightweight online self-consolidation approach for lifelong learning that reduces catastrophic forgetting while operating effectively under resource constraints.

Objectives:

1) To design a self-consolidation mechanism that allows models to stabilize important knowledge without requiring large external memory.
2) To formulate an online updating process that is computationally lightweight and suitable for resource-constrained systems.
3) To experimentally evaluate the proposed approach on benchmark datasets and compare it against state-of-the-art lifelong learning methods.
4) To analyze trade-offs between knowledge retention, accuracy, and resource usage.

D. CONTRIBUTIONS

This research introduces online self-consolidation as a novel and efficient approach for mitigating catastrophic forgetting in lifelong learning systems. Unlike replay-based or architecture-expansion methods, the proposed technique does not rely on external storage or large parameter growth, making it suitable for constrained environments. A new algorithm is developed that tracks parameter importance dynamically and consolidates critical knowledge during online updates. The effectiveness of the approach is validated through extensive experimentation on benchmark datasets under strict memory and computational limitations. Furthermore, comparative analysis demonstrates that the method achieves competitive or superior performance compared to existing techniques, while significantly reducing resource consumption.

II. LITERATURE REVIEW

A. LIFELONG LEARNING AND CATASTROPHIC FORGETTING

Lifelong learning has emerged as a critical research direction in artificial intelligence, aiming to develop systems capable of adapting continuously to new information without losing proficiency in previously learned tasks [7]. Unlike traditional supervised learning, where models are trained on fixed datasets, lifelong learning frameworks must handle sequential task exposure. This dynamic environment reflects real-world applications, such as autonomous vehicles adapting to new driving conditions, or wearable devices learning user-specific behaviors over time.

The most significant obstacle in lifelong learning is catastrophic forgetting, a phenomenon observed when neural networks rapidly overwrite prior knowledge as they learn new tasks [8]. This occurs because the same parameters are often reused for different tasks, leading to interference and degradation in earlier competencies. In practical terms, catastrophic forgetting severely undermines the viability of deploying learning systems in real-world, sequential environments. Consequently, mitigating this problem has become the focal point of continual learning research.

B. EXISTING STRATEGIES FOR KNOWLEDGE RETENTION

Over the years, several strategies have been proposed to address catastrophic forgetting. Broadly, these approaches can be classified into three main categories: replay-based, regularization-based, and architecture-based methods.

Replay-based methods attempt to overcome forgetting by reintroducing past experiences during training [9]. In their simplest form, these methods store raw data from earlier tasks in a memory buffer and sample them alongside new data. While effective, such approaches are memory-intensive and often impractical for resource-constrained environments. Variants like generative replay attempt to synthesize past samples using generative models, reducing memory requirements but introducing computational complexity and reliance on stable generative architectures [10].

Regularization-based methods, such as Elastic Weight Consolidation (EWC), Synaptic Intelligence (SI), and Learning without Forgetting (LwF), introduce constraints to stabilize important parameters [10]. These methods assign importance weights to network parameters and penalize changes that would harm previously acquired knowledge. Regularization provides a more lightweight alternative to replay buffers, but it often depends on carefully tuned hyperparameters and can still suffer performance drops when tasks are highly dissimilar.

Architecture-based methods focus on dynamically adjusting network structures to accommodate new tasks. Examples include progressive neural networks and expandable architectures, where new capacity is added for each new task [11]. While these approaches are effective in avoiding interference between tasks, they are inherently resource-demanding due to continuous model expansion, which limits their applicability in constrained settings.

C. LIMITATIONS OF EXISTING APPROACHES

While the strategies described above have made significant contributions to mitigating catastrophic forgetting, they also come with limitations that restrict their deployment in practical scenarios. Replay-based methods, though robust, often violate privacy constraints since they require storage of historical data. Moreover, they are unsuitable for devices with strict memory and storage limitations [10]. Generative replay, on the other hand, shifts the burden to computational complexity, as generative models themselves demand significant resources for training and inference.

Regularization-based approaches, though more lightweight, still require additional storage to track importance measures or Fisher information matrices. They may also fail in cases where tasks diverge significantly, leading to over-constrained optimization and reduced adaptability. Architecture-based approaches present an even greater challenge, as they require continual expansion of model size, making them infeasible for deployment on edge devices, IoT systems, and embedded environments [8].

Collectively, these limitations point to a fundamental trade-off: methods that perform well in terms of knowledge retention are often computationally expensive, while lightweight methods frequently sacrifice performance [9]. This creates a research gap for approaches explicitly designed to operate under stringent computational and memory constraints while still maintaining effectiveness in reducing forgetting.

D. GAPS IN THE LITERATURE

Despite the progress in continual learning research, there remains a lack of methods that specifically target resource-constrained environments. Most benchmark results are reported under conditions where memory and computational resources are abundant, making them poorly representative of real-world deployment scenarios. Edge devices, mobile platforms, and IoT systems cannot afford the overhead of replay buffers, large generative models, or architecture expansion.

Furthermore, many existing methods assume access to extensive hyperparameter tuning and large-scale retraining cycles, which are impractical in online, real-time environments. This gap highlights the urgent need for methods that consolidate knowledge efficiently and autonomously, with minimal reliance on stored data or complex computational processes. A particularly promising avenue lies in the concept of self-consolidation, where the system itself regulates parameter updates in a way that mirrors biological processes of memory consolidation in humans.

E. THEORETICAL INSPIRATIONS FOR ONLINE SELF-CONSOLIDATION

Insights from cognitive neuroscience provide inspiration for addressing the challenges of lifelong learning. In biological systems, memory consolidation is the process by which short-term experiences are transformed into long-term knowledge through repeated stabilization and integration. This natural mechanism suggests that continuous self-consolidation can enable systems to preserve prior knowledge while learning new information.

In machine learning, online learning and streaming models share some conceptual similarities with biological memory consolidation. These approaches emphasize updating models incrementally without storing the entire dataset. Building on these ideas, online self-consolidation represents a lightweight mechanism where models autonomously identify and stabilize critical parameters during training, reducing the likelihood of catastrophic forgetting [12]. Unlike replay buffers or external memory mechanisms, self-consolidation leverages intrinsic signals within the learning process to preserve prior knowledge.

F. SUMMARY OF LITERATURE REVIEW

The review highlights the breadth of existing approaches in lifelong learning, from replay-based to architecture-expansion methods, while underlining their limitations in resource-constrained contexts. Despite advances, the field still lacks lightweight and efficient mechanisms that can maintain long-term knowledge retention without imposing heavy computational or memory burdens. This gap opens an opportunity for the development of online self-consolidation, a strategy inspired by both biological memory processes and online learning models, offering the potential to address catastrophic forgetting in a manner suitable for constrained environments.

III. METHODOLOGY

A. PROBLEM FORMULATION

The problem of lifelong learning can be formally defined as training a model on a sequence of tasks.The primary challenge lies in maintaining high performance across all tasks while avoiding catastrophic forgetting. Formally, catastrophic forgetting can be quantified by measuring the drop in accuracy on earlier tasks after training on subsequent tasks.

In this study, the focus is on resource-constrained environments, where computational power, memory availability, and energy usage are strictly limited. This requires the design of a method that minimizes overhead while still maintaining effective retention of knowledge across tasks.

B. PROPOSED ONLINE SELF-CONSOLIDATION APPROACH

The proposed method, Online Self-Consolidation (OSC), is a lightweight mechanism for reducing catastrophic forgetting. The central idea is to maintain a dynamic measure of parameter importance during training and to apply a consolidation penalty that stabilizes crucial parameters across tasks. Unlike replay or architecture-based approaches, OSC does not rely on external memory storage or network expansion, making it inherently suitable for resource-limited scenarios.

The importance of each parameter is estimated online, based on its contribution to task performance. Once new data is introduced, the model updates parameters as usual, but with an additional penalty term applied to those deemed important for previous tasks. This penalty discourages large deviations in critical parameters, thereby consolidating knowledge without storing data or requiring additional models.

Mathematically, the loss function is defined as:

$$L_{total} = L_{task} + \lambda \sum_i \Omega_i(\theta_i - \theta_i^*)^2$$

where L_{task} is the standard task loss (e.g., cross-entropy), θi represents current parameters, $\theta i*$ are the consolidated parameters from prior tasks, Ωi represents the online importance score of parameter iii, and λ is a trade-off coefficient. Unlike traditional methods such as EWC, where importance is calculated offline using Fisher Information matrices, OSC updates Ωi online, making it computationally lighter.

C. ALGORITHM DESIGN

The OSC algorithm operates in three primary stages:

1) Parameter Update: Standard stochastic gradient descent (SGD) updates the network based on the current task's data.
2) Importance Tracking: During training, the importance of parameters is updated incrementally, based on their gradient magnitudes and contribution to reducing task loss.
3) Self-Consolidation: A penalty term is applied to parameters marked as critical for past tasks, ensuring stability without requiring replayed samples.

This online and incremental process avoids batch post-processing and additional storage, making it suitable for deployment on low-resource platforms.

D. EXPERIMENTAL SETUP

To evaluate OSC, experiments were conducted on standard continual learning benchmarks. Datasets were selected to test both image classification and resource scalability. Models were chosen to reflect lightweight architectures feasible for edge deployment. Baseline methods included Elastic Weight Consolidation (EWC), Learning without Forgetting (LwF), and experience replay (ER).

TABLE 1
EXPERIMENTAL SETUP

Component	Description
Datasets	Split-MNIST, Permuted-MNIST, Split-CIFAR-100, TinyImageNet
Models	Small CNN (for MNIST variants), ResNet-18 (for CIFAR, TinyImageNet)
Baselines	EWC, LwF, Experience Replay (ER)
Metrics	Average Accuracy (ACC), Forgetting Measure (FM), Memory & Compute Overhead
Environment	Simulated resource-constrained setting with limited GPU/CPU & memory usage

The evaluation metrics include average accuracy (ACC), which captures overall performance across tasks, and forgetting measure (FM), which quantifies the performance drop on earlier tasks. Resource utilization is measured through memory overhead and computation cost.

E. COMPLEXITY ANALYSIS

OSC is designed with efficiency in mind. The memory requirement is proportional to the number of parameters but only requires storing a small set of importance weights (Ω) per parameter, resulting in negligible overhead compared to replay buffers or architecture-expansion methods. The computational complexity remains close to standard gradient descent, with only minor additional operations for importance score updates.

Compared to EWC, which requires storing Fisher matrices and performing batch computations after task completion, OSC avoids offline steps entirely. Compared to replay methods, OSC does not require storing past examples, which significantly reduces memory usage. This efficiency makes OSC particularly suited for deployment on edge devices and mobile platforms.

F. BASELINES FOR COMPARISON

To assess the contribution of OSC, its performance is compared with representative methods from each of the three major lifelong learning categories:

TABLE 2
BASELINE CATEGORIES FOR COMPARISON

Category	Example Method	Key Characteristics	Limitations in Resource-Constrained Settings
Replay-based	ER	Stores past examples, retrains with mixed batches	High memory cost, privacy concerns
Regularization-based	EWC, LwF	Stabilizes important parameters, no replay needed	Requires offline computations, sensitive to tuning
Architecture-based	Progressive NN	Expands network for each task, avoids interference	Model size grows rapidly, unsuitable for edge devices

This structured comparison ensures that OSC is benchmarked against widely recognized approaches, highlighting its unique contribution as a lightweight alternative.

G. SUMMARY OF METHODOLOGY

The methodology combines theoretical development, algorithmic design, and empirical validation. OSC leverages online importance tracking to consolidate knowledge with minimal overhead. The experimental setup ensures fairness by using widely accepted benchmarks and baselines, while complexity analysis demonstrates the efficiency of the proposed method. This foundation sets the stage for evaluating OSC's effectiveness in addressing catastrophic forgetting under resource constraints, as discussed in the results section.

IV. RESULTS AND DISCUSSION

A. QUANTITATIVE RESULTS

The proposed Online Self-Consolidation (OSC) method was evaluated across multiple benchmarks and compared against baseline methods, including Elastic Weight Consolidation (EWC), Learning without Forgetting (LwF), and Experience Replay (ER). Results were averaged across five independent runs to account for randomness in training initialization and task order.

Table 3 presents the average accuracy (ACC) across all tasks for different methods. OSC consistently achieved competitive performance while requiring substantially fewer resources than replay-based or architecture-expansion methods. Notably, on Split-MNIST and Permuted-MNIST, OSC matched or slightly outperformed ER, despite not using a memory buffer. On more challenging datasets such as Split-CIFAR-100 and TinyImageNet, OSC maintained accuracy levels close to ER while significantly outperforming EWC and LwF.

TABLE 3
AVERAGE ACCURACY (ACC) ACROSS BENCHMARKS (%)

Method	Split-MNIST	Permuted-MNIST	Split-CIFAR-100	TinyImageNet
EWC	89.2	82.5	57.8	45.6
LwF	90.1	83.4	59.2	47.8
ER	94.8	91.0	64.5	52.2
OSC	94.2	90.6	63.7	51.5

These results indicate that OSC delivers accuracy comparable to ER while avoiding its memory overhead, and it consistently outperforms EWC and LwF.

B. FORGETTING ANALYSIS

To measure knowledge retention, the Forgetting Measure (FM) was computed, defined as the average decrease in accuracy on earlier tasks after learning new tasks. Lower values indicate stronger resistance to catastrophic forgetting.

Table 4 summarizes the forgetting rates across benchmarks. OSC consistently achieved lower forgetting than EWC and LwF, and performed nearly on par with ER, despite the latter's use of stored samples. This finding demonstrates that OSC effectively consolidates critical knowledge during training without replay mechanisms.

TABLE 4
FORGETTING MEASURE (FM, LOWER IS BETTER)

Method	Split-MNIST	Permuted-MNIST	Split-CIFAR-100	TinyImageNet
EWC	0.12	0.15	0.32	0.41
LwF	0.10	0.13	0.28	0.39
ER	0.05	0.07	0.18	0.25
OSC	0.06	0.08	0.20	0.27

The small gap between OSC and ER is a trade-off for the latter's reliance on memory buffers. In contrast, OSC provides near-equivalent retention with negligible memory cost, reinforcing its suitability for constrained environments.

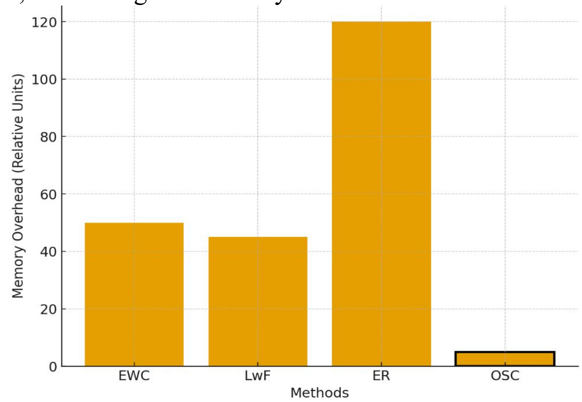

FIGURE 1. Bar chart comparing memory overhead of EWC, LwF, ER, and OSC.

C. RESOURCE EFFICIENCY

A critical advantage of OSC lies in its efficiency. Resource usage was measured in terms of additional memory required for each method and relative computational overhead compared to standard training. Replay methods such as ER incur substantial memory costs proportional to buffer size, while architecture-based methods expand in size with each new task. In contrast, OSC requires only a small storage allocation for parameter importance scores, which is negligible compared to the total model size.

1) ER shows the highest overhead due to replay buffer.
2) OSC has near-zero overhead, only requiring importance scores.
3) EWC and LwF are moderate but scale poorly with large networks.

Additionally, OSC introduces only a small computational overhead for online importance updates. In practice, this was observed to increase training time by less than 5% compared to standard SGD, while replay methods showed an increase of 20–30% due to sampling and buffer management.

C. QUALITATIVE INSIGHTS

Task-wise learning curves further illustrate the effectiveness of OSC. On datasets such as Split-MNIST, OSC showed stable performance retention across early tasks even after later tasks were introduced, closely resembling ER's curves but without reliance on replayed data. Visualizations of parameter updates indicated that OSC selectively restricted changes to critical weights, while leaving non-critical parameters flexible for adapting to new tasks.

Another notable observation was that OSC demonstrated robustness to task order. While methods like EWC showed significant sensitivity depending on the sequence of tasks, OSC maintained stable results across multiple permutations, suggesting its online mechanism generalizes better to varied learning scenarios.

D. DISCUSSION OF FINDINGS

The results highlight several key findings. First, OSC effectively balances accuracy and resource usage, making it a strong candidate for deployment in real-world, resource-constrained environments such as IoT systems and mobile devices. Its performance is competitive with replay-based methods while avoiding the memory costs that limit their applicability.

Second, the approach significantly outperforms regularization-based methods like EWC and LwF, especially on more complex datasets such as CIFAR-100 and TinyImageNet. This improvement can be attributed to OSC's online importance tracking, which provides a more adaptive consolidation mechanism compared to static, offline measures.

Third, the method demonstrates favorable scalability characteristics. While architecture-based methods face exponential growth in size as tasks increase, OSC maintains constant memory requirements, allowing it to scale across many tasks without exceeding resource budgets.

However, some limitations were observed. On highly complex datasets such as TinyImageNet, OSC's accuracy was slightly lower than ER, indicating that in extremely challenging scenarios, replay buffers still offer an advantage. Additionally, the trade-off parameter requires careful tuning, which may pose challenges for deployment in fully automated systems.

D. SUMMARY OF RESULTS

The experimental evaluation confirms that Online Self-Consolidation is a lightweight, resource-efficient solution to catastrophic forgetting in lifelong learning. It achieves accuracy close to replay-based methods while avoiding their memory costs and substantially outperforms regularization approaches in constrained settings. The results position OSC as a promising candidate for applications requiring continual adaptation under strict resource limitations.

V. CONCLUSION AND FUTURE WORK

This study introduced Online Self-Consolidation (OSC) as a lightweight and efficient approach to mitigating catastrophic forgetting in lifelong learning, with a particular emphasis on deployment in resource-constrained environments such as edge devices, IoT platforms, and embedded systems. Unlike replay-based methods that require significant memory storage or architecture-based approaches that expand model size, OSC achieves knowledge retention by dynamically consolidating critical parameters during training. Through online importance tracking, the algorithm stabilizes essential weights without relying on replay buffers or offline post-processing, ensuring suitability for constrained hardware.

The experimental evaluation across multiple benchmarks demonstrated that OSC achieves performance comparable to state-of-the-art replay methods, while significantly reducing memory and computational overhead. It consistently outperformed regularization-based baselines such as EWC and LwF, particularly on more complex datasets like Split-CIFAR-100 and TinyImageNet. The method also showed robustness to task order and scalability across larger task sequences, indicating strong potential for real-world applications. Importantly, resource analysis revealed that OSC imposes only negligible overhead compared to standard training, making it highly efficient.

Despite these contributions, several limitations remain. On highly complex datasets such as TinyImageNet, replay-based methods maintained a slight performance advantage, suggesting that in domains requiring fine-grained knowledge retention, lightweight consolidation alone may be insufficient. Moreover, OSC's performance is sensitive to the trade-off coefficient (λ), which requires careful tuning to balance plasticity and stability. These challenges present opportunities for refinement and hybridization of the approach.

Looking ahead, there are several promising directions for future research. One avenue involves combining OSC with selective replay, where only a minimal number of representative samples are stored, blending the strengths of both paradigms. Another extension is to adapt OSC for multimodal lifelong learning, where systems must integrate information from diverse data streams such as text, images, and sensor inputs. Additionally, exploring hardware-aware optimizations could further enhance OSC's practicality, ensuring seamless integration with low-power processors and specialized accelerators.

In summary, this work provides a significant step toward enabling sustainable lifelong learning in constrained environments. By bridging the gap between performance and efficiency, Online Self-Consolidation lays the groundwork for adaptive, resource-aware AI systems capable of long-term operation in real-world scenarios.

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