Privacy-Preserving Continual Learning for Intelligent Cockpit: An Open-World Approach

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Abstract

This research proposal introduces a novel Open-World Class Incremental Learning (CIL) framework tailored for Intelligent Cockpit systems. To address the critical challenges of catastrophic forgetting, out-of-distribution (OOD) action detection, and strict on-device privacy constraints, we propose a Parameter-Efficient Fine-Tuning (PEFT) approach utilizing a frozen Vision Transformer (ViT) backbone. By integrating an energy-based novelty detector with a lightweight Adapter and knowledge distillation, the system enables continuous personalization of driver behaviors using severely limited local memory. Preliminary feasibility tests confirm its efficiency on edge-level hardware.

Index Terms

Class Incremental Learning, Intelligent Cockpit, Out-of-Distribution Detection, Parameter-Efficient Fine-Tuning, Edge AI.

I. Introduction

Personalized driver behavior monitoring is becoming crucial for Intelligent Cockpits [1]. However, deploying these systems faces significant challenges...

II. Related Work

A. Continual Learning and Catastrophic Forgetting

Catastrophic forgetting remains a fundamental challenge. Classic methods like iCaRL [2] use herding and knowledge distillation to preserve old knowledge.

B. Parameter-Efficient Fine-Tuning (PEFT)

Recent advances in Vision Transformers [3] have introduced prompt-based and adapter-based tuning, significantly reducing the memory footprint for continual learning.

C. Out-of-Distribution (OOD) Detection

Open-world continual learning [4] requires the system to reject unknown classes before incrementally learning them.

III. PROPOSED METHODOLOGY

A. Problem Formulation

The model learns on a continuous data stream $\mathcal{D} = \{\mathcal{D}_1, \mathcal{D}_2, ..., \mathcal{D}_T\}$. At stage t, the training set is $\mathcal{D}_t = \{(x_i^t, y_i^t)\}_{i=1}^{N_t}$, where $y_i^t \in \mathcal{C}_t$. The system can only access a severely memory-constrained local Replay Buffer $\mathcal{M}$.

B. Frozen Perception Backbone

To meet automotive edge chip constraints, we instantiate a pre-trained Vision Transformer (ViT-B/16) and explicitly freeze its parameters. The backbone outputs a high-dimensional feature $h = f(x)$.

C. Open-World Novelty Detector

The system calculates the distance between feature h and known class prototypes. A dynamic threshold τ flags OOD samples.

D. Parameter-Efficient CIL Updater

We insert a lightweight Adapter layer into the Transformer Blocks. The optimizer exclusively updates the Adapter and the Classifier Head.

E. Episodic Memory and Distillation

We utilize a Herding algorithm to retain K exemplars per class. The total loss is formulated as:

$$\mathcal{L}_{total} = \mathcal{L}_{CE}(y, \hat{y}) + \lambda \mathcal{L}_{KD}(p_{old}, p_{new}) \tag{1}$$

where $\mathcal{L}_{CE}$ is the Cross-Entropy loss and $\mathcal{L}_{KD}$ is the Distillation loss.

IV. Experimental Setup

A. Datasets

Algorithm Benchmarking will use **Split-CIFAR-100**. Cockpit Scenario Validation will use the **State Farm Distracted Driver** dataset.

B. Evaluation Metrics

The Average Forgetting (AF) metric is defined as:

$$AF = \frac{1}{T-1} \sum_{i=1}^{T-1} \max_{t \in \{1,\ldots,T-1\}} (A_{t,i} - A_{T,i}) \tag{2}$$

C. Implementation Details

All algorithms will be implemented using PyTorch and validated on an NVIDIA RTX 4090 GPU to simulate high-performance edge computing.

V. Research Plan

References

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