AUXILIARY CLASSIFIERS IMPROVE STABILITY AND EFFICIENCY IN CONTINUAL LEARNING

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ABSTRACT

Continual learning is crucial for applications in dynamic environments, where machine learning models must adapt to changing data distributions while retaining knowledge of previous tasks. Despite significant advancements, catastrophic forgetting — where performance on earlier tasks degrades as new information is learned — remains a key challenge. In this work, we investigate the stability of intermediate neural network layers during continual learning and explore how auxiliary classifiers (ACs) can leverage this stability to improve performance. We show that early network layers remain more stable during learning, particularly for older tasks, and that ACs applied to these layers can outperform standard classifiers on past tasks. By integrating ACs into several continual learning algorithms, we demonstrate consistent and significant performance improvements on standard benchmarks. Additionally, we explore dynamic inference, showing that AC-augmented continual learning methods can reduce computational costs by up to 60% while maintaining or exceeding the accuracy of standard methods. Our findings suggest that ACs offer a promising avenue for enhancing continual learning models, providing both improved performance and the ability to adapt the network computation in environments where such flexibility might be required.

1 INTRODUCTION

The field of continual learning provides theories and algorithms for learning from non-i.i.d. data streams (De Lange et al., 2021). The most commonly studied scenario involves data arriving in sequences of tasks, where the learner cannot access previously seen tasks when learning new ones. Continual learning scenarios may involve tasks with different data distributions (domain-incremental learning) or new classes (class-incremental learning) and also vary based on whether task identity is available during classification (task-incremental learning) (Van de Ven & Tolias, 2019). The primary challenge in continual learning, *catastrophic forgetting*, refers to a significant drop in performance on past tasks throughout the learning (McCloskey & Cohen, 1989; Kirkpatrick et al., 2017). Various strategies have been proposed to address this challenge, including parameter isolation (Rusu et al., 2016; Serra et al., 2018; Mallya & Lazebnik, 2018), weight and data regularization (Aljundi et al., 2018; Kirkpatrick et al., 2017; Li & Hoiem, 2017), and rehearsal methods (Rebuffi et al., 2017; Chaudhry et al., 2018). Despite these efforts, continual learning remains an open problem, especially in the widely applicable class-incremental setting that is the focus of our work.

Several works have observed that continual learning mainly results in changes in the later layers of the network (Liu et al., 2020a; Ramasesh et al., 2020; Zhao et al., 2023) and that deep networks trained for image classification split into parts that build their representations differently (Masarczyk et al., 2023). However, these works do not exploit these observations to improve the performance. In this paper, we analyze whether the higher stability of intermediate layers can be leveraged to improve accuracy on previous tasks. First, we examine the stability of representations at different network levels during continual learning, confirming that early layers change less during continual learning, especially for the old data. Next, we evaluate the performance of auxiliary classifiers (ACs) learned on top of such representations through linear probing and show that they perform comparable or even better than the final network classifier on older tasks. We also examine the diversity of the prediction across the added classifiers and demonstrate that they learn to classify different subsets of data, with some samples being correctly predicted at only a single intermediate layer. Finally, we compare the performance of multi-classifier networks with ACs trained jointly and separately with the rest of the model modules and show that joint training improves the performance of early classifiers with almost no negative effect on the later ones.

Motivated by the findings from our analysis, we advocate for the use of ACs in continual learning. We enhance various standard continual learning methods (LwF (Li & Hoiem, 2017), EWC (Kirkpatrick et al., 2017), ER (Riemer et al., 2018), BiC (Wu et al., 2019), SSIL (Ahn et al., 2021), ANCL (Kim et al., 2023), LODE (Liang & Li, 2024)) with the ACs and show that by combining the predictions from multiple classifiers we can robustly outperform a standard, single-classifier network on standard benchmarks such as CIFAR100 and ImageNet100 on equally-sized tasks and in the warm-start scenario (Magistri et al.; Goswami et al., 2024). Inspired by early-exit literature (Panda et al., 2016; Teerapittayanon et al., 2016; Kaya et al., 2019), we also experiment with dynamic inference in AC-based networks that enables the user to adapt the average network computation to the available resources without any additional training. We show that AC networks used with such inference can maintain the performance of the single-classifier baseline while using only 40-70% of the original network computation. We perform a thorough ablation study of architectural modifications of AC networks and show that our approach robustly improves performance across all tested cases and does not require any meticulous hyperparameter optimization. Our work demonstrates that continual methods enhanced with ACs exhibit better stability in continual learning, achieve higher accuracy, and can be an alternative to standard models in scenarios that require faster inference or the ability to control the compute in the network. The main contributions of our work are:

- We perform a thorough analysis of intermediate representations in continual learning and show that they enable learning diverse classifiers that perform well on different subsets of data. We show that early representations are more stable and the classifiers learned on top of such representations are less prone to forgetting the older tasks.
- We leverage the diversity and robustness of intermediate representations by enhancing the networks with auxiliary classifiers (ACs). We integrate ACs into several continual learning methods and demonstrate that AC-enhanced methods consistently outperform standard single-classifier approaches, achieving an average 10% relative improvement.
- We show that ACs can help reduce the average computational cost during network inference through dynamic prediction. AC-enhanced methods can achieve similar accuracy to single-classifier models while using only 40-70% of the computational resources.

2 Related works

Continual learning. Continual learning methodologies (Parisi et al., 2019; De Lange et al., 2021; Masana et al., 2022) can be broadly classified into three categories: *regularization-based*, *replay-based*, and *parameter-isolation* methods. *Regularization-based* approaches typically introduce a regularization term in the loss function to constrain changes to parameters relevant to prior tasks. These can further be categorized as data-focused (Li & Hoiem, 2017; Kim et al., 2023), leveraging knowledge distillation from previously trained models, or prior-focused (Kirkpatrick et al., 2017; Zenke et al., 2017; Aljundi et al., 2018), estimating parameter importance as a prior for the new model. Recent research proposed enforcing weight updates within the null space of feature covariance (Wang et al., 2021; Tang et al., 2021). *Replay-based* methods rely on memory and rehearsal mechanisms to recall episodic memories of past tasks during training, thereby keeping the loss low in those tasks. Two main strategies are: exemplar replay - which stores selected training samples (Riemer et al., 2018; Buzzega et al., 2020; Chaudhry et al., 2018; Prabhu et al., 2020; Chaudhry et al., 2019; Liang & Li, 2024) and generative replay - with models that synthesize previous data with generative models (Shin et al., 2017; Wu et al., 2018). *Parameter isolation* methods aim to learn task-specific sub-networks within a shared network. Various techniques, such as Piggyback (Mallya et al., 2018), PackNet (Mallya & Lazebnik, 2018), SupSup (Wortsman et al., 2020), HAT (Serra et al., 2018), and Progressive Neural Network (Rusu et al., 2016), allocate and combine parameters for individual tasks. While effective in task-aware settings, these methods are most suited for scenarios with a known task sequence or oracle.

Intermediate representations in neural networks. Understanding and comparing the representations at different layers in deep neural networks is an active area of research, and tools such as CKA (Kornblith et al., 2019) emerged to measure the similarity of representations across layers.

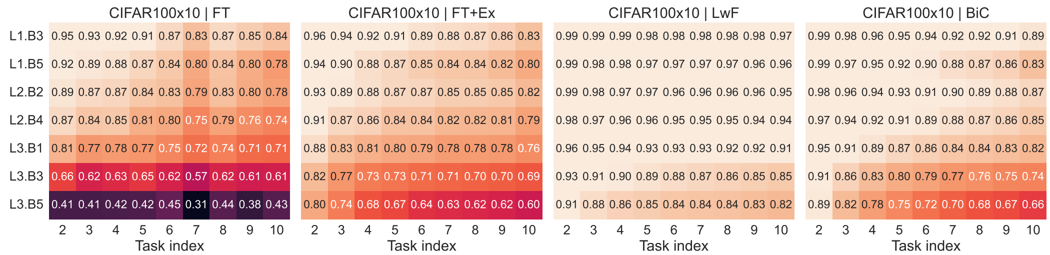

Figure 1: CKA of the first task representations across different ResNet32 layers (L1.B3-L3.B5) through continual learning on CIFAR100 split into 10 tasks. Representations at the early layers are more similar across the continual learning, hinting at the potential for more stability that could be leveraged to improve the performance.

Several works have investigated how network representations behave during continual learning: Ramasesh et al. (2020) noticed that the most forgetting occurs in the deeper network layers, Zhao et al. (2023) likewise demonstrated that only a subset of modules is sensitive to the changes during continual learning, and recent work of Masarczyk et al. (2023) showed that neural networks split into parts that build different representations. Similar insights motivated continual learning methods that enforce stability through replay (Liu et al., 2020a; Pawlak et al., 2022) or regularization (Douillard et al., 2020) at the level of intermediate network layers. In representation learning, several works demonstrated that probing classifiers learned on top of intermediate network representations tend to perform relatively well (Davari et al., 2022), although usually worse than the final classifier. Early-exit techniques (Panda et al., 2016; Teerapittayanon et al., 2016; Kaya et al., 2019) use intermediate representations to reduce the inference cost through dynamic inference that enables skipping later model layers. Several works on early-exits also propose more advanced strategies (Liao et al., 2021; Sun et al., 2021; Han et al., 2022; Wójcik et al., 2023) that improve the effectiveness. Use of multiple classifiers in continual learning has been explored in an ensembling-like manner (Liu et al., 2020b), and (Yan et al., 2024) utilized intermediate classifiers for online continual learning and different motivations. Our method is dedicated for offline continual learning.

3 Intermediate layer representations in continual learning

In this section, we analyze the stability of intermediate representations in continual learning and the use of *auxiliary classifiers* (ACs) - additional classifiers trained on to the intermediate representations of the network - as a means to leverage this stability.

We consider a supervised continual learning scenario, where a learner (neural network) is trained over T classification tasks and its goal is to learn to classify the new classes while avoiding catastrophic forgetting of the previously learned ones. We focus on the more challenging class-incremental learning setting (De Lange et al., 2021; Masana et al., 2022), where the learner needs to distinguish between all the classes encountered so far without having access to a task identity. At each task t, the model can only access the dataset $\mathcal{D}_t = \{\mathcal{X}_t, \mathcal{Y}_t\}$, which is composed of a set of input images $\mathcal{X}_t$ and corresponding labels $\mathcal{Y}_t$. We analyze an offline learning scenario, where the learner can pass through the data samples from the current task multiple times.

For our initial analysis, we conduct experiments on CIFAR100 (Krizhevsky, 2009). We present most of the results on the 10-task split and include corresponding results on the 5-task split in Appendix A, as they are very similar. We consider naive *finetuning (FT)* scenario without any additional continual learning technique and standard continual learning methods such as finetuning with exemplars (FT+Ex), exemplar-free LwF (Li & Hoiem, 2017) and BiC (Wu et al., 2019). We believe this set of methods to be a good overview across the continual learning method landscape, as they involve either replay, regularization or both. In the setting with exemplars, we utilize a memory buffer to store part of the training data and for each task $t > 1$ we train the model on the original dataset $\mathcal{D}_t$ extended with the exemplar samples from the memory. We keep the size of the memory buffer fixed and update it after we finish training on each task. Refer to the Section 5 and Appendix K for more details on our experimental setup.

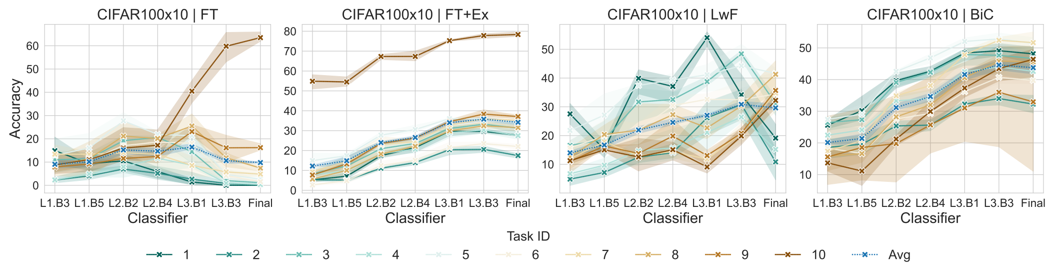

Figure 2: Per-task final accuracy of the auxiliary classifiers trained with linear probing on top of several network layers and final network classifier on CIFAR100 split into 10 tasks. For most tasks, some of the auxiliary classifiers outperform the final classifiers, as higher stability of intermediate representations across the training leads to reduced forgetting.

3.1 Stability of intermediate representations

We begin our investigation by analyzing the stability of the representations at the different layers of ResNet32 (He et al., 2016) over the course of continual learning on CIFAR100. We investigate the stability through similarity between the original representations of the first task data learned after the first task and the representations of this data after learning each subsequent task t. We select a subset of 6 intermediate layers (L1.B3-L3.B3) uniformly spread by the compute similarly to Kaya et al. (2019) alongside the final feature layer L3.B5 that precedes the classifier and present their representational similarity measured with CKA (Kornblith et al., 2019) in Figure 1.

Consistently with previous research, we observe that the early layer representations change less and exhibit more stability through the learning phase. In contradiction, the final layer representations usually change the most during the training, and the phenomenon gets stronger if we train on more tasks. While continual learning methods such as FT+Ex, LwF, or BiC are more stable than naive FT, the trend of CKA increasing for early layer representations persists. The higher stability of early representations indicates the potential for their use in continual learning, as we can expect them to be less prone to forgetting.

3.2 Measuring intermediate representation quality with linear probing

Representational similarity across tasks might not directly translate to strong continual learning performance. To assess whether intermediate representations are suitable for class-incremental learning, we employ linear probing (Davari et al., 2022), a well-known technique used to measure the quality of representations through a downstream performance of auxiliary classifiers (ACs) continually trained on intermediate representations (without gradient propagation from the classifiers to the original network). For ACs, we use a simple pooling layer to reduce the feature dimensionality and apply a linear layer to classify the samples as in a final classifier. We evaluate the final task-agnostic accuracy across different tasks and average results for selected classifiers, as shown in Figure 2.

We observe that the average accuracy of the penultimate classifier matches or even surpasses that of the final classifier on the older tasks data. In the case of naive finetuning, for all tasks aside from the last one intermediate classifiers achieve the highest accuracy. For exemplar-free LwF there is no clear pattern, but intermediate classifiers also outperform the final classifier on many tasks. In the case of exemplar-based methods such as FT+Ex and BiC, the performance on each task more or less steadily improves with the deeper classifiers, but the deepest two intermediate classifiers show comparable performance to the final one. Overall, our results further confirm the potential benefits of auxiliary intermediate classifiers in continual learning scenarios.

3.3 Diversity of the auxiliary classifier predictions

Our previous analysis suggests that intermediate representations in the network exhibit higher stability than and can be used for classification in continual learning with performance comparable to the final classifier, at least in the deeper classifiers. Due to the better stability of the representations, in exemplar-free scenarios, the classifiers built on top of intermediate representations might

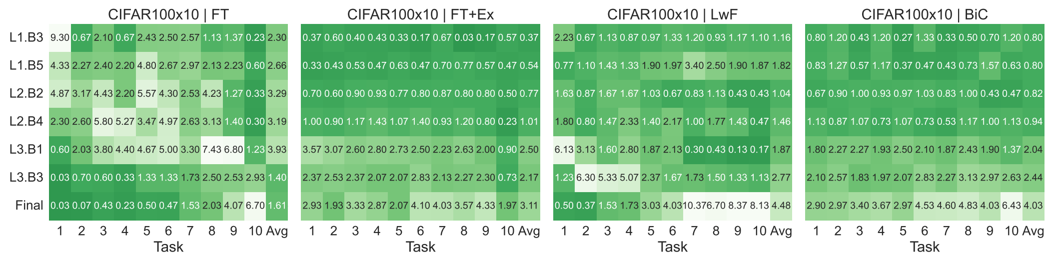

Figure 3: Unique accuracy (a subset of samples that a single given classifier classifies correctly) of auxiliary classifiers and final network classifier for different task data on CIFAR100 split into 10 tasks. Classifiers built on the intermediate representations enable the correct classification of the subsets of data not covered by the final classifier.

significantly outperform the final classifier when evaluated in isolation. When using exemplars, later classifiers usually perform better than the early ones on all tasks, but our previous experiment did not verify if those classifiers learn to cover the same subsets of data, or if they learn to operate differently from each other. In the context of continual learning, multiple classifiers could forget and remember different sets of data, which could be leveraged to improve the overall performance.

To investigate the diversity among the auxiliary classifiers, we measure *unique accuracy* - the percentage of the samples that are correctly predicted only by this classifier. If a given classifier has 10% unique accuracy, it means that 10% of all task data is correctly classified by only this classifier and misclassified by all other classifiers. We present the results in Figure 3. The intermediate classifiers learn to specialize to some degree, especially on the older tasks. The trend is again more visible for the naive and exemplar-free settings, but it occurs for all analyzed methods, and all intermediate classifiers exhibit some degree of unique accuracy. This means that attaching auxiliary classifiers can enhance the network with the knowledge that it cannot learn in a standard process, potentially enabling better classification in continual learning settings.

3.4 Improving ACs performance through gradient propagation

The results presented in the previous section indicate that auxiliary classifiers (ACs) learned through linear probing could be utilized to greatly improve performance in continual learning. However, we hypothesize that the performance of the classifiers would further improve if trained with enabled gradient propagation from classifiers through the network. To verify our hypothesis, we jointly train the same network with 6 ACs with enabled gradient propagation and plot in Figure 4 the difference between the final average accuracy for each classifier in comparison to linear probing.

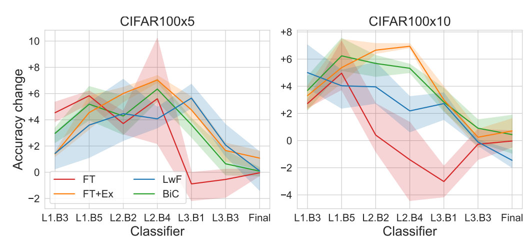

Figure 4: Change in classifier in accuracy after allowing the gradient propagation.

Training classifiers together with the network generally improves the performance of early and middle classifiers. While the performance of later classifiers slightly degrades for FT and to a degree for LwF, in the other settings we observe significant accuracy gains for the intermediate layers and no degradation in the deeper ones. We hypothesize that higher gains in the exemplar-based settings can be attributed to the fact that the networks can better retain the knowledge during training, which is consistent with our findings from Section 3.1 where those settings exhibit higher stability.

In Appendix B, we perform the experiments from Sections 3.1 to 3.3 for networks with ACs trained together with the main network and demonstrate that our previous observations also hold in this setup. As the classifiers trained jointly with the backbone network with enabled gradient propagation demonstrate better accuracy, in all later stages of our work we use this setup.

4 ENHANCING CONTINUAL LEARNING WITH AUXILIARY CLASSIFIERS

4.1 COMBINING PREDICTIONS FROM MULTI-CLASSIFIER NETWORKS

Our analysis in Section 3 demonstrates that auxiliary classifiers (ACs) can learn to classify different subsets of data than just a standard, single-classifier network, which hints that combining their predictions should yield improved accuracy. Therefore, we advocate the use of such multi-classifier networks in continual learning. Formally, we consider a neural network composed of backbone $f = f_N(...(f_1(x)))$ and final classifier g, where $f_1, ..., f_N$ are submodules in the backbone. The standard network prediction y for a given input x can be written as $y = g(f(x))$. We introduce additional $N-1$ auxiliary classifiers $\hat{g}_i$ on top of the backbone sub-modules $f_1, f_2, ..., f_{N-1}$. During inference with such multi-classifier network, we obtain N predictions: $y_1 = \hat{g}_1(f_1(x)), y_2 = \hat{g}_2(f_2(x)), ..., y_{N-1} = g_{\hat{N-1}}(f_{N-1}(x)), y_N = g(f(x))$ and select the prediction y_i where the class predicted by the corresponding probability distribution p_i has maximum confidence. Therefore, we return $y = y_{\arg\max_{i \in \{1,...,N\}} \max_k p_i^{(k)}}$, where $p_i^{(k)}$ represents the predicted probability for class k in the distribution p_i. We refer to this simple inference paradigm as *static inference* and use it in most of the experiments, as we find it performs well across all tested settings.

Inspired by the early-exit models (Panda et al., 2016; Teerapittayanon et al., 2016; Kaya et al., 2019), we also consider using ACs as a means to reduce the average computational cost of the classification through *dynamic inference*. Specifically, in this scenario, we perform inference sequentially through the classifiers $\hat{g_1}, \hat{g_2}, ..., g$, and at each stage i, we compute the probability distribution p_i corresponding to the prediction of i-th classifier. If the confidence exceeds a set threshold λ, we return the corresponding prediction y_i. If no prediction satisfies the threshold, we use the static inference rule to determine the prediction. Formally, we define this process as:

$$y = \begin{cases} y_{\min\{i \in \{1,...,N\} \mid \max_k p_i^{(k)} \geq \lambda\}} & \text{if such } i \text{ exists,} \\ y_{\arg\max_{i \in \{1,...,N\}} \max_k p_i^{(k)}} & \text{otherwise.} \end{cases} \tag{1}$$

By varying the confidence threshold, one can trade off the amount of computation performed by the network for slightly lower performance, which allows such a model to be deployed in settings requiring computational adaptability.

Note that our use of ACs is different from the early-exit literature, where the model accuracy usually monotonically improves when going through subsequent classifiers and the model returns the prediction of the last classifier in case no classifier can satisfy the exit threshold. As we already demonstrated in Section 3, in continual learning the accuracy and quality of intermediate predictions significantly vary for different tasks, and the last classifier is not always the best one for a given subset of data. Please refer to Appendix D for a comparison between the performance of the standard early-exit inference rule and our method of using the ACs.

4.2 AC-ENHANCED CONTINUAL LEARNING METHODS

To demonstrate the effectiveness of our idea, we extend several continual learning methods with auxiliary classifiers (ACs) and examine their performance. In total, we investigate ACs with the following continual learning methods: FT (Masana et al., 2022), GDUMB (Prabhu et al., 2020), EWC (Kirkpatrick et al., 2017), LwF (Li & Hoiem, 2017), ER (Riemer et al., 2018), BiC (Wu et al., 2019), SSIL (Ahn et al., 2021), ANCL (Kim et al., 2023) and LODE (Liang & Li, 2024). FT (finetuning) is a naive scenario where the network is trained without any additional continual learning loss, and the stability can only be enforced through the additional use of exemplars (FT+Ex, where we simply mix the exemplars with the training data from the new task and do not balance the training batches). EWC and LwF improve the stability of the network through additional regularization loss that penalizes change either to model weights or activations, and we use both methods without exemplars, as Masana et al. (2022) shows that they do not gain any improvement from replay. ER uses replay with balanced memory batches, where each batch contains the same amount of old and new samples. BiC and SSIL employ distillation and replay but also provide additional mechanisms to counter task recency bias. ANCL uses knowledge distillation from two networks, one 'stable' as in LwF and the other 'plastic' overfitted to the new task. Finally, LODE uses replay and disentangles the training loss between stability and plasticity terms to reduce forgetting.

Table 1: Final accuracy of several continual learning methods on CIFAR100 and ImageNet100 benchmarks before and after enhanced with auxiliary classifiers (ACs). Adding ACs improves the performance of all tested methods across all the benchmarks, demonstrating the robustness of our idea.

Method	FT	FT+Ex	GDumb	ANCL	BiC	ER	EWC	LwF	LODE	SSIL	Avg
CIFAR100x5											
Base	18.68±0.31	38.35±0.86	19.09±0.44	37.71±1.14	47.66±0.43	34.55±0.21	18.95±0.29	38.26±0.98	42.82±0.84	45.62±0.16	34.17±0.27
+AC	**28.18±1.07**	**38.75±0.26**	**23.29±0.54**	**39.83±1.22**	**50.40±0.68**	**39.77±0.32**	**28.96±1.13**	**40.55±0.95**	**49.13±0.35**	**48.35±0.50**	**38.72±0.61**
Δ	+9.49±0.96	+0.39±0.90	+4.20±0.16	+2.12±1.03	+2.74±0.83	+5.22±0.38	+10.02±1.39	+2.29±0.25	+6.31±0.81	+2.72±0.42	+4.55±0.43
CIFAR100x10											
Base	10.27±0.05	34.51±0.40	22.22±0.72	30.69±0.62	42.87±1.51	32.31±0.82	10.20±0.35	29.56±0.44	38.87±0.45	42.29±0.49	29.38±0.26
+AC	**16.88±1.08**	**36.97±0.39**	**27.74±0.73**	**31.37±0.94**	**46.19±1.47**	**37.32±0.28**	**19.12±0.88**	**30.31±1.14**	**45.67±0.52**	**44.17±0.28**	**33.57±0.22**
Δ	+6.62±1.06	+2.46±0.31	+5.52±1.13	+0.68±0.79	+3.31±2.62	+5.01±0.98	+8.92±1.06	+0.74±0.91	+6.80±0.93	+1.88±0.77	+4.20±0.47
ImageNet100x5											
Base	23.27±0.39	44.05±0.69	21.29±0.59	60.79±0.06	62.55±0.53	38.65±0.43	23.36±0.64	59.60±0.27	49.88±0.56	60.54±0.32	44.40±0.08
+AC	**34.93±0.65**	**46.75±0.61**	**25.30±1.14**	**62.99±0.30**	**65.22±0.27**	**44.46±0.47**	**35.09±0.17**	**61.07±0.57**	**56.23±0.66**	**63.89±0.18**	**49.59±0.08**
Δ	+11.67±0.77	+2.71±0.85	+4.01±0.61	+2.21±0.35	+2.67±0.79	+5.81±0.66	+11.73±0.71	+1.47±0.45	+6.35±1.22	+3.35±0.48	+5.20±0.13
ImageNet100x10											
Base	14.40±0.30	35.94±0.86	22.55±0.62	49.96±0.46	56.32±0.47	32.45±0.35	14.69±0.20	49.15±0.38	45.75±0.50	56.35±0.51	37.76±0.22
+AC	**22.14±0.16**	**39.26±0.61**	**25.93±0.52**	**52.07±0.50**	**57.23±0.87**	**37.10±1.20**	**23.25±0.55**	**49.51±0.71**	**51.39±0.91**	**57.71±0.08**	**41.56±0.24**
Δ	+7.74±0.37	+3.32±0.90	+3.38±0.37	+2.11±0.32	+0.91±0.42	+4.65±0.88	+8.56±0.39	+0.36±1.05	+5.64±0.90	+1.35±0.59	+3.80±0.12

For all the methods, we replicate the method logic (loss) across all the classifiers and do not introduce classifier-specific parameters. If the original method introduces a hyperparameter, we use the same value for this hyperparameter across all the classifiers. We also use the same batches of data for each classifier during the training. Similar to Kaya et al. (2019), to prevent overfitting the network to the early layer classifiers we scale the total loss of each classifier according to its position so that the losses from early classifiers are weighted less than the losses for the final classifier.

5 Experimental results

In this section, we show the main results for AC-enhanced networks on standard continual learning benchmarks. We use FACIL Masana et al. (2022) framework and conduct the experiments on CIFAR100 (Krizhevsky, 2009) and ImageNet100 Deng et al. (2009) (the first 100 classes from ImageNet) splits into tasks containing different classes. We use ResNet32 for experiments on CIFAR100 and ResNet18 He et al. (2016) for experiments on ImageNet100 and add 6 ACs for the main experiments in both settings. For ResNet32, we follow the previously described AC placement, and for ResNet18 we attach the AC to residual all blocks, excluding the first and last one followed by the final classifier. For all exemplar-based methods (BiC, ER, GDUMB, LODE and SSIL) we use a fixed-size memory budget of 2000 exemplars that is updated after each task. We report the results averaged over 3 random seeds. For more details, please refer to Appendix K.

5.1 Classic continual learning benchmarks with auxiliary classifiers

We present our main results on CIFAR100 and ImageNet100 split into 5 and 10 disjoint, equally sized tasks in Table 1. Adding auxiliary classifiers improves the final performance across all methods and settings, with the average relative improvement over all tested methods exceeding 10% of the baseline accuracy in all tested scenarios. Naive methods such as FT and EWC improve significantly, and exemplar-based methods (BiC, LODE, SSIL) usually achieve a bigger boost from the addition of auxiliary classifiers compared to distillation-based ANCL and LwF. We also observe slightly better improvements on ImageNet100 as compared to CIFAR100, which we attribute to the better network capacity that enables more expressivity in the intermediate representations. The results prove the robustness of our idea, even though our utilization of auxiliary classifiers is motivated by simplicity and we did not optimize classifier placement, architecture, or training schemes beyond the simple well-known recipes.

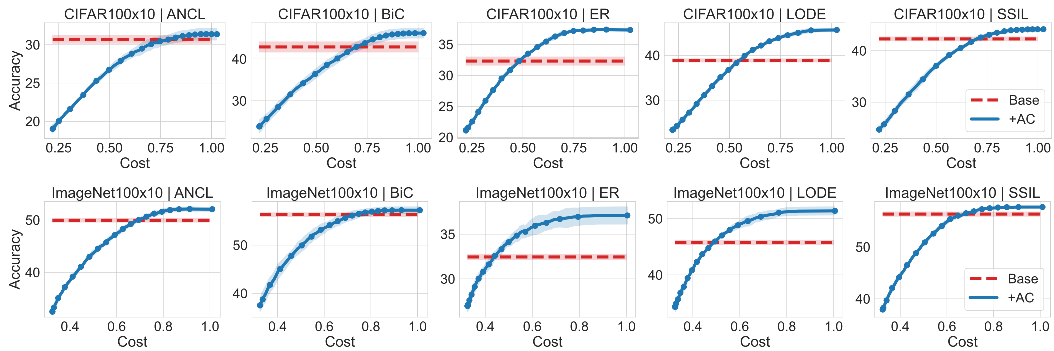

Figure 5: Dynamic inference plots for several continual learning methods extended with auxiliary classifiers compared with the baselines for CIFAR100 (top row) and ImageNet100 (bottom row) split into 10 tasks. Adding auxiliary classifiers not only improves the performance but also can be used to reduce the computational cost of the inference across all the methods. We report cost in FLOPs relative to the non-AC version of the method. We evaluate dynamic inference using $\lambda \in \{0.01, 0.02, ..., 0.99, 1.00\}$ and denote the results for every 5% confidence threshold with the dots.

5.2 Reducing the network computation through auxiliary classifiers

Our results in Section 5.1 demonstrate that enhancing continual learning methods with auxiliary classifiers results in improved final performance at the full computational budget of the network. In this section, we instead investigate dynamic inference described in Section 4 as a means to accelerate network inference. Namely, we evaluate the performance of selected continual learning methods on CIFAR100 and ImageNet100 split into 10 tasks using a dense grid of confidence thresholds ($\lambda \in \{0.01, 0.02, ..., 0.99, 1.00\}$) and measure the average FLOPS per sample relative to the cost of using a standard, single-classifier method. We plot resulting cost-accuracy characteristics in comparison with the standard counterparts' performance in Figure 5. In Appendix F, we also provide dynamic inference plots for the setting analyzed in this section.

Using ACs and dynamic inference, we are able to match the performance of single-classifier methods using approximately 50%-70% of their computation on CIFAR100 and approximately 40%-70% of the computation on ImageNet100. Interestingly, for most methods, performance seems to saturate at 80%-90% of compute, which means we can potentially save this much computation without any accuracy decrease. Similar to the previous section, the improvement on ImageNet is slightly better, which we attribute to the better capacity of ResNet18 used in this setting. Dynamic inference is fairly robust to the thresholding, with any confidence thresholds above 75% still outperforming the baseline and thresholds above 90% achieving close to no degradation in performance in all settings.

5.3 ACs in warm-start continual learning

Table 2: Adding auxiliary classifiers (ACs) is beneficial to the final network accuracy when starting from a pre-trained state, which we simulate by using CIFAR splits with 50 classes in the first task. ACs significantly outperform the baselines on most methods.

Method	FT	FT+Ex	GDumb	ANCL	BiC	ER	EWC	LwF	LODE	SSIL	Avg
						CIFAR100x6					
Base	$16.18_{\pm 0.65}$	$\mathbf{40.38}_{\pm 0.75}$	$17.38_{\pm 0.33}$	$42.85_{\pm 1.07}$	$45.87_{\pm 2.53}$	$\mathbf{38.11}_{\pm 0.10}$	$17.08_{\pm 1.11}$	$42.72_{\pm 0.60}$	$42.28_{\pm 0.46}$	$46.78_{\pm 0.15}$	$34.96_{\pm 0.41}$
+AC	$\mathbf{22.37}_{\pm 1.28}$	$38.12_{\pm 0.77}$	$\mathbf{22.60}_{\pm 0.31}$	$\mathbf{43.97}_{\pm 0.41}$	$\mathbf{48.99}_{\pm 0.80}$	$37.81_{\pm 0.58}$	$\mathbf{25.49}_{\pm 0.97}$	$\mathbf{43.45}_{\pm 0.74}$	$\mathbf{44.95}_{\pm 0.28}$	$\mathbf{48.97}_{\pm 0.28}$	$\mathbf{37.67}_{\pm 0.30}$
Δ	$+6.19_{\pm 1.72}$	$-2.26_{\pm 0.35}$	$+5.22_{\pm 0.19}$	$+1.12_{\pm 1.35}$	$+3.11_{\pm 3.29}$	$-0.30_{\pm 0.68}$	$+8.40_{\pm 0.71}$	$+0.72_{\pm 1.13}$	$+2.67_{\pm 0.28}$	$+2.19_{\pm 0.36}$	$+2.71_{\pm 0.32}$
						CIFAR100x11					
Base	$7.90_{\pm 0.30}$	$36.41_{\pm 1.06}$	$16.55_{\pm 0.41}$	$33.86_{\pm 0.11}$	$42.38_{\pm 0.64}$	$34.86_{\pm 0.56}$	$8.01_{\pm 0.88}$	$32.13_{\pm 0.72}$	$38.17_{\pm 0.17}$	$41.46_{\pm 0.84}$	$29.17_{\pm 0.05}$
+AC	$\mathbf{11.91}_{\pm 1.59}$	$\mathbf{36.80}_{\pm 0.45}$	$\mathbf{22.73}_{\pm 0.74}$	$\mathbf{34.94}_{\pm 0.95}$	$\mathbf{45.37}_{\pm 0.44}$	$\mathbf{36.80}_{\pm 0.53}$	$\mathbf{16.05}_{\pm 0.96}$	$\mathbf{35.31}_{\pm 1.42}$	$\mathbf{40.97}_{\pm 0.22}$	$\mathbf{45.70}_{\pm 0.59}$	$\mathbf{32.66}_{\pm 0.35}$
Δ	$+4.00_{\pm 1.48}$	$+0.39_{\pm 0.63}$	$+6.17_{\pm 0.38}$	$+1.08_{\pm 0.85}$	$+2.99_{\pm 0.21}$	$+1.94_{\pm 1.07}$	$+8.04_{\pm 0.67}$	$+3.18_{\pm 0.77}$	$+2.80_{\pm 0.35}$	$+4.24_{\pm 1.10}$	$+3.48_{\pm 0.31}$

Table 3: Difference w.r.t. baseline single-classifier methods when using a different number of auxiliary classifiers (ACs). ACs robustly improve the final accuracy of continual learning methods, regardless of the number of classifiers used.

	FLOPS	FT	FT+Ex	GDumb	ANCL	BiC	ER	EWC	LwF	LODE	SSIL	Avg
NoAC	69.90M (1x)											
						CIFAR100x5						
3AC	70.72M (1.01x)	$+7.61_{\pm 0.68}$	$+0.70_{\pm 0.83}$	$+5.08_{\pm 0.87}$	$+2.14_{\pm 1.05}$	$+2.62_{\pm 0.60}$	$+4.63_{\pm 0.38}$	$+8.94_{\pm 0.40}$	$+0.95_{\pm 1.18}$	$+4.19_{\pm 0.63}$	$+2.65_{\pm 0.58}$	$+3.95_{\pm 0.39}$
6AC	71.55M (1.02x)	$+9.49_{\pm 0.96}$	$+0.39_{\pm 0.90}$	$+4.20_{\pm 0.16}$	$+2.12_{\pm 1.03}$	$+2.74_{\pm 0.83}$	$+5.22_{\pm 0.38}$	$+10.02_{\pm 1.39}$	$+2.29_{\pm 0.25}$	$+6.31_{\pm 0.81}$	$+2.72_{\pm 0.42}$	$+4.55_{\pm 0.43}$
12AC	72.97M (1.04x)	$+9.09_{\pm 0.81}$	$+1.67_{\pm 1.28}$	$+5.15_{\pm 0.08}$	$+2.45_{\pm 0.74}$	$+3.57_{\pm 0.47}$	$+4.46_{\pm 0.54}$	$+9.97_{\pm 0.35}$	$+2.75_{\pm 1.26}$	$+5.43_{\pm 0.65}$	$+2.92_{\pm 0.53}$	$+4.74_{\pm 0.20}$
						CIFAR100x10						
3AC	70.84M (1.01x)	$+6.48_{\pm 0.43}$	$+3.05_{\pm 0.99}$	$+5.74_{\pm 0.47}$	$+1.71_{\pm 0.31}$	$+2.85_{\pm 2.19}$	$+4.44_{\pm 1.00}$	$+7.92_{\pm 0.61}$	$+0.53_{\pm 0.44}$	$+6.13_{\pm 0.23}$	$+2.02_{\pm 1.69}$	$+4.09_{\pm 0.42}$
6AC	71.77M (1.03x)	$+6.62_{\pm 1.06}$	$+2.46_{\pm 0.31}$	$+5.52_{\pm 1.13}$	$+0.68_{\pm 0.79}$	$+3.31_{\pm 2.62}$	$+5.01_{\pm 0.98}$	$+8.92_{\pm 1.06}$	$+0.74_{\pm 0.91}$	$+6.80_{\pm 0.93}$	$+1.88_{\pm 0.77}$	$+4.20_{\pm 0.47}$
12AC	73.36M (1.05x)	$+4.63_{\pm 1.46}$	$+2.59_{\pm 1.19}$	$+6.12_{\pm 0.78}$	$+1.85_{\pm 1.49}$	$+3.98_{\pm 2.01}$	$+4.95_{\pm 1.05}$	$+6.57_{\pm 0.97}$	$+1.14_{\pm 0.38}$	$+6.68_{\pm 0.79}$	$+1.98_{\pm 0.91}$	$+4.05_{\pm 0.60}$

A common scenario in continual learning is warm start (Magistri et al.; Goswami et al., 2024) that simulates starting from a pre-trained model checkpoint. In this scenario, the model is trained continually, but the first task contains a large portion of the whole data so that during this task the network can already accumulate a lot of knowledge, as in the case of pre-training. Such a scenario is an interesting study for continual learning due to the practical benefits of using pre-trained models and the difference in learning dynamics when starting from a trained model.

To validate how our model behaves in a warm start scenario, we train the methods from the previous sections on CIFAR100 and use 50 classes for the first task to simulate a pre-training phase. After the first task, we split the remaining classes evenly into 5 or 10 additional tasks (we refer to both settings as 6 and 11 task split). Aside from the task split, we perform the experiments as described in the previous sections and report the results in Table 2. We observe that the performance of the methods enhanced with the ACs generally improves, aside from ER and FT+Ex on 6 tasks; however, those methods are quite naive and ACs work for them in the other setting. Overall, our idea is almost universally beneficial and its performance in the changed setting proves its robustness.

5.4 Ablation studies

In this section, we perform ablation studies that test the robustness of our idea against the number of used classifiers (Section 5.4.1 and the classifier architecture (Section 5.4.2). In Appendices I and J we also provide additional ablations for dynamic inference performance when learning without gradient propagation and training ViT (Dosovitskiy, 2020) models with ACs.

5.4.1 Number of ACs

Our approach requires deciding the AC placement, which will affect the performance. To test the robustness of our idea, we perform an ablation where we change the number of classifiers, using either half of them or twice as much (we either drop every other classifier in our standard setting or attach an additional one to the ResNet blocks in between the previously selected classifiers). We measure the improvement obtained upon the baseline (already reported in Table 1) and the additional computational cost incurred by the ACs when using 3, 6 (standard setting), and 12 ACs and report it in Table 3. While the best setup across several continual learning methods varies, the number of ACs does not significantly affect the accuracy and their addition does not significantly increase the computation in the network. In all cases, the networks with auxiliary classifiers achieve an improvement upon the baseline, underlining the robustness of our idea.

5.4.2 Alternative AC architectures

In our main work, we investigate a simple setup with independent classifiers. Early-exit works such as (Wójcik et al., 2023) propose more complex dynamic architectures, where subsequent classifiers are connected and their predictions are combined through a weighted ensemble. Those architectures induce only a slight parameter and computation overhead, but in a standard supervised learning setting can improve the performance of intermediate classifiers through sharing the knowledge between them. We investigate those architectures in continual learning on the set of methods analyzed in previous sections on split CIFAR100 benchmarks and present the results in Table 4. Similar to the AC density ablation, we do not observe a clear improvement from changing the setup. We hypothesize

Table 4: Difference w.r.t. baseline single-classifier methods when using a different auxiliary classifier architecture: cascading (C) and ensebling (E) from Wójcik et al. (2023). Similar to Table 3, ACs universally improve the accuracy with small differences in performance between the architectures.

Method	FT	FT+Ex	GDumb	ANCL	BiC	ER	EWC	LwF	LODE	SSIL	Avg
						CIFAR100x5					
AC	+5.70$\pm$5.24	+0.24$\pm$0.67	+2.52$\pm$2.30	+1.27$\pm$1.37	+1.65$\pm$1.61	+3.13$\pm$2.87	+6.01$\pm$5.57	+1.37$\pm$1.27	+3.79$\pm$3.50	+1.63$\pm$1.52	+2.73$\pm$2.51
AC+C	+5.41$\pm$4.99	-0.72$\pm$0.70	+2.49$\pm$2.27	+1.20$\pm$1.37	+1.16$\pm$1.06	+2.57$\pm$2.37	+6.16$\pm$5.62	+0.66$\pm$0.77	+2.89$\pm$2.66	+1.26$\pm$1.23	+2.31$\pm$2.12
AC+E	+6.47$\pm$5.91	+0.38$\pm$1.03	+2.00$\pm$1.83	+1.28$\pm$39.62	+1.30$\pm$1.20	+2.32$\pm$2.16	+6.58$\pm$6.01	+1.14$\pm$1.18	+2.79$\pm$2.61	+1.29$\pm$1.23	+2.56$\pm$2.11
						CIFAR100x10					
AC	+6.62$\pm$1.06	+2.46$\pm$0.31	+5.52$\pm$1.13	+0.68$\pm$0.79	+3.31$\pm$2.62	+5.01$\pm$0.98	+8.92$\pm$1.06	+0.74$\pm$0.91	+6.80$\pm$0.93	+1.88$\pm$0.77	+4.20$\pm$0.47
AC+C	+6.98$\pm$1.05	+2.63$\pm$0.92	+5.56$\pm$0.96	+1.60$\pm$0.70	+3.63$\pm$1.51	+5.19$\pm$1.08	+8.35$\pm$0.39	+1.27$\pm$0.47	+5.45$\pm$0.17	+2.53$\pm$0.56	+4.32$\pm$0.16
AC+E	+7.35$\pm$0.14	+3.27$\pm$0.74	+5.09$\pm$0.40	+2.28$\pm$0.21	+3.68$\pm$2.16	+4.77$\pm$0.52	+8.62$\pm$1.12	+1.18$\pm$0.30	+5.85$\pm$0.68	+1.53$\pm$0.67	+4.36$\pm$0.33

that connecting the classifiers makes them no longer independent, which negates the benefits yielded in continual learning by the classifier diversity.

6 Conclusions

We have explored the potential of leveraging intermediate representations in neural networks to improve the performance and efficiency of continual learning through the use of auxiliary classifiers (ACs). Through our analysis, we confirmed that early network layers are more stable during continual learning, particularly in retaining information from older tasks. Building on this observation, we introduce ACs, lightweight classifiers trained on intermediate layers, as a novel enhancement to standard continual learning methods. Our results show that ACs not only help mitigate catastrophic forgetting by maintaining strong performance on older tasks but also foster diversity in classification, as different ACs specialize in classifying distinct data subsets. We demonstrate that integrating ACs into several established continual learning methods consistently yields superior performance compared to single-classifier models on benchmarks such as CIFAR100 and ImageNet100. Additionally, the addition of the ACs enables computational savings and adaptability through dynamic inference, allowing models to maintain the accuracy of the baseline while reducing computational costs during inference by up to 70%. Our findings suggest that ACs can serve as a powerful tool in continual learning, not only enhancing performance but also offering efficient alternatives to standard methods in resource-constrained environments, where balancing accuracy and efficiency is critical.

Limitations. ACs introduce an additional memory footprint that varies depending on the network architecture, and in principle make training more complex due to the introduction of additional hyperparameters. The dynamic inference procedure in our paper is also intentionally kept simple and its efficiency could be further optimized with more complex approaches explored in the early-exit community. Finally, developing continual learning methods based on the multi-classifier architecture or dynamic inference and extending our work to settings like online continual learning or test-time adaptation could be interesting directions for future work.

Ethics statement. Our research primarily focuses on fundamental machine learning problems and we do not identify any specific ethical concerns associated with our work. Nonetheless, given the potential ramifications of machine learning technologies, we advise approaching their development and implementation with caution.

Reproducibility statement. All our experiments were done on publicly available datasets. For easy reproducibility, we use the FACIL framework. We publish the anonymized version of our code at `https://anonymous.4open.science/r/cl-auxiliary-classifiers` and we will make it public upon the acceptance of the paper.

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