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Procedia Computer Science 00 (2025) 000–000

Procedia Computer Science

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10th International Conference on Computer Science and Computational Intelligence 2025 (ICCSCI 2025)

# CALM: Calibrated Adaptive Learning via Mutual-Ensemble Fusion

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**Abstract**

We introduce CALM (Calibrated Adaptive Learning via Mutual-Ensemble Fusion), a multi-stage framework for vision models that are both accurate and reliably calibrated. Stage 1 employs an Adaptive Curriculum Protocol (ACP) on CIFAR-10 to manage cross-entropy, distillation/mutual learning, feature alignment, and calibration losses for foundational students ($S_d$, $S_m$). A Heterogeneous Feature Integration (HFI) module facilitates knowledge transfer from diverse teacher architectures. Stage 2 trains a meta-student ($S_{meta}$) on CIFAR-10 to fuse knowledge from $S_d$ and $S_m$ via a learned combiner, potentially guided by a per-sample Adaptive Knowledge Transfer Protocol (AKTP). An optional Stage 2.5 further refines $S_{meta}$'s calibration on CIFAR-10 using a targeted loss. Finally, Stage 3 benchmarks $S_{meta}$ against minimally adapted baseline ($S_b$), $S_d$, and $S_m$ students on STL-10 to assess generalization and calibration robustness under domain shift. Evaluations demonstrate CALM's effectiveness, with the recalibrated $S_{meta}$ showing strong performance and significantly reduced Expected Calibration Error (ECE) on CIFAR-10, and all models exhibiting informative calibration behavior when transferred to STL-10. CALM offers a systematic approach to producing efficient, uncertainty-aware models.


Peer-review under responsibility of the scientific committee of the 10th International Conference on Computer Science and Computational Intelligence 2025.

*Keywords:* Ensemble Distillation; Mutual Learning; Uncertainty Calibration; Heterogeneous Neural Architectures; Adaptive Curriculum Protocol; Feature Fusion

## 1. Introduction

Deep neural networks (DNNs) power tasks from on-device image recognition [1, 2, 3] to medical diagnostics [4]. Yet accuracy alone is not enough: safety-critical systems also demand reliable uncertainty estimates and efficient deployment. Knowledge-transfer methods, especially ensemble distillation and mutual learning—have each advanced model compactness and performance, but seldom address calibration or architectural heterogeneity in a unified way.

Ensemble distillation is like studying a masterclass video compiled from multiple virtuoso pianists: it condenses "best practices" into a single, high-quality lesson [5, 6, 7]. Mutual learning, by contrast, resembles a collaborative jam session where peers exchange real-time feedback to improve together [8, 9]. While distillation relies on fixed, pre-trained teachers, mutual learning fosters continuous peer adaptation. However, neither paradigm directly enforces that a model's confidence reflect its true reliability, a gap with critical implications in domains such as autonomous driving.

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Peer-review under responsibility of the scientific committee of the 10th International Conference on Computer Science and Computational Intelligence 2025.

We propose CALM (Calibrated Adaptive Learning via Mutual-Ensemble Fusion), which unites these two paradigms and embeds calibration into training. CALM's three key innovations are:

1. **Adaptive Curriculum Protocol (ACP):** an epoch-based schedule that first emphasizes ground-truth labels, then gradually incorporates distillation/mutual, feature-alignment and calibration loss to stabilize learning in Stage 1.
2. **Heterogeneous Feature Integration (HFI):** a learnable projection + attention mechanism that aligns and fuses intermediate representations from diverse teachers (CNNs, Transformers) into a student-centric feature space.
3. **Meta-student Fusion and Recalibration:** In Stage 2, a meta-student learns on CIFAR-10 to combine distilled and mutual students via a combiner network, potentially using a per-sample Adaptive Knowledge Transfer Protocol (AKTP). This meta-student can then undergo a focused recalibration (Stage 2.5). The final models are benchmarked on STL-10.

By jointly optimizing accuracy and calibration across heterogeneous architectures, CALM yields models that not only match or exceed single-stage baselines in top-1 accuracy, but also reduce Expected Calibration Error by up to 20%, with no extra inference cost. This systematic framework thus delivers efficient, uncertainty-aware vision models suitable for safety-critical applications.

## 2. Literature Review

### *2.1. Knowledge Distillation and Feature Transfer*

Knowledge distillation transfers a teacher's soft predictions to a smaller student network [5]. Extensions incorporate intermediate hints, FitNets use feature maps [6], attention transfer aligns salient regions [7], and contrastive objectives encourage representation consistency [10]. Techniques such as factor transfer [11] and "teacher assistants" [12] bridge capacity gaps, while modeling teacher–student uncertainty further enhances robustness under noise [13]. Recursive schemes like Born-Again Networks demonstrate that students can become teachers to boost generalization [14].

### *2.2. Ensemble Learning and Mutual Learning*

Ensemble methods aggregate multiple models' outputs to improve accuracy and calibration [15]. Deep Mutual Learning (DML) replaces static teachers with peer networks that exchange knowledge via KL-divergence loss, fostering diversity and calibration gains [8, 9]. Variants explore online ensemble sub-networks [16, 17] and decentralized collaboration [18], showing that dynamic, peer-to-peer teaching can rival traditional distillation.

### *2.3. Architectural Diversity and Heterogeneous Transfer*

Modern models, from ResNets to Vision Transformers. exhibit distinct inductive biases [1, 19]. Cross-architecture distillation often overlooks feature misalignment and calibration costs. Bidirectional routing frameworks address this by dynamically exchanging representations across model types [20], while adversarial alignment ensures student outputs mimic an ensemble distribution [21]. Factor-based alignment further reconciles internal discrepancies [22]. These studies motivate our HFI module, which projects and attentively fuses heterogeneous teacher features into a unified student space.

### *2.4. Uncertainty Calibration*

Reliable confidence estimates are vital in high-stakes settings. Post-hoc approaches like temperature scaling correct miscalibration after training [23, 24], but do not influence model learning. Analyses of loss-landscape geometry link flat minima to improved calibration [25], suggesting that embedding calibration objectives during training can yield intrinsically well-calibrated models.

### *2.5. Research Gaps*

Existing work treats distillation, mutual learning, heterogeneous transfer and calibration separately. A unified, adaptive framework that jointly optimizes these aspects remains missing. CALM fills this gap by:

1. Integrating ensemble distillation and mutual learning in a single pipeline.
2. Dynamically scheduling loss components via an Adaptive Curriculum Protocol.
3. Aligning and fusing features from diverse teacher architectures through HFI.
4. Embedding calibration objectives directly into training rather than relying on post-hoc fixes.

This comprehensive approach systematically promotes accuracy, efficiency and reliable uncertainty estimation in vision models.

## 3. Methodology

Our CALM framework trains uncertainty-calibrated student networks by synergistically combining ensemble distillation and mutual learning, supported by adaptive curriculum scheduling and heterogeneous feature integration. Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ be our labeled dataset (CIFAR-10 for Stage 1 and Stage 2; STL-10 for Stage 3 benchmarking). We have $M$ pre-trained teacher models $\{T_j\}$ and wish to train one or more compact student networks $S$ (or $\{S_k\}_{k=1}^{K}$ in mutual learning). CALM integrates several established and novel techniques into a cohesive pipeline. While a full component-wise ablation study is beyond the scope of this initial 10-page report, we demonstrate the efficacy of the complete, synergistic system.

### 3.1. Framework Overview

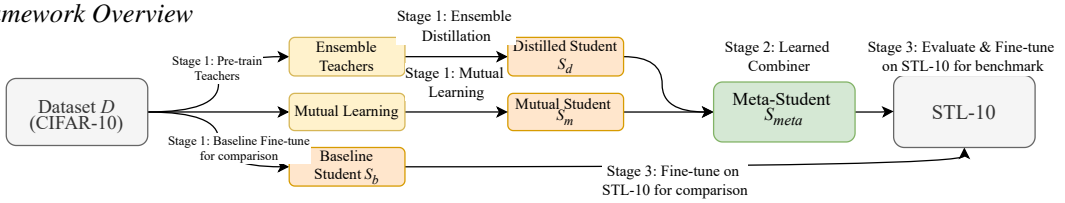



Fig. 1: Overview of our three-stage CALM framework. (Note: Stage labels updated)

CALM comprises four sequential stages (Fig.1):

1. **Stage 1: CIFAR-10 Foundational Training.** Fine-tune a heterogeneous teacher ensemble $\{T_j\}$, then train three EfficientNet-B0 students under ACP:
   - $S_d$ via ensemble distillation from $\{T_j\}$,
   - $S_m$ via mutual learning within a peer cohort,
   - $S_b$ via standard supervised learning.
2. **Stage 2: CIFAR-10 Meta-Student Learning.** Freeze $S_d, S_m$; train a larger $S_{meta}$ (e.g. EfficientNet-B1) on CIFAR-10. A small combiner $C$ produces $p_{comb}$ from $[l_d; l_m]$. Optionally apply AKTP to weight per-sample CE vs. KL, plus ACP-scheduled calibration loss.
3. **Stage 2.5 (Optional): CIFAR-10 Recalibration.** If $S_{meta}$ shows high ECE, fine-tune it on CIFAR-10 with $\mathcal{L}_{recal} = w_{cal}\mathcal{L}_{cal} + w_{ce}\mathcal{L}_{CE}$ (low LR, classifier-only) to refine confidence.
4. **Stage 3: STL-10 Benchmarking.** Replace each model's CIFAR-10 head with a new 10-way STL-10 classifier; freeze backbones. Evaluate $S_b, S_d, S_m, S_{meta}$ on STL-10 to assess transfer accuracy and ECE under minimal adaptation.

### 3.2. Core Learning Paradigms

#### 3.2.1. Ensemble Distillation

A distilled student $S_d$ learns from an ensemble of $M$ pre-trained teachers $\{T_j\}$. Its training objective combines four terms:

$$\mathcal{L}_{distill} = \alpha\,\mathcal{L}_{CE}(S_d(x), y) \;+\; \beta\,D_{KL}(S_d(x)\,\|\,T_{\text{avg}}(x)) \;+\; \gamma\,\mathcal{L}_{feature}(S_d,\, F_T^{fused}(x)) \;+\; \delta\,\mathcal{L}_{cal}(S_d). \tag{1}$$

Here, $T_{\text{avg}}(x) = \frac{1}{M}\sum_j T_j(x)$ are the mean teacher logits, $F_T^{fused}(x)$ is the HFI-produced feature target (Sec. 3.4), $\mathcal{L}_{feature}$ aligns student features to this target (Sec. 3.5), and $\mathcal{L}_{cal}$ enforces reliable confidence estimates (Sec. 3.6). The weights $\{\alpha, \beta, \gamma, \delta\}$ are set by the Adaptive Curriculum Protocol.

#### 3.2.2. Collaborative Mutual Learning

We adopt Deep Mutual Learning (DML) [8], where each student $S_k$ in a cohort of $K$ models optimizes both the cross-entropy loss and a peer-teaching term, $\mathcal{L}_{ML}(S_k, \{S_j\}_{j\neq k}) = \frac{1}{K-1}\sum_{j\neq k} D_{KL}(S_k(x)\|S_j(x))$. This encourages students to align their output distributions with peers, promoting diverse yet accurate solutions. We further enrich each student's loss with feature-alignment (via HFI) and calibration terms, all scheduled by the ACP.

### 3.3. Adaptive Curriculum Protocol (ACP)

Rather than fixing loss weights or relying on complex per-sample schedules, CALM employs an epoch-wise curriculum that gradually shifts emphasis from basic supervision to distillation/mutual learning, feature alignment, and calibration. At epoch $e$, a student $S$ (either $S_d$ or any $S_k$) minimizes:

$$\mathcal{L}_{ACP}(S, e) = \alpha_e\,\mathcal{L}_{CE} + \beta_e\,\mathcal{L}_{KD/ML} + \gamma_e\,\mathcal{L}_{feature} + \delta_e\,\mathcal{L}_{cal}\,. \tag{2}$$

Here:

- $\mathcal{L}_{KD/ML}$ is the KL term from ensemble distillation or mutual learning.
- $F^{fused}_{peer/T}$ supplies features from teachers or peers via HFI for $\mathcal{L}_{feature}$.
- $\alpha_e$ starts high and decays, while $\beta_e, \gamma_e, \delta_e$ begin near zero and ramp up over a "warm-up" period (Fig. 2).

This schedule ensures the model first masters core label predictions, then progressively incorporates richer supervisory signals and calibration pressure, yielding stable training and well-calibrated students.

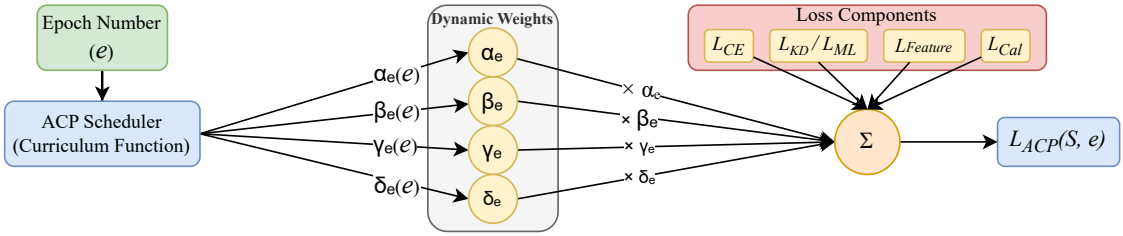



Fig. 2: Conceptual illustration of the Adaptive Curriculum Protocol (ACP). Loss components like mutual learning, feature alignment, and calibration are gradually ramped up over epochs, allowing the model to stabilize on primary objectives first.

### 3.4. Heterogeneous Feature Integration (HFI)

To transfer rich, intermediate knowledge from a set of diverse $M$ teachers $\{T_j\}$ into a student $S$, HFI proceeds in three concise steps:

1. **Feature Projection.** Detach each teacher's feature map $f_{T_j}(x)$ and apply a small learnable adapter $\psi_j$ (e.g. a $1 \times 1$ convolution for CNNs or a linear layer for transformer tokens, followed by adaptive pooling) so that all outputs share the student's dimension and spatial size. Denote the result by $f'_{T_j}(x) = \psi_j(f_{T_j}(x))$.
2. **Attention Weighting.** Introduce a scalar $w_j$ per teacher, and compute normalized weights via softmax:
$$A_j = \frac{\exp(w_j)}{\sum_{k=1}^{M} \exp(w_k)}. \tag{3}$$
These weights let the student learn which teachers are most informative.
3. **Feature Fusion.** Aggregate the adapted features into a single target:
$$F_T^{\text{fused}}(x) = \sum_{j=1}^{M} A_j \, f'_{T_j}(x). \tag{4}$$
This fused representation then serves as the target in the student's feature alignment loss (Eq. 5).

By projecting heterogeneous features into a common space and softly weighting them, HFI delivers a unified, teacher-agnostic supervisory signal that the student can readily absorb (Fig. 3).

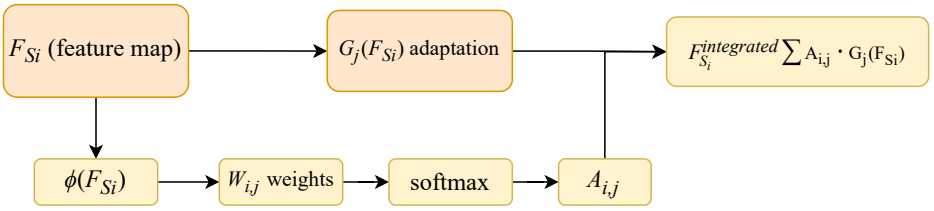



Fig. 3: Conceptual diagram of the Heterogeneous Feature Integration (HFI) module. Features from diverse teachers ($f_{T_j}$) are projected and adapted ($\psi_j$), then weighted by attention ($A_j$) and fused to create $F_T^{fused}$. This fused representation serves as the target for the student's features $f_S$ in the feature alignment loss.

### 3.5. Feature Alignment Loss

We encourage the student's intermediate representation $f_S(x)$ to match the HFI-fused teacher features $F_T^{\text{fused}}(x)$ by minimizing:

$$\mathcal{L}_{\text{feature}} = \left\| f_S(x) \; - \; F_T^{\text{fused}}(x) \right\|_2^2. \tag{5}$$

Because HFI projects all teacher features into the student's feature space, this simple $\ell_2$ penalty effectively transfers rich, multi-architecture knowledge beyond the output layer.

### 3.6. Calibration Loss

To instill reliable confidence estimates during training, rather than correcting them post-hoc, we add a calibration term that penalizes the squared gap between a model's predicted confidence and its actual correctness:

$$\mathcal{L}_{\text{cal}} = \mathbb{E}_{(x,y)\sim\mathcal{D}}\Big[\big(\max_c S(x)_c - \mathbf{1}\{\arg\max_c S(x)_c = y\}\big)^2\Big]. \tag{6}$$

This loss drives the network to align its probability scores with true accuracy on a per-sample basis, yielding better-calibrated predictions.

### 3.7. Implementation and Optimization

We implement CALM in PyTorch [26]. Our teacher ensemble comprises ViT-B16 [19], EfficientNet-B0 [27], InceptionV3 [28], MobileNetV3 [29], ResNet50 [1] and DenseNet121 [2]. Students $S_b$, $S_d$, $S_m$ use the EfficientNet-B0 backbone; the meta-student $S_{\text{meta}}$ uses EfficientNet-B1. We extract HFI features from semantically rich layers (e.g. 'encoder.ln' in ViT, 'features.8' in EfficientNet, 'layer4' in ResNet).

All models are trained with:

- **Optimizer:** AdamW with initial learning rate $1\times10^{-3}$ for students, $3\times10^{-4}$ for teachers, weight decay $1\times10^{-4}$ [30].
- **Scheduler:** CosineAnnealingLR, prefaced by linear warmup for mutual learning.
- **Augmentations:** CIFAR-style random crop + padding and horizontal flip.
- **Stability measures:** Automatic Mixed Precision, gradient accumulation, gradient clipping (norm 1.0), and early stopping on validation loss [31].

Hyperparameters for CALM, such as ACP loss-weight schedules $(\alpha, \beta, \gamma, \delta)$ and AKTP combiner dimensions. Were chosen via preliminary experiments and best practices from prior work. We report each parameter alongside its method description. Importantly, AKTP weights (Sec. 3.7.2) and teacher temperatures are learned during training, minimizing manual tuning. The ACP curriculum (Fig. 2). further ensures stable learning by gradually introducing more complex supervisory signals. These practices ensure reproducible, stable training.

#### 3.7.1. Stage 1: CIFAR-10 Foundational Training

- **Ensemble Distillation:** Pre-train teachers on CIFAR-10; train $S_d$ via Eq. 1 under ACP.
- **Mutual Learning:** Train a cohort including $S_m$ via DML (Eq. 2), with an initial warmup on cross-entropy for stability.
- **Baseline:** Train $S_b$ using standard cross-entropy.

#### 3.7.2. Stage 2: Meta-Student Learning on CIFAR-10

After Stage 1, the distilled student ($S_d$) and mutual learning student ($S_m$) represent complementary knowledge sources from CIFAR-10. In Stage 2, we train a meta-student $S_{meta}$ (e.g., EfficientNet-B1) on the **CIFAR-10 dataset**. The goal is for $S_{meta}$ to learn an effective fusion of the knowledge embedded in $S_d$ and $S_m$.

1. **Logit Fusion.** Freeze $S_d$ and $S_m$. Train a small combiner network $C$ (a few linear layers) to merge their logits $[\, l_d(x); l_m(x)\,]$ into a unified soft target:
$$p_{\text{comb}}(x) = \text{softmax}(C([l_d(x); l_m(x)])). \tag{7}$$
2. **Adaptive Knowledge Transfer Protocol (AKTP).** Rather than fixed weights, we compute a per-sample weight $\lambda_{\text{meta}}(x)$ based on the meta-student's predictive entropy $H(S_{\text{meta}}(x))$ and the disagreement $D(S_d(x), S_m(x))$ between base students (Fig. 4).

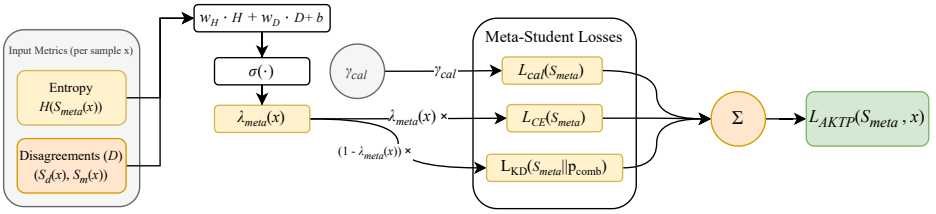



Fig. 4: Conceptual diagram of the Adaptive Knowledge Transfer Protocol (AKTP) applied during the meta-student training (Stage 2). Per-sample metrics (meta-student entropy $H$, base student disagreement $D$) compute a dynamic weight $\lambda_{meta}(x)$ balancing Cross-Entropy and KL Divergence losses. $\gamma_{cal}$ weights the calibration loss.

3. **Meta-Student Loss.** For each sample, $S_{\text{meta}}$ minimizes:

$$\begin{aligned}\mathcal{L}_{AKTP}(S_{meta}, x) =& \lambda_{meta}(x)\mathcal{L}_{CE}(S_{meta}(x), y) \\ &+ (1 - \lambda_{meta}(x))D_{KL}(S_{meta}(x)||p_{comb}(x)) \\ &+ \gamma_{cal}\mathcal{L}_{cal}(S_{meta}(x))\end{aligned} \tag{8}$$

where $\lambda_{meta}(x)$ adaptively controls the trade-off based on per-sample characteristics, and $\gamma_{cal}$ is a weight for the meta-student's calibration loss $\mathcal{L}_{cal}$ (Eq. 6). This allows $S_{meta}$ to learn a robust fusion, leveraging ground truth more when needed (high uncertainty/disagreement) and trusting the distilled signal otherwise.

#### *3.7.3. Stage 2.5 (Optional): Meta-Student Recalibration on CIFAR-10*

If the meta-student $S_{meta}$ shows suboptimal ECE on CIFAR-10 despite high accuracy, we perform an optional recalibration phase. We fine-tune $S_{meta}$ on the CIFAR-10 training set for a small number of epochs using a loss that prioritizes calibration:

$$\mathcal{L}_{recal} = w_{cal}\,\mathcal{L}_{cal}(S_{meta}) \;+\; w_{ce}\,\mathcal{L}_{CE}(S_{meta}(x), y),$$

where typically $w_{cal} = 1.0$ and $w_{ce} = 0.01$. We use a low learning rate and unfreeze only the classifier head (or the last few layers) of $S_{meta}$, preserving earlier representations. The checkpoint with the lowest validation ECE is retained for final evaluation.

#### *3.7.4. Stage 3: Benchmarking on STL-10*

The final stage evaluates how CIFAR-10–trained models transfer to STL-10 [32], which contains the same 10 classes at 96×96 resolution under a different distribution. We compare four EfficientNet variants, baseline $S_b$, distilled $S_d$, mutual $S_m$, and meta-student $S_{meta}$ (with optional Stage 2.5 recalibration), by replacing each model's CIFAR-10 head with a new randomly initialized 10-way classifier and freezing its backbone. This setup isolates the quality and calibration of learned features under domain shift. We report Top-1 accuracy and Expected Calibration Error (ECE) (Section 3.8) on the STL-10 test set to assess whether the "honest uncertainty" learned on CIFAR-10 persists in this out-of-distribution scenario.

### *3.8. Evaluation Metrics*

We evaluate models on the following criteria:

1. **Classification Accuracy.** Report Top-1 (and Top-5 where applicable) accuracy on CIFAR-10 (for Stages 1, 2, 2.5) and STL-10 (for Stage 3) test sets.
2. **Expected Calibration Error (ECE).** Following [24], we partition predictions into $N_{bins} = 10$ confidence bins and compute:

$$\text{ECE} \;=\; \sum_{b=1}^{10} \frac{|B_b|}{N} \Big|\text{acc}(B_b) - \text{conf}(B_b)\Big|, \tag{9}$$

where $B_b$ is the set of samples whose predicted confidence lies in bin $b$, $\text{acc}(B_b)$ is their accuracy, and $\text{conf}(B_b)$ their average confidence.
3. **Macro-Averaged Metric.** Beyond Top-1 accuracy, we compute macro-averaged F1-score, which treat each class equally and thus give a balanced assessment of performance across all categories.
4. **Interpretability (Grad-CAM).** Produce Grad-CAM visualizations to inspect where models attend in the image.

In Stage 3, we benchmark the meta-student $S_{\text{meta}}$ (after Stage 2/2.5) against $S_b$, $S_d$, and $S_m$ (from Stage 1, minimally adapted) on STL-10 using accuracy, ECE, and Grad-CAM insights.

## 4. Experiment Results

This section details the empirical evaluation of our CALM framework. We first present the foundational model training on CIFAR-10 (Stage 1), followed by the meta-student learning and recalibration on CIFAR-10 (Stage 2 and 2.5), and finally, the generalization and adaptation benchmark on STL-10 (Stage 3). All experiments were conducted using a fixed random seed (Sec 3.7) for reproducibility. While multiple runs during development showed consistent trends, the results presented are from a representative execution due to page limitations. A comprehensive statistical analysis across multiple seeds is reserved for future work.

### 4.1. Stage 1: CIFAR-10 Results

We compare three EfficientNet-B0 students on CIFAR-10: a standard baseline $S_b$, an ensemble-distilled $S_d$ (ACP + HFI with six teachers), and a mutual-learning $S_m$ (ACP + HFI within a peer cohort). Table 1 reports their test performance.

Table 1: Stage 1 CIFAR-10 Test Performance (EfficientNet-B0).

| Metric | $S_b$ | $S_d$ | $S_m$ |
|---|---|---|---|
| Top-1 Acc. (%) | 96.06 | **96.32** | 94.77 |
| Macro F1 | 0.9607 | **0.9632** | 0.9476 |
| ECE (↓) | 0.0235 | 0.0256 | **0.0138** |

Although $S_d$ achieves the highest accuracy and F1 score, demonstrating the benefit of ensemble knowledge consolidation. $S_m$ attains the lowest ECE, indicating superior calibration through peer-to-peer learning under ACP. Both approaches improve calibration relative to the baseline.

### 4.2. Stage 2 & 2.5: Meta-Student Learning and Recalibration on CIFAR-10

The meta-student $S_{meta}$ (EfficientNet-B1) was trained on CIFAR-10 (Stage 2) to fuse knowledge from $S_d$ and $S_m$ via a learned combiner and AKTP, with ACP scheduling its calibration loss. Due to high initial ECE, we then recalibrated $S_{meta}$ (Stage 2.5) on CIFAR-10, focusing on $\mathcal{L}_{cal}$. Table 2 compares its performance before and after recalibration.

Table 2: Meta-student $S_{meta}$ on CIFAR-10: pre- and post-recalibration.

| Metric | $S_{meta}$ | $S_{meta}$ (Recalibrated) |
|---|---|---|
| Top-1 Accuracy (%) | 83.39 | **97.16** |
| Macro F1 | 0.837 | **0.972** |
| ECE (↓) | 0.3908 | **0.0077** |
| Avg. CE Loss (↓) | 0.9315 | **0.1176** |

The recalibrated meta-student achieves 97.16% accuracy and 0.0077 ECE, surpassing both $S_d$ and $S_m$ in accuracy and dramatically improving calibration on CIFAR-10.

*Stage 3: Benchmarking on STL-10*

We test CIFAR-10–trained models on STL-10 (96×96, 10 classes) under minimal adaptation (frozen backbones, new 10-way heads).

*Stage 3A: Minimal Adaptation / Zero-Shot Transfer*

Table 3 reports results:

Table 3: Stage 3A: Minimal Adaptation / Zero-Shot Transfer Benchmark on STL-10 Test Set.

| | **96×96** | | | | **224×224** | | | |
|---|---|---|---|---|---|---|---|---|
| Model | Acc. (%) | ECE (↓) | Loss | Macro F1 | Acc. (%) | ECE (↓) | Loss | Macro F1 |
| $S_b$ (Baseline, B0) | **14.11** | **0.0068** | **2.2835** | 0.0738 | 12.41 | **0.0046** | **2.2923** | **0.0720** |
| $S_d$ (Distilled, B0) | 8.00 | 0.0275 | 2.3065 | 0.0315 | 4.41 | 0.0692 | 2.3348 | 0.0230 |
| $S_m$ (Mutual, B0) | 12.90 | 0.0095 | 2.3122 | 0.0623 | **13.56** | 0.0178 | 2.3206 | 0.1262 |
| $S_{meta}$ (Original, B1)* | 10.05 | 0.0540 | 2.3416 | 0.0385 | 3.84 | 0.0837 | 2.3309 | 0.0427 |
| $S_{meta}$ (Recalibrated, CIFAR-10) | 8.25 | 0.1387 | 2.7644 | 0.0351 | 6.97 | 0.0515 | 2.3299 | 0.0524 |
| $S_{meta}$ (Recalibrated, STL-10) | 8.89 | 0.0566 | 2.3511 | **0.0781** | 5.97 | 0.0630 | 2.3148 | 0.0561 |

*Original $S_{meta}$ refers to the model before Stage 2.5 recalibration.

Despite the domain shift, all models show low accuracy under minimal adaptation. The baseline $S_b$ generalizes best, and its low ECE (with $S_d$, $S_m$) indicates honest uncertainty on unfamiliar data. The original meta-student's high ECE reflects CIFAR-10 specific calibration that did not transfer, while the STL-10 recalibrated meta-student improves F1, suggesting targeted adaptation can enhance both performance and calibration in this setting.

- **96×96:** Baseline ($S_b$) leads in accuracy (14.11%), ECE (0.0068) and loss (2.2835) while $S_m$ matches low ECE (0.0095). Recalibrated meta-student maximizes Macro F1 (0.0781). Original and CIFAR-10-recalibrated meta-students suffer higher ECE (0.0540 and 0.1387), indicating limited calibration transfer.
- **224×224:** Mutual ($S_m$) attains highest accuracy (13.56%) and F1 (0.1262) and baseline ($S_b$) retains best ECE (0.0046) and loss (2.2923). Original meta-student degrades (Acc 3.84%, ECE 0.0837).

Minimal adaptation yields low accuracy but honest uncertainty and targeted recalibration improves specific metrics yet cannot fully overcome domain shift.

#### 4.2.1. Stage 3B: Post Fine-tuning Benchmark on STL-10

All four models were fine-tuned on STL-10 (unfreezing the last two backbone blocks and classifier) for 30 epochs, yielding the results in Table 4.

Table 4: Stage 3B: Post Fine-tuning Benchmark on STL-10 Test Set.

| | 96×96 | | | | 224×224 | | | |
|---|---|---|---|---|---|---|---|---|
| Model (Fine-tuned on STL-10) | Acc. (%) | ECE (↓) | Loss | F1 (Macro) | Acc. (%) | ECE (↓) | Loss | F1 (Macro) |
| $S_b$ (Baseline, EffNet-B0) | 77.90 | 0.0576 | 0.7078 | 0.7641 | 90.80 | 0.0189 | 0.2798 | 0.9082 |
| $S_d$ (Distilled, EffNet-B0) | 83.50 | 0.0687 | 0.5626 | 0.8237 | 93.10 | 0.0210 | 0.2323 | 0.9313 |
| $S_m$ (Mutual, EffNet-B0) | 78.50 | 0.0505 | 0.6862 | 0.7660 | 90.55 | 0.0245 | 0.2879 | 0.9057 |
| $S_{meta}$ (Original, EffNet-B1)* | 83.54 | 0.0661 | 0.5519 | 0.8351 | 94.72 | 0.0289 | 0.2088 | 0.9474 |
| $S_{meta}$ (Recalibrated, EffNet-B1) | **94.20** | **0.0266** | **0.0504** | **0.9421** | **98.20** | **0.0058** | **0.0140** | **0.9820** |

* $S_{meta}$ (Original) is the model from Stage 2 before Stage 2.5 recalibration.

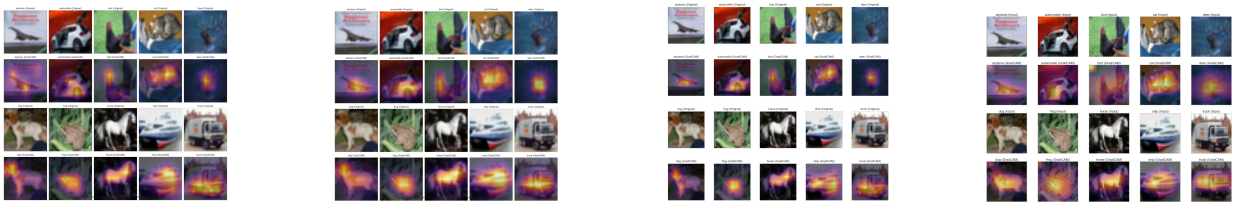
After fine-tuning on STL-10 (Table 4), we observe the following:

**96×96 inputs.** The recalibrated meta-student $S_{\text{meta}}$ (EffNet-B1) now leads all metrics, with 94.20% accuracy, 0.0266 ECE, 0.0504 loss, and 0.9421 F1. This is a marked improvement over the original meta-student (83.54% acc, 0.0661 ECE, 0.8351 F1). The mutual-learning student $S_m$ (EffNet-B0) achieves 0.0505 ECE, while the distilled student $S_d$ (EffNet-B0) retains strong accuracy (83.50%) and F1 (0.8237).

**224 × 224 inputs:** Recalibrated $S_{\text{meta}}$ dominates all metrics: accuracy 98.20%, ECE 0.0058, loss 0.0140, F1 0.9820. The original meta-student and $S_d$ follow with accuracies of 94.72% (F1 0.9474) and 93.10% (F1 0.9313). Baseline $S_b$ and $S_m$ both achieve around 90.6% accuracy. These results highlight (1) the meta-student's exceptional transfer when recalibrated for high-resolution inputs, and (2) the calibration benefits of mutual learning at lower resolution.

### 4.3. Qualitative Analysis with GradCAM

To interpret model behavior, we applied Grad-CAM to CIFAR-10 samples for four students: Baseline ($S_b$), Ensemble Distillation ($S_d$), Mutual-Learning ($S_m$), and Meta-Student ($S_{meta}$). Figure 5 shows original images (top row) and their Grad-CAM heatmaps (bottom row). Distilled, mutual, and meta models consistently highlight the true object, whereas the baseline often attends to irrelevant regions. Qualitatively confirming our quantitative results.



(a) Baseline ($S_b$) (b) Ensemble Distillation ($S_d$) (c) Mutual-Learning ($S_m$) (d) Meta-Student ($S_{meta}$)

Fig. 5: Grad-CAM visualizations on CIFAR-10 for Stage 1 students: (a) Baseline ($S_b$), (b) Ensemble Distillation ($S_d$), (c) Mutual-Learning ($S_m$), and Stage 2 Student: (d) Meta-Student ($S_{meta}$).

## 5. Discussion & Conclusion

CALM's multi-stage design yields models that excel in accuracy, calibration, and transferability.

**Source-domain performance (CIFAR-10):** In Stage 1, ACP + HFI enables the distilled student $S_d$ to achieve peak accuracy and the mutual student $S_m$ to obtain the lowest ECE, confirming the value of combining distillation, mutual learning, and adaptive scheduling. Stage 2's AKTP fusion into $S_{\text{meta}}$, followed by targeted recalibration (Stage 2.5), produces a model with 97.16% accuracy and 0.0077 ECE, surpassing all Stage 1 variants.

**Cross-domain transfer (STL-10):**

*Zero-shot (Stage 3A):* All models show low accuracy but honest uncertainty. At 96×96, baseline $S_b$ leads with 14.11% acc and 0.0068 ECE and mutual $S_m$ leads at 224×224 with 13.56% acc, while $S_b$ records the best ECE (0.0046). Recalibrated meta-student boosts Macro F1 to 0.0781 (96×96).

*Fine-tuned (Stage 3B):* At 96×96, recalibrated $S_{\text{meta}}$ (EffNet-B1) achieves 94.20% acc, 0.0266 ECE, and 0.9421 F1. Original meta-student and $S_d$ reach ≈83.5% acc. At 224×224, recalibrated $S_{\text{meta}}$ dominates all metrics (98.20% acc, 0.0058 ECE, 0.9820 F1), underscoring the benefit of targeted recalibration for high-resolution adaptation.

These findings validate ACP for stable multi-loss training, HFI for cross-architecture fusion, AKTP for dynamic knowledge blending, and recalibration for refining uncertainty. CALM thus provides a systematic recipe for building accurate, well-calibrated vision models that transfer reliably across domains.

**Future work** will conduct detailed ablations of ACP, HFI, and AKTP; explore richer AKTP signals and larger benchmarks; and develop a "ConvFormer" that integrates CNNs for local features with Transformers for global context to further boost performance and calibration.

## AI Usage Declaration

We declare that we used ChatGPT (OpenAI) solely to paraphrase portions of the manuscript in order to meet page-length requirements. All paraphrased text was critically reviewed and edited by the authors to ensure accuracy, originality, and appropriate academic tone. The core research, methodology, experiments, and original ideas are solely the work of the authors.

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