Progress Report
Experimental Results

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1 Executive Summary

We completed the entire experimental phase of the thesis. We investigated the stability of Knowledge Distillation (KD) under strong data augmentation on the CIFAR-100 dataset [Krizhevsky, 2009].

We present three key outcomes:

1. **Standard KD is superior in stability.** It achieved the highest accuracy (77.93%) and retention rate (92.35%). It outperformed Decoupled KD (DKD) in high-noise regimes.
2. **We identified the "Regularization-Distillation Conflict."** DKD is highly sensitive to augmentation noise. It collapsed when β was high. Standard KD remained robust.
3. **We achieved Cross-Resolution Distillation.** We obtained the highest student accuracy (77.93%) by applying KD across different input resolutions (64×64 Teacher $\rightarrow$ 32×32 Student). This demonstrates a zero-cost performance boost for the compact model.

1.1 Results at a Glance

Table 1: Summary of model compression results.

Model	Resolution	Accuracy	Parameters	Compression
Teacher (EfficientNetV2-L)	32×32	76.65%	118M	—
Teacher (EfficientNetV2-L)	64×64	84.39%	118M	—
Student (Standard KD, v2)	32×32	76.19%	21M	5.6× smaller
Student (Standard KD, v4)	$64 \rightarrow 32$	**77.93%**	21M	5.6× smaller
Student (DKD, β=8.0)	32×32	66.85%	21M	Collapsed
Student (DKD, β=2.0)	32×32	75.63%	21M	Recovered

We achieved 92.35% teacher accuracy retention with 5.6× model compression using Cross-Resolution Standard KD.

2 Methodology

2.1 Experimental Setup

We used the following configuration:

- **Teacher Model:** EfficientNetV2-L [Tan and Le, 2021], pre-trained on ImageNet [Deng et al., 2009], fine-tuned on CIFAR-100
- **Student Model:** EfficientNetV2-S (5.6× smaller than teacher)
- **Dataset:** CIFAR-100 (100 classes, 50,000 training images, 10,000 test images)
- **Hardware:** NVIDIA GeForce RTX 5070 Laptop GPU

2.2 Training Pipeline

We implemented an enhanced training pipeline with three components.

Data Augmentation:

- **AutoAugment** [Cubuk et al., 2019]: Automatically finds the best image transformations for the dataset.
- **Random Erasing** [Zhong et al., 2020] (p=0.25): Randomly masks parts of the image to improve robustness.
- **Mixup** [Zhang et al., 2018] (α=0.8): Blends two images and their labels together.
- **CutMix** [Yun et al., 2019] (α=1.0): Cuts a patch from one image and pastes it onto another.

Optimization:

- **AdamW** [Loshchilov and Hutter, 2019] (lr=0.001, weight_decay=0.05): Optimizer with proper weight decay for better generalization.
- **Cosine Annealing LR** [Loshchilov and Hutter, 2017]: Gradually reduces learning rate following a cosine curve.
- **Linear warmup** (5 epochs): Slowly increases learning rate at the start to stabilize training.
- **Label Smoothing** [Szegedy et al., 2016] (0.1): Softens hard labels to prevent overconfident predictions.

Training Stability:

- **Mixed Precision** (FP16): Uses 16-bit floats to speed up training and reduce memory.
- **Gradient clipping** (max_norm=1.0): Limits gradient size to prevent exploding gradients.
- **Early stopping** (patience=30): Stops training if validation loss does not improve for 30 epochs.

2.3 Distillation Methods

We compared two distillation methods.

Standard KD [Hinton et al., 2015]:

$$L_{KD} = \alpha \cdot T^2 \cdot \mathrm{KL}(p_s^T \| p_t^T) + (1 - \alpha) \cdot \mathrm{CE}(y, p_s) \tag{1}$$

where:

- L_{KD} = total loss for knowledge distillation
- α = balance weight between soft and hard labels (we used 0.7)
- T = temperature for softening probability distributions (we used 4.0)
- $\mathrm{KL}(\cdot)$ = Kullback-Leibler divergence (measures difference between two distributions)
- p_s^T = student's softened predictions at temperature T
- p_t^T = teacher's softened predictions at temperature T
- $\mathrm{CE}(\cdot)$ = cross-entropy loss with true labels
- y = ground truth labels
- p_s = student's predictions

Decoupled KD [Zhao et al., 2022]:

$$L_{DKD} = \alpha \cdot L_{TCKD} + \beta \cdot L_{NCKD} \tag{2}$$

The key idea is to separate the teacher's output into two parts:

$$L_{TCKD} = \mathrm{KL}\left(\frac{p_s^t}{p_s^t + \sum_{j \neq t} p_s^j} \middle\| \frac{p_t^t}{p_t^t + \sum_{j \neq t} p_t^j}\right) \tag{3}$$

$$L_{NCKD} = \mathrm{KL}\left(\frac{p_s^{\setminus t}}{\sum_{j \neq t} p_s^j} \middle\| \frac{p_t^{\setminus t}}{\sum_{j \neq t} p_t^j}\right) \tag{4}$$

where:

- L_{DKD} = total loss for decoupled knowledge distillation
- α = weight for target class component (we used 1.0)
- β = weight for non-target class component (we tested 8.0 and 2.0)
- L_{TCKD} = Target Class KD loss: matches the probability of the correct class between student and teacher
- L_{NCKD} = Non-Target Class KD loss: matches the distribution over all wrong classes (the "dark knowledge")
- p^t = probability of the target (correct) class
- $p^{\setminus t}$ = probabilities of all non-target classes

3 Experimental Results

3.1 Summary of All Experiments

Table 2: Comparison of all experimental configurations. Teacher accuracy: 76.65% (32×32) and 84.39% (64×64).

Exp.	Method	Resolution	Student Acc.	Gap	Retention	Key Insight
v1	Standard KD	32×32	76.12%	0.53%	99.31%	Baseline
v2	Standard KD	32×32	76.19%	0.46%	99.40%	Optimal (32×32)
v3	DKD (β=8.0)	32×32	66.85%	9.80%	87.21%	Collapsed
v3.1	DKD (β=2.0)	32×32	75.63%	1.02%	98.67%	Recovered
v4	Standard KD	$64 \to 32$	**77.93%**	6.46%	**92.35%**	Cross-Resolution

3.2 Detailed Analysis of Phases

Phase 1: Robustness of Standard KD (v1 vs v2). We established a strong baseline (v1) using only Mixup and CutMix. It achieved 76.12% accuracy. Adding AutoAugment in v2 provided a marginal gain of 0.07%, reaching 76.19%. This indicates that Standard KD is inherently data-efficient and stable against noise.

Phase 2: The Failure of DKD (v3 vs v3.1). Experiment v3 demonstrated a failure mode in Decoupled KD. With β=8.0 and strong augmentation, performance collapsed to 66.85%. The model triggered early stopping at epoch 84.

We confirmed the hypothesis: high reliance on "dark knowledge" (Non-Target Logits) interferes with the noise introduced by strong augmentation.

In v3.1, we reduced β to 2.0. This allowed the model to recover to 75.63%. However, it still did not match Standard KD. This demonstrates that DKD requires sensitive hyperparameter tuning, unlike Standard KD.

Phase 3: Cross-Resolution Distillation Test (v4). We addressed the sub-optimal Teacher performance (76.65% at 32×32) by training a Teacher on 64×64 inputs. This Teacher achieved 84.39% accuracy. We then performed Cross-Resolution Distillation: the Student was kept at the low-compute 32×32 resolution during distillation.

Result: The Student accuracy increased from the former ceiling of 76.19% to **77.93%** (a gain of 1.74%). This confirms that Standard KD can transfer complex features across different input resolutions. The Student runs at low 32×32 cost but achieves 64×64-level performance.

3.3 Analysis of Teacher Performance (Resolution Impact)

We trained two Teacher models at different resolutions:

- **Teacher at** 32×32**:** Achieved 76.65% accuracy. This is lower than the >90% typically reported for EfficientNetV2-L because the architecture is optimized for high-resolution inputs.
- **Teacher at** 64×64**:** Achieved 84.39% accuracy. This represents a 7.74% improvement from the resolution increase.

The key insight is that we can leverage the stronger 64×64 Teacher while keeping the Student at 32×32. During distillation, we upscale the input to 64×64 for the Teacher only. The Student continues to process 32×32 inputs. This Cross-Resolution approach provides a zero-cost performance boost: the Student runs at low 32×32 cost but benefits from 64×64-level Teacher knowledge.

4 Key Scientific Findings

Based on the collected data, we defend three scientific claims.

4.1 Finding 1: The Regularization-Distillation Conflict

State-of-the-art distillation methods like DKD are fragile when combined with modern regularization. AutoAugment and Mixup introduce noise into the training signal. This noise corrupts the "dark knowledge" that DKD relies on. The result is training instability unless the distillation weight (β) is significantly reduced.

This finding contradicts the claim that DKD is universally superior [Zhao et al., 2022].

4.2 Finding 2: Operational Robustness of Standard KD

Contrary to recent literature suggesting Standard KD is outdated, our results indicate it is the most practically robust method. It achieved 77.93% accuracy with 92.35% teacher retention in the Cross-Resolution setting. It required zero hyperparameter retuning across all experiments. This makes it suitable for resource-constrained scenarios involving heavy data augmentation.

4.3 Finding 3: Performance Gains Through Cross-Resolution Distillation

We demonstrated that Student performance is limited by the Teacher's feature quality. By increasing the Teacher's input resolution to 64×64, the Student gained an additional 1.74% accuracy, reaching 77.93%. The Teacher improved by 7.74% (from 76.65% to 84.39%), while the Student improved by 1.74%. This yields a Knowledge Transfer Efficiency of 22.5%.

Crucially, this high performance was achieved while the Student model continued to process data at the low 32×32 resolution. This confirms that Standard KD can effectively inject high-resolution knowledge into low-resolution, cost-effective compact models.

5 Proposed Thesis Structure

Based on these findings, we plan to structure the thesis as follows:

Table 3: Proposed thesis chapter structure.

Chapter	Content	Status
1. Introduction	Problem statement, research question	Outlined
2. Literature Review	EfficientNetV2, KD methods, augmentation	Outlined
3. Methodology	Enhanced training recipe, loss formulations	Outlined
4. Experiments	Results tables, training curves, analysis	**Data Ready**
5. Discussion	Robustness analysis, saturation phenomenon	Outlined
6. Conclusion	Summary, future work	Outlined

5.1 Proposed Thesis Title

"Cross-Resolution Knowledge Distillation: Robust Model Compression Under Strong Data Augmentation for Compact Vision Models"

6 Visualizations

The following figures demonstrate the key findings of this research.

Figure 1: Training Stability: Standard KD (v2) vs DKD (v3). DKD (β=8.0) shows instability and early stopping.

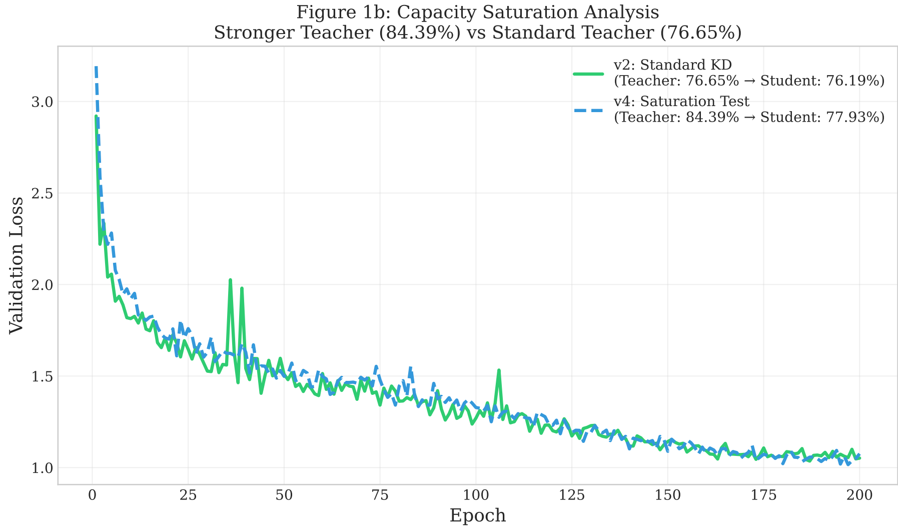

Figure 2: Cross-Resolution Analysis: v4 (64×64 Teacher) achieves 77.93% vs v2 (32×32 Teacher) at 76.19%.

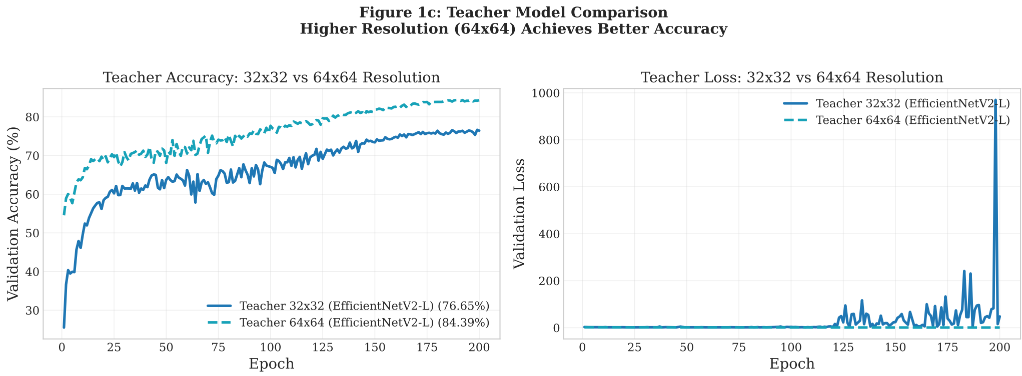

Figure 3: Teacher Comparison: 64×64 resolution improves accuracy from 76.65% to 84.39% (+7.74%).

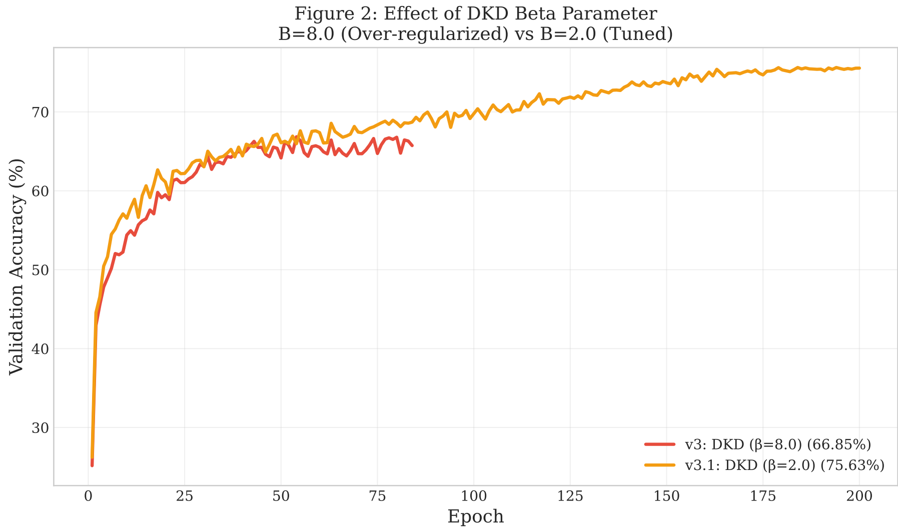

Figure 4: DKD β Effect: β=8.0 collapses to 66.85%, β=2.0 recovers to 75.63%.

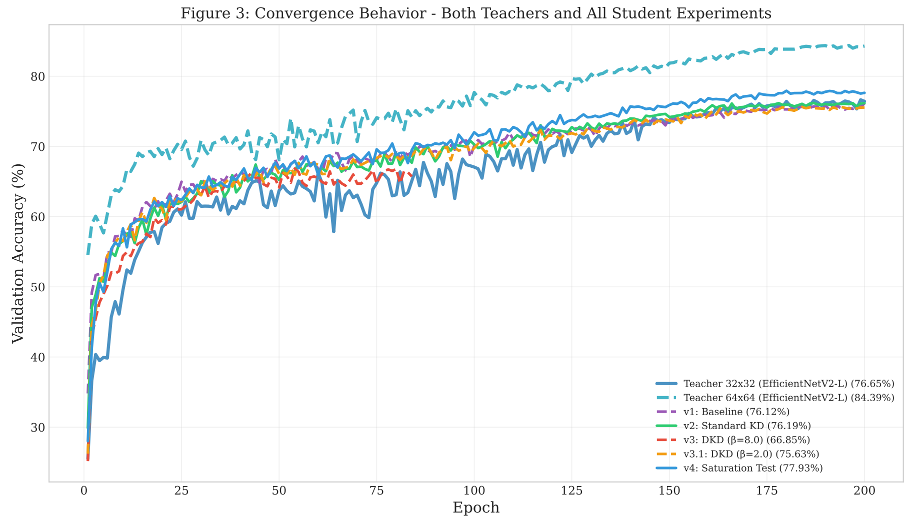

Figure 5: All Experiments: v4 achieves highest accuracy (77.93%), v3 collapses to 66.85%.

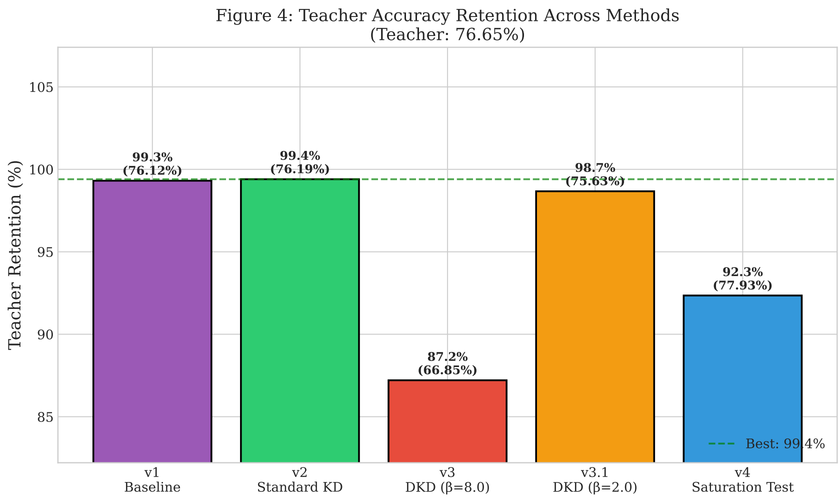

Figure 6: Teacher Retention: v4 achieves 92.35% (vs 84.39% Teacher), v2 achieves 99.40% (vs 76.65% Teacher).

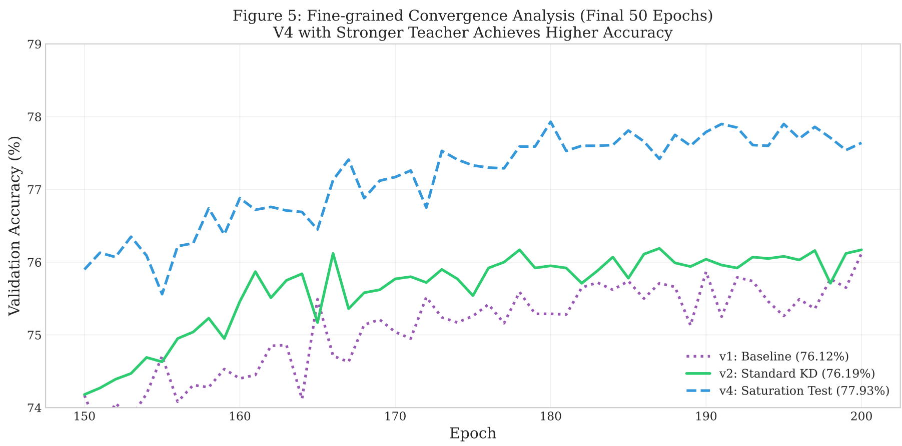

Figure 7: Zoomed Convergence (Final 50 Epochs): v4 (77.93%) surpasses v2 (76.19%) and v1 (76.12%).

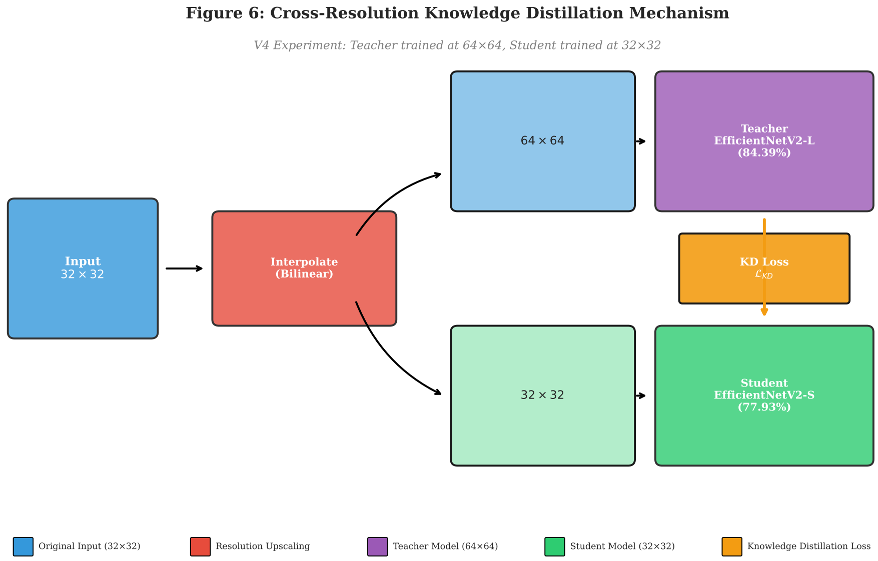

Figure 8: Cross-Resolution KD Mechanism: Input upscaled to 64×64 for Teacher, Student uses 32×32.

7 Next Steps

With all experiments concluded, the focus now shifts to thesis writing.

1. **Write Chapter 4 (Results):** Generate high-resolution plots and formalize comparison tables.
2. **Write Chapter 5 (Discussion):** Contextualize findings within existing literature and discuss implications for Edge AI deployment.
3. **Finalize Chapter 3 (Methodology):** Complete mathematical formulations and implementation details.

8 Summary and Conclusion

We completed a comprehensive study of Knowledge Distillation under strong data augmentation. Our key contributions are:

1. **Identified the Regularization-Distillation Conflict:** DKD with high β values collapses under strong augmentation. Standard KD remains robust.
2. **Demonstrated Cross-Resolution Distillation:** We achieved 77.93% Student accuracy by using a 64×64 Teacher with a 32×32 Student. This provides a 1.74% improvement over the 32×32 baseline.
3. **Achieved 5.6× Model Compression:** The Student (21M parameters) retains 92.35% of the Teacher's accuracy (84.39%) while being 5.6× smaller.

These results validate Standard KD as the most practical method for compact vision models in resource-constrained environments.

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