Shape Classification on Synthetic Dataset: Methodology, Results, and Key Insights

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1. Methodology

1. **Synthetic Data Generation**
    - Generated **2,400** images (3 shapes × 4 conditions × 200 each) at **256×256** pixels.
    - **Shapes:** circle, square, triangle
    - **Conditions** (`CONDITIONS = ["FLFR","FLRR","RLFR","RLRR"]`):
        - **FLFR**: Fixed size = 70 px, fixed rotation = 90°
        - **FLRR**: Fixed size = 70 px, random rotation ∈ [0,360°]
        - **RLFR**: Random size ∈ [50–80 px], fixed rotation = 90°
        - **RLRR**: Random size ∈ [50–80 px], random rotation ∈ [0,360°]
    - **Backgrounds:** random solid color + Gaussian noise ($\sigma = 5$), introducing mild variability.
2. **Data Splitting**
    - **Baseline (Random-Split):**
        - Train: 1,680
        - Val: 360
        - Test: 360

        (Stratified by `shape` and `condition`.)
    - **Held-Out RLRR:**

    - Train: 1,440 (all but RLRR)
    - Val: 360
    - Test: 600 (RLRR only)
3. **Preprocessing & Augmentation**
    - **Resize** (to 256×256), **ToTensor**, then **Normalize** using computed mean/std.
    - **Train transforms:** full-range rotations, horizontal flips.
    - **Eval transforms:** resize + normalize only.
4. **Data Preparation**
    - Resized to 256×256, converted to tensors, and normalized per-channel using computed mean/std.
    - Training transforms: random rotations, horizontal flips.
    - Validation/test transforms: resize + normalize only.
5. **Model & Training**
    - **Architecture:** ResNet-18 (random init), final layer adjusted for 3 classes.
    - **Loss:** Cross-entropy; **Optimizer:** AdamW (lr=1e-3, weight_decay=1e-4); **Scheduler:** CosineAnnealingLR.
    - **Training:** up to 20 epochs with early stopping (stop when val_acc ≥ 99% or no improvement for 5 epochs).
    - **Metrics logged:** train/val loss & accuracy per epoch.

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2. Results

2.1 Baseline (Random-Split Test)

- **Train samples:** 1,680
- **Val samples:** 360
- **Test samples:** 360

- **Training accuracy:** climbed to ~100%
- **Validation accuracy:** similarly near-perfect when patterns matched
- **Test accuracy: 33%** (chance level on 3 classes), indicating the model had learned condition-specific shortcuts rather than true shape features.

2.2 Held-Out RLRR Experiment

- **Train:** 1,440 (all but RLRR)
- **Val:** 360
- **Test (RLRR only):** 600
- **Validation accuracy:** fluctuated, with early stopping at epoch 16 (val_acc ≈ 87.5%)
- **Held-out RLRR test accuracy: 92.2%**, showing strong generalization to fully random size+rotation once RLRR was truly unseen during training.

2.3 Training Dynamics

- **Training vs. Validation Loss & Accuracy**
  - Training loss steadily decreased to near zero; train accuracy reached ~98–100%.
  - Validation curves showed spikes—episodes of overfitting followed by recovery at epochs 4, 9, 11, 14.

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3. Observations & Conclusions

1. **Chance-Level Baseline**
   - On a random train/val/test split, test accuracy was 33%, exactly chance, revealing the model had not learned generalizable shape concepts when all conditions were mixed.
2. **Condition-Dependent Learning**
   - Near-perfect validation on seen patterns but poor random-split test performance indicates the model was exploiting “pixel-level shortcuts” tied to specific size/rotation combinations.

3. **Generalization via Held-Out Test**
    - Reserving RLRR for final evaluation provided a realistic stress test: achieving 92.2% demonstrates the network can truly learn geometry when those extreme variations are withheld from training.
4. **Data Homogeneity Concerns**
    - Uniform noise and background style allowed the network to use consistent background cues. Real-world data would require far more diverse backgrounds and noise patterns.

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4. Next Steps

- **Augmentation Enhancements:** full 360° rotations, random affine warps, color/contrast jitter, dynamic noise.
- **Transfer Learning:** leverage ImageNet-pretrained weights for stronger low-level feature extraction.
- **Regularization:** add dropout, increase weight decay, use label smoothing.
- **Cross-Condition Validation:** rotate held-out conditions (FLFR, FLRR, RLFR, RLRR) for a comprehensive generalization profile.
- **Simpler Architectures:** test TinyConvNet or MobileNetV2 to balance capacity and data size.
- **Evaluation Feedback:** inspect misclassified edge cases and visualize feature embeddings (t-SNE) to refine data or model.

In summary, our early 33% test result under a random split highlighted the need for condition-aware evaluation. The held-out RLRR strategy and targeted improvements confirm robust shape learning—and pave the way to even higher, more reliable accuracy on completely unseen variations.