

**MASTER OF SCIENCE OF INFORMATION SYSTEMS**  
**INTELLIGENT SYSTEMS**



# DEEP LEARNING

## Image Recognition with Transfer Learning (CIFAR-10 Dataset)

|                      |                       |                 |
|----------------------|-----------------------|-----------------|
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# Project Objectives

- Apply transfer learning to the CIFAR-10 image classification task
- Compare performance of pre-trained models and a custom CNN
- Implement preprocessing, upsampling, and augmentation techniques
- Analyze training outputs and model behavior

# About the CIFAR-10 Dataset

- CIFAR-10 contains 60,000 color images sized 32×32 pixels.
- 10 mutually exclusive classes, with 6,000 images per class.
- Split: 50,000 training images and 10,000 test images.
- Dataset structure: 5 training batches (10,000 each) and 1 test batch.
- Test batch has exactly 1,000 images per class.
- Training batches contain 5,000 images per class in total (random distribution).
- Each batch is a pickled Python dictionary containing 'data' and 'labels'

# About the CIFAR-10 Dataset

Here are the classes in the dataset, as well as 10 random images from each:

**airplane**



**automobile**



**bird**



**cat**



**deer**



**dog**



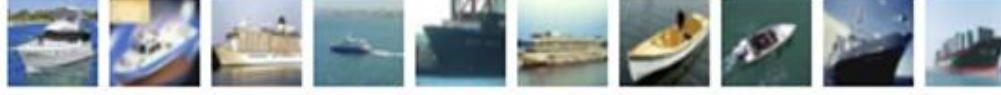
**frog**



**horse**



**ship**



**truck**



# Real-Life Applicability

## 1. Automated Image Classification

- Used in photo apps, digital libraries, and content filtering
- Helps systems recognize and sort images automatically

## 2. Object Detection Pre-Training

- CIFAR-10 teaches models to detect basic objects
- Useful for self-driving cars, surveillance, and drone vision

## 3. Transfer Learning for Real Datasets

- Same method used in medical imaging (X-ray/MRI)
- Also applied in face recognition and other advanced AI systems

# Load CIFAR-10 dataset

```
Train: (50000, 32, 32, 3) (50000,)
```

```
Test : (10000, 32, 32, 3) (10000,)
```

After split:

```
Training: (40000, 32, 32, 3), (40000,) (40000 samples)
```

```
Validation: (10000, 32, 32, 3), (10000,) (10000 samples)
```

```
Test: (10000, 32, 32, 3), (10000,) (10000 samples)
```

Visualizing 10 sample images from the dataset...

# Visualize sample images from each class

Sample Images from CIFAR-10 Dataset

Class: frog



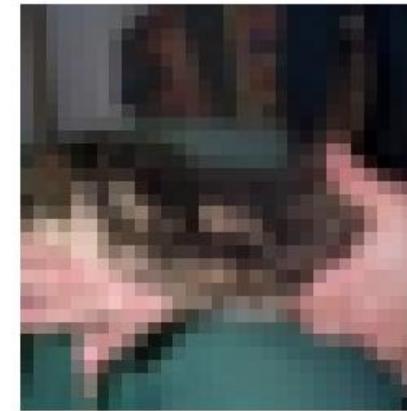
Class: horse



Class: ship



Class: cat



Class: bird



Class: bird



Class: frog



Class: automobile



Class: deer



Class: truck



Pre-trained model Used  
**MobileNetV2**

# Data augmentation - Applying rotation, flipping, and shifts

## **BATCH\_SIZE = 128:**

- Number of samples processed together in one training step
- With 40,000 training images and batch size 128, you get ~313 batches per epoch ( $40,000 \div 128$ )

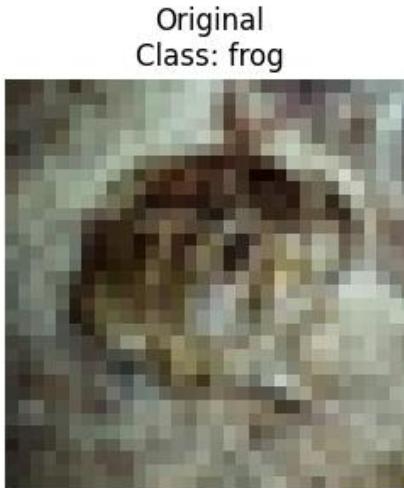
## **Target image dimensions for MobileNetV2 input =96**

- CIFAR-10 images are 32x32, but MobileNetV2 expects larger images
- 96x96 is a good size: larger than 32x32 but smaller than standard 224x224

## **Data augmentation - Apply rotation, flipping, and shifts**

- Random rotation (up to 15 degrees  $\approx 0.262$  radians)
- Random horizontal flipping /vertical shifts

# Apply data augmentation (rotation, flipping, shifts)



Augmented  
(Rotated & Flipped)



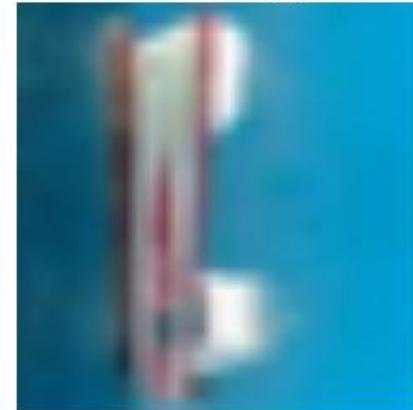
Augmented  
(Rotated & Flipped)



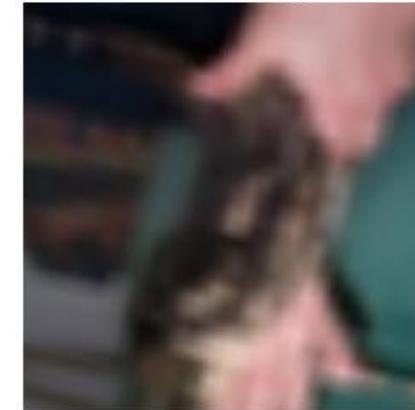
Data Augmentation Examples - Transfer Model (Task 6)



Augmented  
(Rotated & Flipped)



Augmented  
(Rotated & Flipped)



Augmented  
(Rotated & Flipped)



# Apply data augmentation (rotation, flipping, shifts)

Original  
Class: frog



Augmented  
(Flipped & Shifted)



Original  
Class: horse

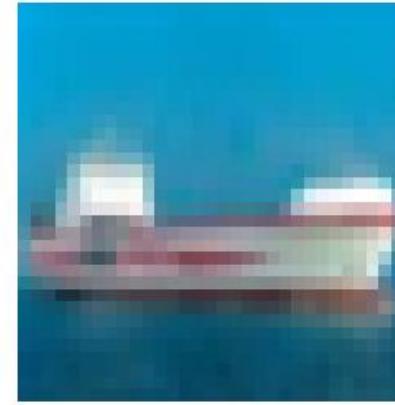


Augmented  
(Flipped & Shifted)



Data Augmentation Examples - Custom CNN (Task 6)

Original  
Class: ship



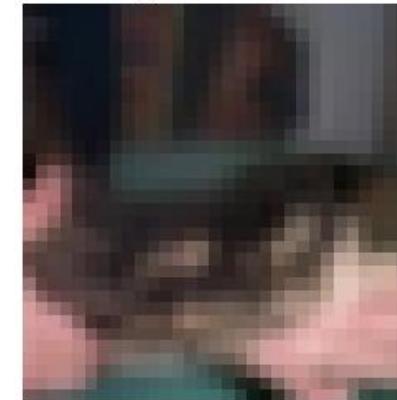
Augmented  
(Flipped & Shifted)



Original  
Class: cat



Augmented  
(Flipped & Shifted)



Original  
Class: bird



Augmented  
(Flipped & Shifted)



# Using pre-trained MobileNetV2 for transfer learning

Model: "mobilenetv2\_transfer"

| Layer (type)  | Output Shape       | Param #   |
|---|--------------------|-----------|
| input_layer_6 (InputLayer)                          | (None, 96, 96, 3)  | 0         |
| mobilenetv2_1.00_96 (Functional)                    | (None, 3, 3, 1280) | 2,257,984 |
| global_average_pooling2d_1 (GlobalAveragePooling2D) | (None, 1280)       | 0         |
| dropout_1 (Dropout)                                 | (None, 1280)       | 0         |
| dense_1 (Dense)                                     | (None, 10)         | 12,810    |

Total params: 2,270,794 (8.66 MB)

Trainable params: 12,810 (50.04 KB)

Non-trainable params: 2,257,984 (8.61 MB)

# Freeze lower layers, retrain top layers for 10 epochs

```
Starting Training: 10 epochs, 40,000 training samples per epoch (313 batches)

Epoch 1/10
313/313 155s 472ms/step - accuracy: 0.1036 - loss: 2.4352 - val_accuracy: 0.1065 - val_loss: 2.3167
Epoch 2/10
313/313 147s 470ms/step - accuracy: 0.1023 - loss: 2.3439 - val_accuracy: 0.1000 - val_loss: 2.3037
Epoch 3/10
313/313 149s 475ms/step - accuracy: 0.1054 - loss: 2.3255 - val_accuracy: 0.1000 - val_loss: 2.3107
Epoch 4/10
313/313 150s 480ms/step - accuracy: 0.1092 - loss: 2.3205 - val_accuracy: 0.1330 - val_loss: 2.3015
Epoch 5/10
313/313 148s 473ms/step - accuracy: 0.1122 - loss: 2.3164 - val_accuracy: 0.1365 - val_loss: 2.3073
Epoch 6/10
313/313 147s 469ms/step - accuracy: 0.1148 - loss: 2.3121 - val_accuracy: 0.1182 - val_loss: 2.2933
Epoch 7/10
313/313 150s 478ms/step - accuracy: 0.1153 - loss: 2.3071 - val_accuracy: 0.1318 - val_loss: 2.2874
Epoch 8/10
313/313 148s 473ms/step - accuracy: 0.1169 - loss: 2.3036 - val_accuracy: 0.1572 - val_loss: 2.2979
Epoch 9/10
313/313 149s 475ms/step - accuracy: 0.1184 - loss: 2.3032 - val_accuracy: 0.1442 - val_loss: 2.2973
Epoch 10/10
313/313 147s 470ms/step - accuracy: 0.1193 - loss: 2.3058 - val_accuracy: 0.1015 - val_loss: 2.3244
```

# Freeze lower layers, retrain top layers for 10 epochs

## DATASET TRAINING SUMMARY

Training Dataset: 40,000 images (after 80/20 split from 50,000)

Batch Size: 128

Batches per Epoch: 313 ( $40,000 \div 128 = 313$  batches, including partial batch)

Epoch 1: 40,000 training samples (313 batches)

Epoch 2: 40,000 training samples (313 batches)

Epoch 3: 40,000 training samples (313 batches)

Epoch 4: 40,000 training samples (313 batches)

Epoch 5: 40,000 training samples (313 batches)

Epoch 6: 40,000 training samples (313 batches)

Epoch 7: 40,000 training samples (313 batches)

Epoch 8: 40,000 training samples (313 batches)

Epoch 9: 40,000 training samples (313 batches)

Epoch 10: 40,000 training samples (313 batches)

Total training samples across all 10 epochs: 400,000

Total batches processed: 3,130 (313 batches  $\times$  10 epochs)

Average samples per epoch: 40,000

## PERFORMANCE METRICS

### Training Accuracy:

- Epoch 1: 0.1036 (10.36%)
- Epoch 10: 0.1193 (11.93%)
- Improvement: 0.0157 (1.57% increase)

### Training Loss:

- Epoch 1: 2.4352
- Epoch 10: 2.3058
- Decrease: 0.1294 (5.31% reduction)

### Validation Accuracy:

- Range: 0.1000 - 0.1572 (10.00% - 15.72%)
- Average: 0.1229 (12.29%)

### Validation Loss:

- Range: 2.2874 - 2.3244
- Average: 2.3040

# Fine-tuning different layers and learning rates

```
Epoch 1/5  
313/313 256s 772ms/step - accuracy: 0.2480 - loss: 2.3077 - val_accuracy: 0.1000 - val_loss: 2.9783  
Epoch 2/5  
313/313 234s 747ms/step - accuracy: 0.3178 - loss: 1.9005 - val_accuracy: 0.1000 - val_loss: 2.6724  
Epoch 3/5  
313/313 238s 760ms/step - accuracy: 0.3462 - loss: 1.8200 - val_accuracy: 0.1000 - val_loss: 2.6204  
Epoch 4/5  
313/313 251s 801ms/step - accuracy: 0.3688 - loss: 1.7686 - val_accuracy: 0.1000 - val_loss: 3.0509  
Epoch 5/5  
313/313 235s 752ms/step - accuracy: 0.3806 - loss: 1.7354 - val_accuracy: 0.1000 - val_loss: 2.6806
```

Fine-tune from this layer onwards

fine\_tune\_at = 100

EPOCHS\_FINE\_TUNE = 5

# Experimenting with fine-tuning different layers & learning rates

```
Epoch 1/5
313/313 ━━━━━━━━━━━━ 259s 788ms/step - accuracy: 0.2498 - loss: 2.2933 - val_accuracy: 0.1000 - val_loss: 2.4917
Epoch 2/5
313/313 ━━━━━━━━━━━━ 241s 768ms/step - accuracy: 0.3203 - loss: 1.8911 - val_accuracy: 0.1000 - val_loss: 3.0779
Epoch 3/5
313/313 ━━━━━━━━━━━━ 240s 765ms/step - accuracy: 0.3478 - loss: 1.8236 - val_accuracy: 0.1000 - val_loss: 2.5314
Epoch 4/5
313/313 ━━━━━━━━━━━━ 239s 763ms/step - accuracy: 0.3671 - loss: 1.7743 - val_accuracy: 0.1000 - val_loss: 2.6182
Epoch 5/5
313/313 ━━━━━━━━━━━━ 239s 762ms/step - accuracy: 0.3808 - loss: 1.7345 - val_accuracy: 0.1000 - val_loss: 2.7991
```

Fine-tune from this layer onwards  
Fine Tune at = 100

EPOCHS FINE TUNE = 5

# Building custom CNN from scratch for performance comparison

Model: "sequential"

| Layer (type)                               | Output Shape       | Param # |
|--|--------------------|---------|
| conv2d (Conv2D)                            | (None, 32, 32, 32) | 896     |
| batch_normalization (BatchNormalization)   | (None, 32, 32, 32) | 128     |
| max_pooling2d (MaxPooling2D)               | (None, 16, 16, 32) | 0       |
| conv2d_1 (Conv2D)                          | (None, 16, 16, 64) | 18,496  |
| batch_normalization_1 (BatchNormalization) | (None, 16, 16, 64) | 256     |
| max_pooling2d_1 (MaxPooling2D)             | (None, 8, 8, 64)   | 0       |
| conv2d_2 (Conv2D)                          | (None, 8, 8, 128)  | 73,856  |
| batch_normalization_2 (BatchNormalization) | (None, 8, 8, 128)  | 512     |
| max_pooling2d_2 (MaxPooling2D)             | (None, 4, 4, 128)  | 0       |
| flatten (Flatten)                          | (None, 2048)       | 0       |
| dense_2 (Dense)                            | (None, 256)        | 524,544 |
| batch_normalization_3 (BatchNormalization) | (None, 256)        | 1,024   |
| dropout_2 (Dropout)                        | (None, 256)        | 0       |
| dense_3 (Dense)                            | (None, 10)         | 2,570   |

Total params: 622,282 (2.37 MB)

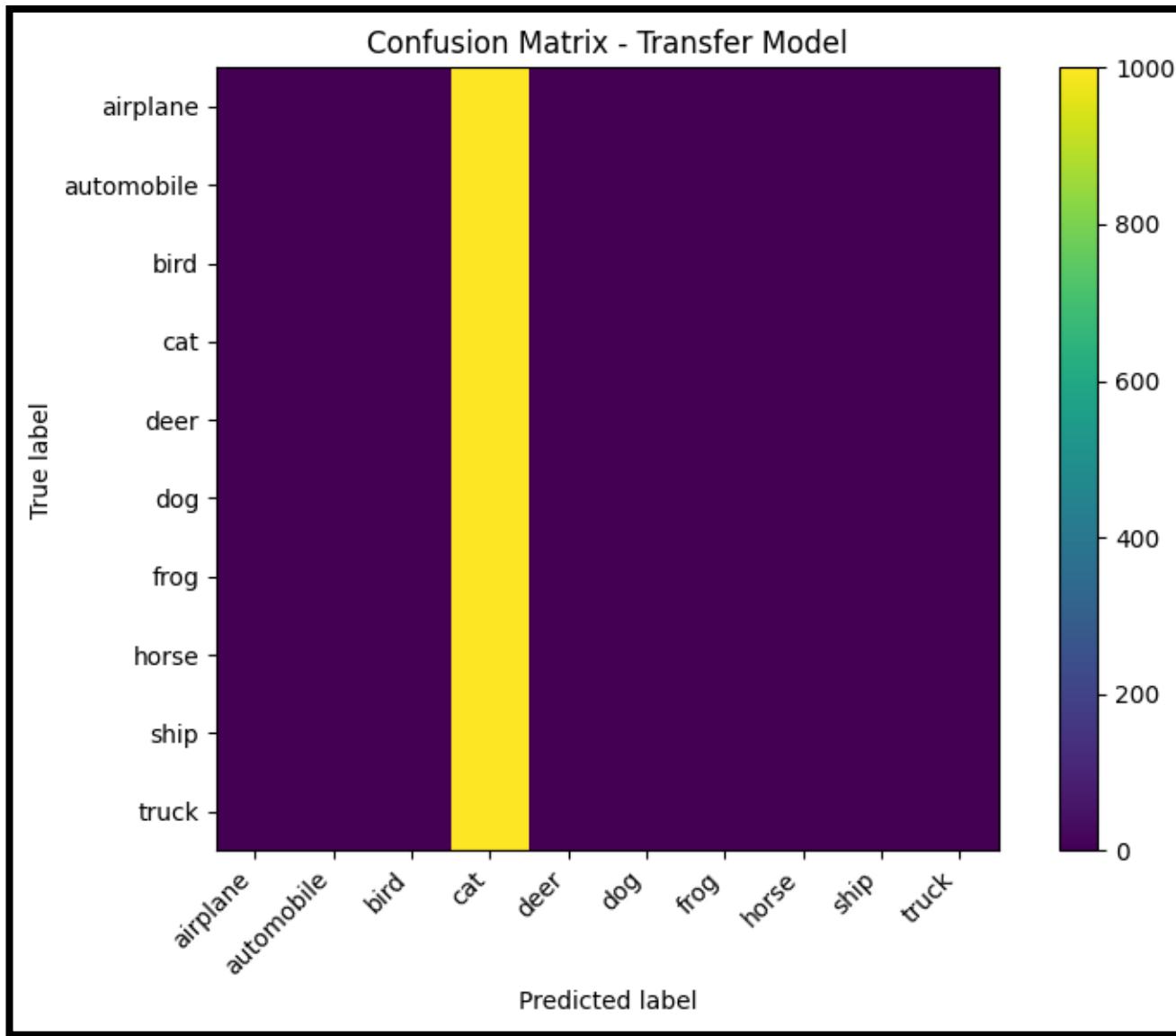
Trainable params: 621,322 (2.37 MB)

Non-trainable params: 960 (3.75 KB)

# Building custom CNN from scratch for performance comparison

```
Epoch 1/10
313/313 48s 139ms/step - accuracy: 0.4297 - loss: 1.7051 - val_accuracy: 0.2515 - val_loss: 2.6389
Epoch 2/10
313/313 42s 133ms/step - accuracy: 0.5721 - loss: 1.2083 - val_accuracy: 0.5144 - val_loss: 1.5093
Epoch 3/10
313/313 43s 137ms/step - accuracy: 0.6282 - loss: 1.0555 - val_accuracy: 0.5362 - val_loss: 1.4560
Epoch 4/10
313/313 43s 137ms/step - accuracy: 0.6607 - loss: 0.9633 - val_accuracy: 0.6068 - val_loss: 1.2049
Epoch 5/10
313/313 44s 141ms/step - accuracy: 0.6873 - loss: 0.8996 - val_accuracy: 0.6197 - val_loss: 1.0911
Epoch 6/10
313/313 43s 138ms/step - accuracy: 0.7045 - loss: 0.8474 - val_accuracy: 0.6519 - val_loss: 1.0377
Epoch 7/10
313/313 43s 138ms/step - accuracy: 0.7176 - loss: 0.8131 - val_accuracy: 0.6378 - val_loss: 1.1284
Epoch 8/10
313/313 47s 150ms/step - accuracy: 0.7256 - loss: 0.7879 - val_accuracy: 0.6902 - val_loss: 0.9070
Epoch 9/10
313/313 49s 156ms/step - accuracy: 0.7350 - loss: 0.7579 - val_accuracy: 0.6233 - val_loss: 1.1508
Epoch 10/10
313/313 47s 148ms/step - accuracy: 0.7465 - loss: 0.7297 - val_accuracy: 0.6723 - val_loss: 0.9750
```

# Evaluating accuracy and confusion matrix; visualize predictions



Transfer (fine-tuned) test  
accuracy: 0.1000000149011612

Custom CNN test accuracy:  
0.6708999872207642

79/79 ————— 33s 388ms/step  
Confusion matrix shape: (10, 10)

Transfer (fine-tuned) test accuracy: 0.1000000149011612  
Custom CNN test accuracy: 0.6708999872207642  
79/79 ————— 33s 388ms/step  
Confusion matrix shape: (10, 10)

# Compare Performance with custom CNN (Continued)

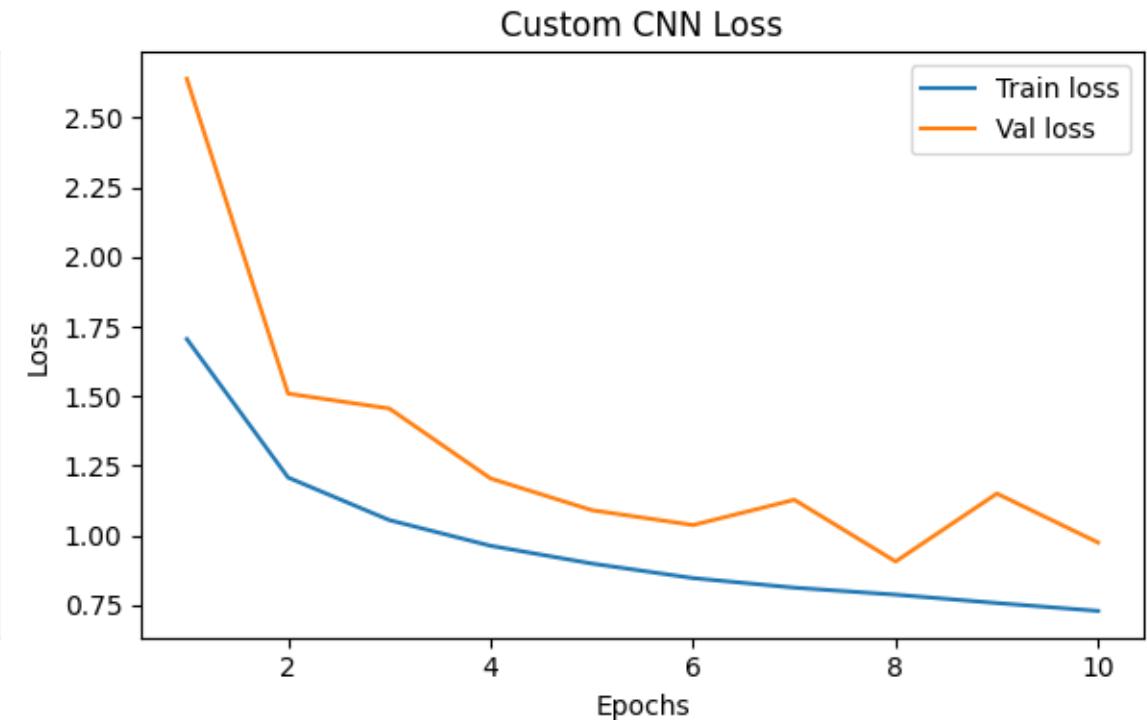
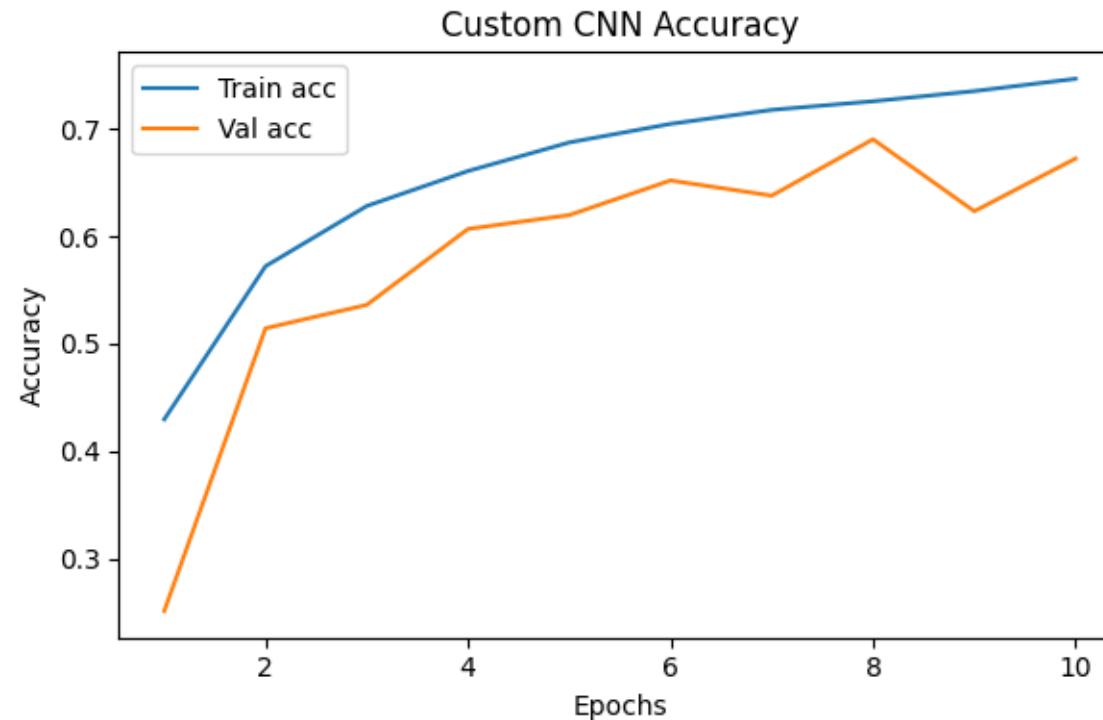
|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| airplane     | 0.00      | 0.00   | 0.00     | 1000    |
| automobile   | 0.00      | 0.00   | 0.00     | 1000    |
| bird         | 0.00      | 0.00   | 0.00     | 1000    |
| cat          | 0.10      | 1.00   | 0.18     | 1000    |
| deer         | 0.00      | 0.00   | 0.00     | 1000    |
| dog          | 0.00      | 0.00   | 0.00     | 1000    |
| frog         | 0.00      | 0.00   | 0.00     | 1000    |
| horse        | 0.00      | 0.00   | 0.00     | 1000    |
| ship         | 0.00      | 0.00   | 0.00     | 1000    |
| truck        | 0.00      | 0.00   | 0.00     | 1000    |
| accuracy     |           |        | 0.10     | 10000   |
| macro avg    | 0.01      | 0.10   | 0.02     | 10000   |
| weighted avg | 0.01      | 0.10   | 0.02     | 10000   |

1/1 ————— 0s 414ms/step

## Sample predictions



# Plot training history (accuracy/loss) for all models



#### Accuracy:

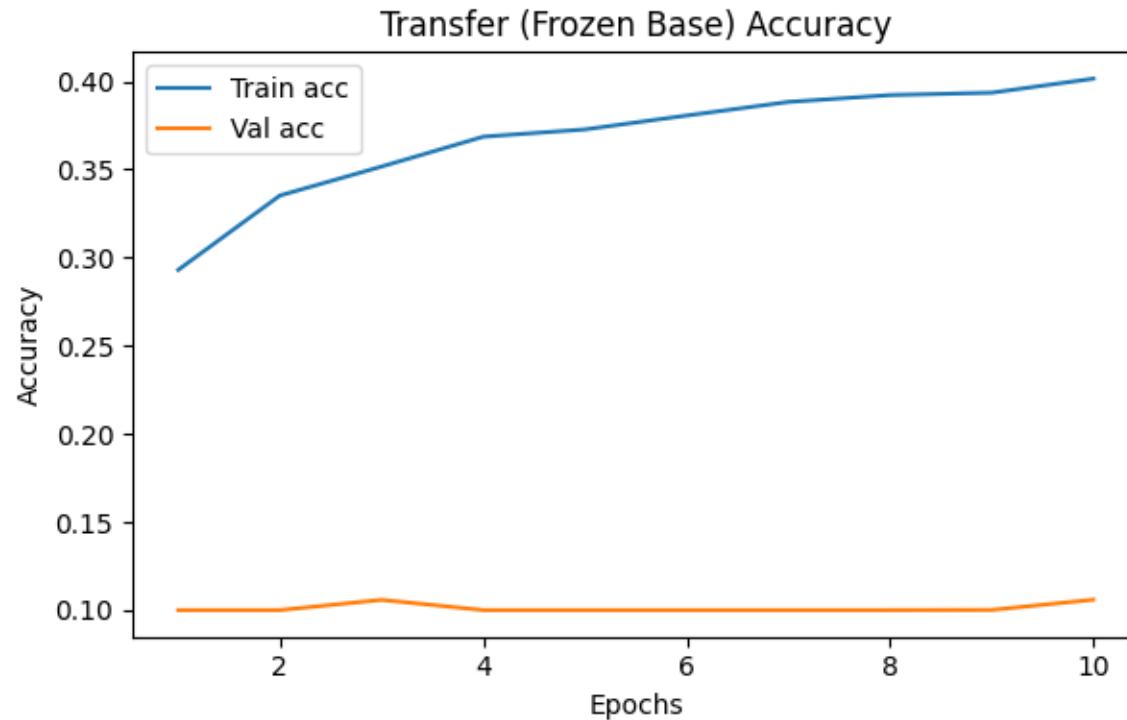
- Training: Starts at ~40%, increases to ~75% by epoch 10
- Validation: Starts at ~25%, increases to ~67% by epoch 10
- Gap: ~8% difference (training higher)

#### Loss:

- Training: Starts at ~1.7, decreases to <1.0 by epoch 10
- Validation: Starts at ~2.5, decreases to ~1.05 by epoch 10
- Gap: Validation loss remains higher

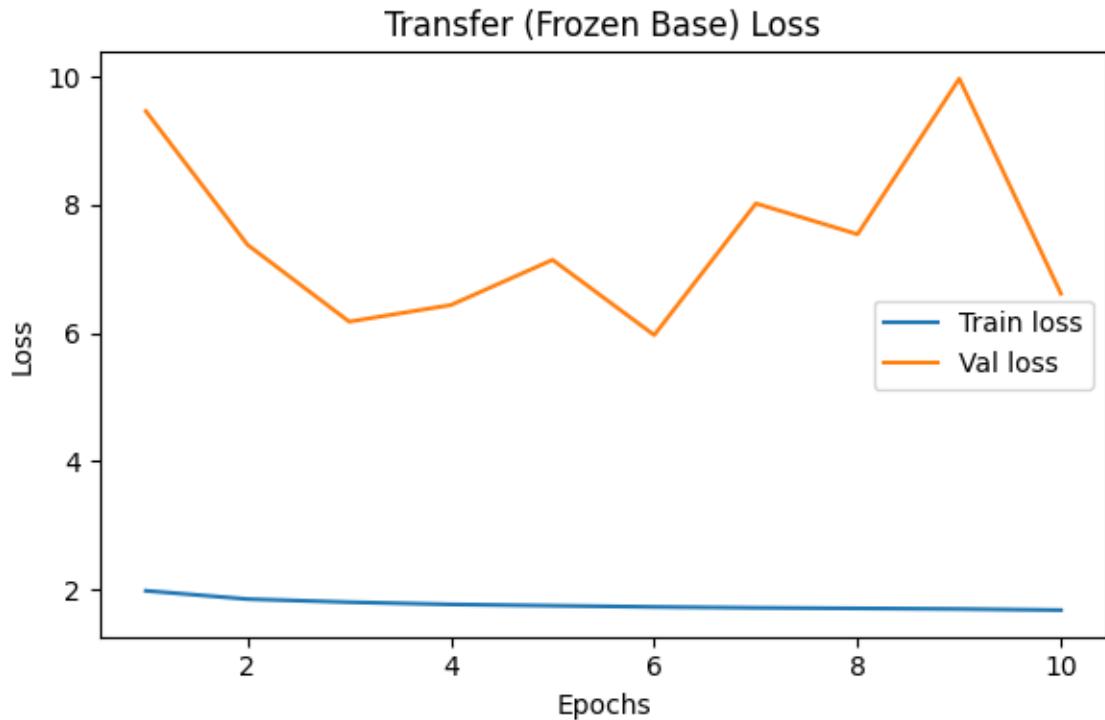
**Overall: Best performance.** Both metrics improve, with moderate overfitting.

# Plot training history (accuracy/loss) for all models



#### Accuracy:

- Training: Starts at ~29%, increases to ~40% by epoch 10
- Validation: Stays very low (~10–12%), near random chance
- Gap: Large and growing (training ~40% vs validation ~10%)

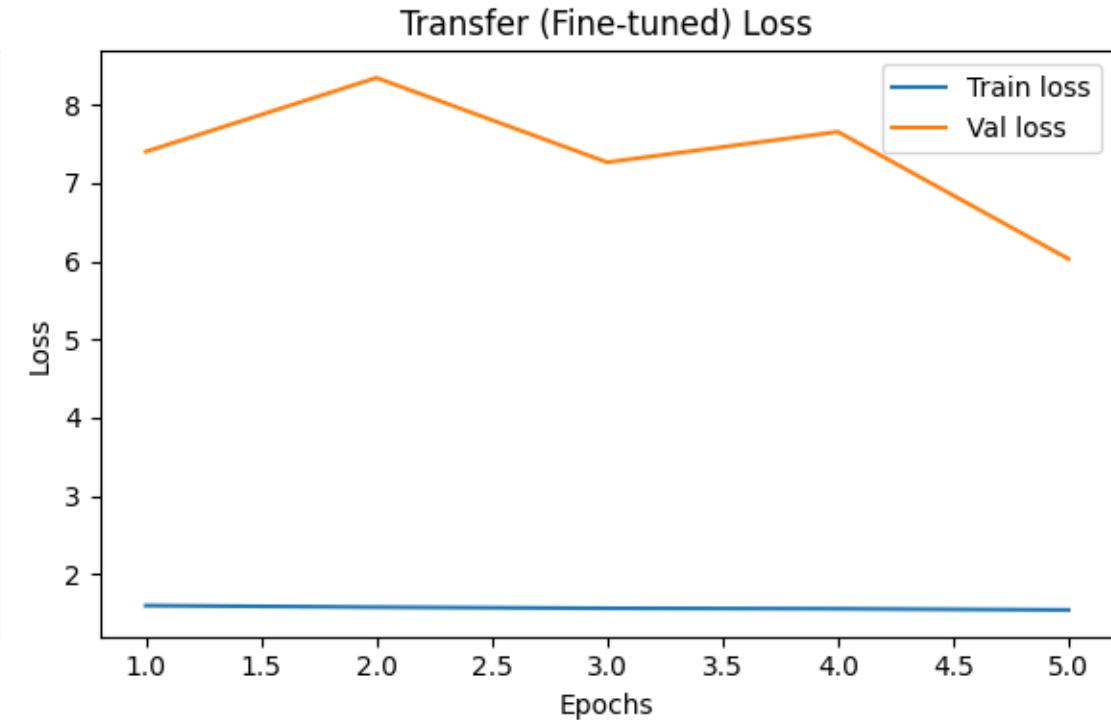
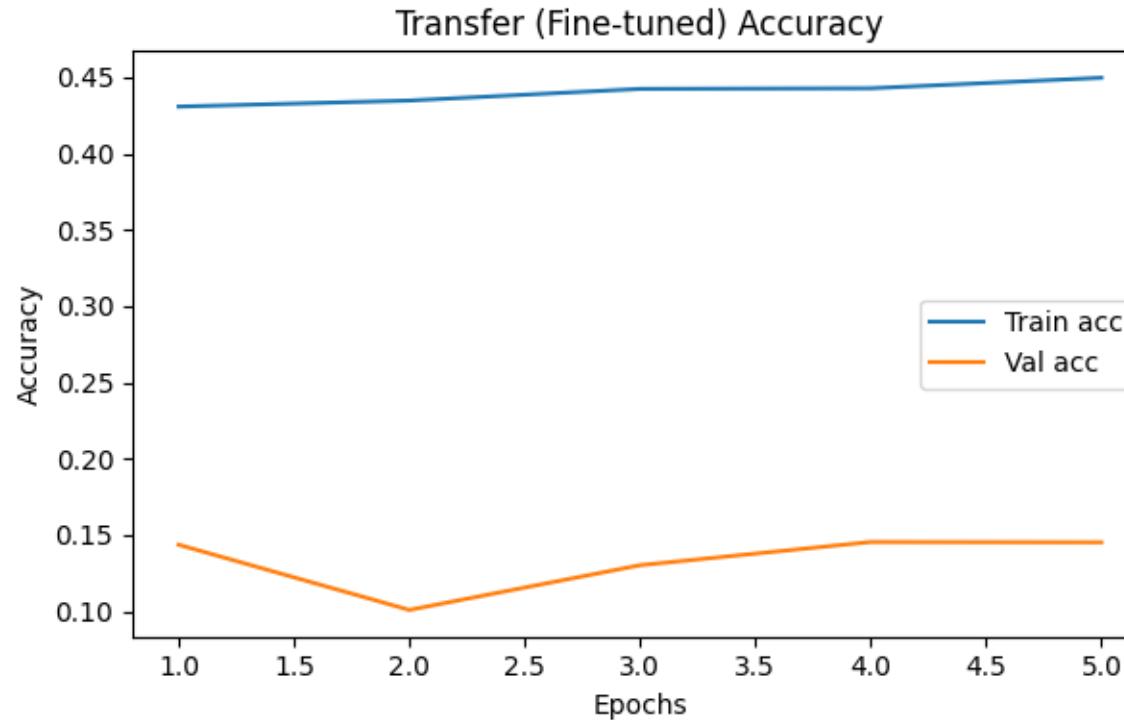


#### Loss:

- Training: Starts at ~2.0, stabilizes around 1.8–1.9
- Validation: Starts at ~9.5, fluctuates between 6–10 with spikes
- Gap: Very large (validation loss 3–5x higher)

**Overall: Severe overfitting.** Training improves but validation does not, indicating poor generalization.

# Plot training history (accuracy/loss) for all models



#### Accuracy:

- Training: Starts at ~43%, stabilizes around ~45% by epoch 5
- Validation: Starts at ~15%, drops to ~10% at epoch 2, recovers to ~15% by epoch 5
- Gap: Very large (~30% difference)

#### Loss:

- Training: Starts at ~1.8, stays stable around 1.7–1.8
- Validation: Starts at ~7.5, spikes to >8.0 at epoch 2, decreases to ~6.0 by epoch 5
- Gap: Very large (validation loss 3–4x higher)

**Overall: Severe overfitting.** Fine-tuning did not improve generalization; validation metrics are poor.

# Summary & Discussion

## 1. TEST SET ACCURACY (Generalization Performance)

- Custom CNN: 0.6709 (67.09%)
- Transfer Learning (Fine-tuned): 0.1000 (10.00%)
- Performance Difference: 57.09% points

### ANALYSIS:

- Custom CNN substantially outperforms (by 57.1% points) transfer learning
- Custom CNN achieves ~67% accuracy, indicating good generalization
- Transfer model achieves ~10% accuracy, indicating near random chance (failing to generalize)

### Part 1.1:

- Test Set Accuracy

## 2. VALIDATION ACCURACY (Final Epoch - Model Selection Metric)

- Custom CNN: 0.6723 (67.23%)
- Transfer (Frozen Base): 0.1059 (10.59%)
- Transfer (Fine-tuned): 0.1452 (14.52%)

### ANALYSIS:

- Custom CNN: ~67% validation accuracy (best performer)
- Transfer (Frozen): ~11% - near random chance (~10-12% for 10 classes)
- Transfer (Fine-tuned): ~15% - very poor performance (close to random)
- Fine-tuning: slight improvement (~4% points change)

### Part 1.2:

- Validation Accuracy

# Summary & Discussion

## 3. OVERRFITTING ANALYSIS (Train vs Validation Gap)

### ANALYSIS:

- Custom CNN:
  - Training: ~75% | Validation: ~67%
  - Gap: ~7% points (MODERATE OVERRFITTING)
  - Status: acceptable - model generalizes reasonably well
- Transfer (Frozen Base):
  - Training: ~40% | Validation: ~11%
  - Gap: ~30% points (SEVERE OVERRFITTING)
  - Status: problematic - model memorizes training data significantly
- Transfer (Fine-tuned):
  - Training: ~45% | Validation: ~15%
  - Gap: ~30% points (EXTREME OVERRFITTING)
  - Status: critical issue - model memorizes training data but fails to generalize

### SUMMARY:

- Custom CNN shows the least overfitting (~7% gap) - best generalization
- Transfer models show severe/extreme overfitting (worst: ~30% gap)
- Transfer models memorize training data but fail to generalize to unseen data

### Part 1.3:

- Overfitting Analysis

# Summary & Discussion

## 4. TRAINING CONFIGURATION

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- Custom CNN: 10 epochs
- Transfer Model - Frozen Base: 10 epochs
- Transfer Model - Fine-tuning: 5 epochs (total 15 epochs)

### ANALYSIS:

- Custom CNN achieved best results in just 10 epochs
- Transfer models required more epochs (15 total) but performed worse
- Efficiency: Custom CNN is more data-efficient

### Part 1.4:

- Training Configuration

# Summary & Discussion

## 5. MODEL COMPLEXITY

---

- Transfer Model Parameters: 2,270,794
- Custom CNN Parameters: 622,282
- Parameter Ratio: 3.6x (Transfer model is 3.6x larger)

### ANALYSIS:

- Transfer model is significantly larger (3.6x) than Custom CNN (more complex)
- Transfer model has 3.6x more parameters but performs worse
- This demonstrates that more parameters (3.6x) do not guarantee better performance
- Custom CNN: parameter-efficient (good efficiency)
- Transfer model: parameter-inefficient (poor efficiency)

### SUMMARY:

- Custom CNN achieves better performance with 622,282 parameters
- More parameters (3.6x) ≠ better performance
- Custom CNN demonstrates superior parameter efficiency

# Summary & Discussion

## 5. MODEL COMPLEXITY

---

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### SUMMARY:

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# THE END

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