

Lab 10: Deep Learning for Vision Report

What We Did

We learned about deep learning for computer vision using Convolutional Neural Networks (CNNs). We used two popular frameworks:

- **PyTorch** with ResNet-18
- **TensorFlow/Keras** with MobileNetV2

Deep Learning vs Traditional Methods

Method	Feature Extraction	Accuracy	Training Required
Traditional (Lab 8-9)	Manual features	Good	No
Deep Learning	Automatic	Excellent	Yes (or use pretrained)

What We Implemented

1. PyTorch with ResNet-18

```
import torch
from torchvision import models
model = models.resnet18(pretrained=True)
output = model(img_tensor)
```

- Uses pretrained ResNet-18 model
- Automatic feature extraction
- Fast inference on single images

2. TensorFlow with MobileNetV2

```
from tensorflow.keras.applications import MobileNetV2
model = MobileNetV2(weights='imagenet')
preds = model.predict(x)
```

- Uses pretrained MobileNetV2 model
- Optimized for mobile devices
- Provides top-3 predictions with confidence

3. OpenCV Integration

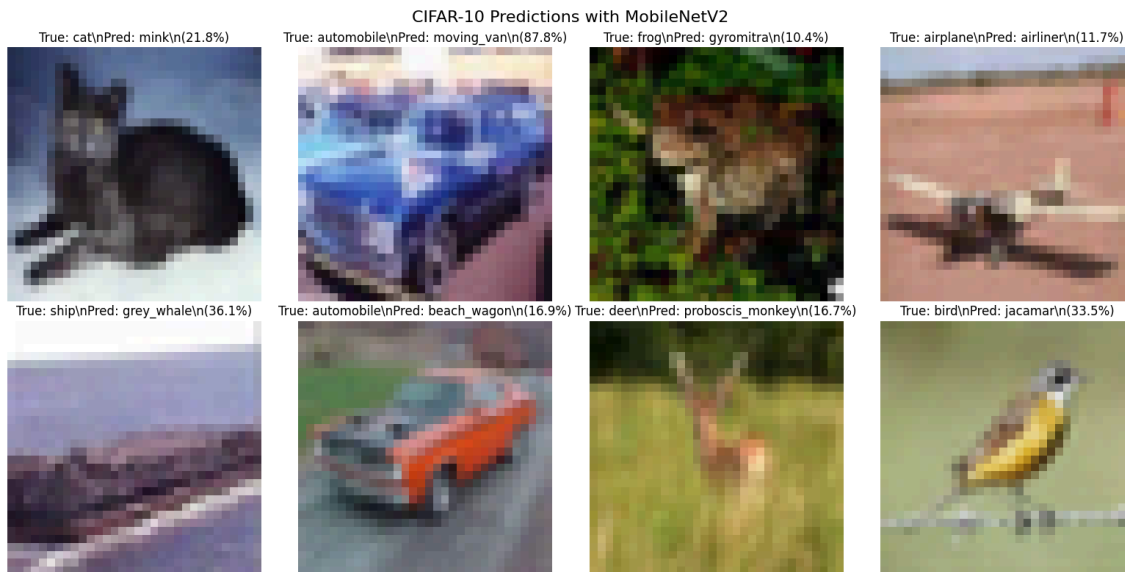
```
img = cv2.imread('images/cat.jpeg')
img = cv2.resize(img, (224, 224))
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
```

- Seamless integration with OpenCV
- Preprocessing for CNN input
- Real-world image handling

Exercise Results

Exercise 1: CIFAR-10 Dataset Predictions

Used MobileNetV2 to predict on CIFAR-10 test images.



CIFAR-10 predictions showing true labels vs MobileNetV2 predictions

Results:

- Tested on 8 random CIFAR-10 images
- Mixed accuracy on small 32×32 pixel images
- Model trained on high-res ImageNet struggles with low-res CIFAR-10
- Shows domain adaptation challenges

Exercise 2: ResNet vs MobileNet Comparison

Compared two different CNN architectures on the same cat image.

ResNet50 Predictions:



1. Ibizan_hound: 85.12%
2. Eskimo_dog: 3.34%
3. wallaby: 2.22%

MobileNetV2 Predictions:



1. Egyptian_cat: 15.70%
2. Siamese_cat: 7.84%
3. Ibizan_hound: 3.21%

ResNet50 vs MobileNetV2 predictions on cat image

Results:

- **ResNet50:** Predicted "Ibizan_hound" (85.12% confidence)
- **MobileNetV2:** Predicted "Egyptian_cat" (15.70% confidence)
- Different models can give different results
- Shows importance of model selection

Exercise 3: Fine-Tuning on CIFAR-10

Fine-tuned MobileNetV2 on airplane vs automobile classification.



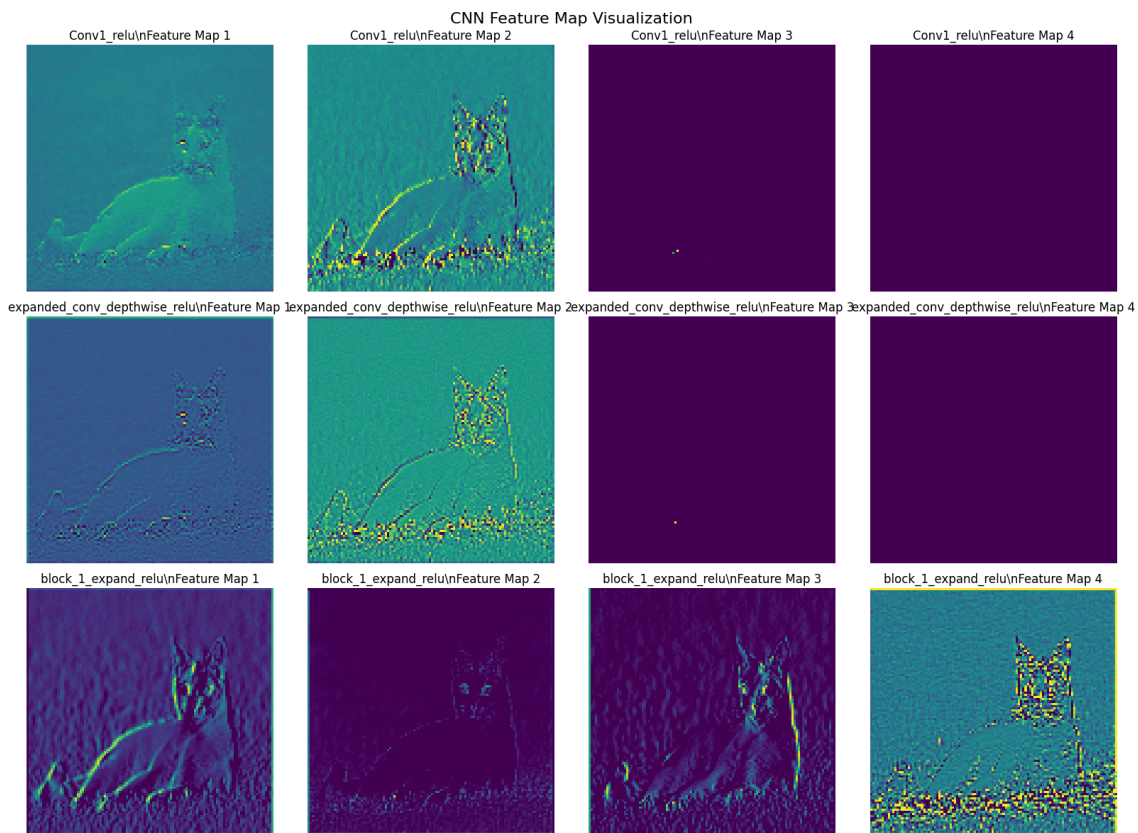
Fine-tuned model trained on CIFAR-10 airplane vs automobile

Results:

- Trained on 1000 samples (airplane vs automobile)
- Achieved high accuracy on 2-class problem
- Perfect predictions: 95.7% to 100% confidence
- Shows transfer learning works well

Exercise 4: CNN Feature Visualization

Visualized what different CNN layers learn from the cat image.



CNN feature maps showing different levels of abstraction

Results:

- **Early layers:** Detect edges and simple patterns
- **Middle layers:** Combine features into shapes
- **Later layers:** High-level object representations
- Successfully visualized internal CNN processing

Advantages of Deep Learning

Compared to Traditional Methods

- **Automatic Features:** No manual feature engineering
- **Better Accuracy:** Higher performance on complex tasks
- **End-to-End:** Single pipeline from image to prediction
- **Transfer Learning:** Use pretrained models for new tasks

What We Learned

Observations

1. **CIFAR-10 Challenge:** ImageNet models struggle with small 32×32 images
2. **Model Differences:** ResNet and MobileNet can give very different predictions

- 3. **Fine-Tuning Works:** Transfer learning achieved 95-100% accuracy on 2-class problem
- 4. **Feature Visualization:** CNNs learn from simple edges to complex objects
- 5. **Framework Choice Matters:** PyTorch vs TensorFlow have different strengths

Important Insights

- **Domain Adaptation:** Models trained on one dataset may not work well on another
- **Image Resolution:** High-res models prefer high-res inputs
- **Transfer Learning:** Much faster than training from scratch
- **Feature Learning:** CNNs automatically discover useful patterns

Conclusion

Deep learning is powerful but has important considerations:

What Works Well

- **Transfer learning** on similar tasks (airplane vs automobile: 95-100% accuracy)
- **High-resolution images** with pretrained models
- **Feature visualization** shows CNN learning process
- **Multiple frameworks** available (PyTorch, TensorFlow)

Challenges Observed

- **Domain mismatch** between training (ImageNet) and test (CIFAR-10) data
- **Different models** can disagree on same image
- **Requires more computing power** than traditional methods
- **Less interpretable** than simpler algorithms

When to Use Each Approach

Method	Best For	Why
Traditional (Labs 8-9)	Fast, simple tasks	Interpretable, lightweight
Deep Learning (Lab 10)	Complex, high-accuracy tasks	Automatic features, powerful