Seeing with CNNs

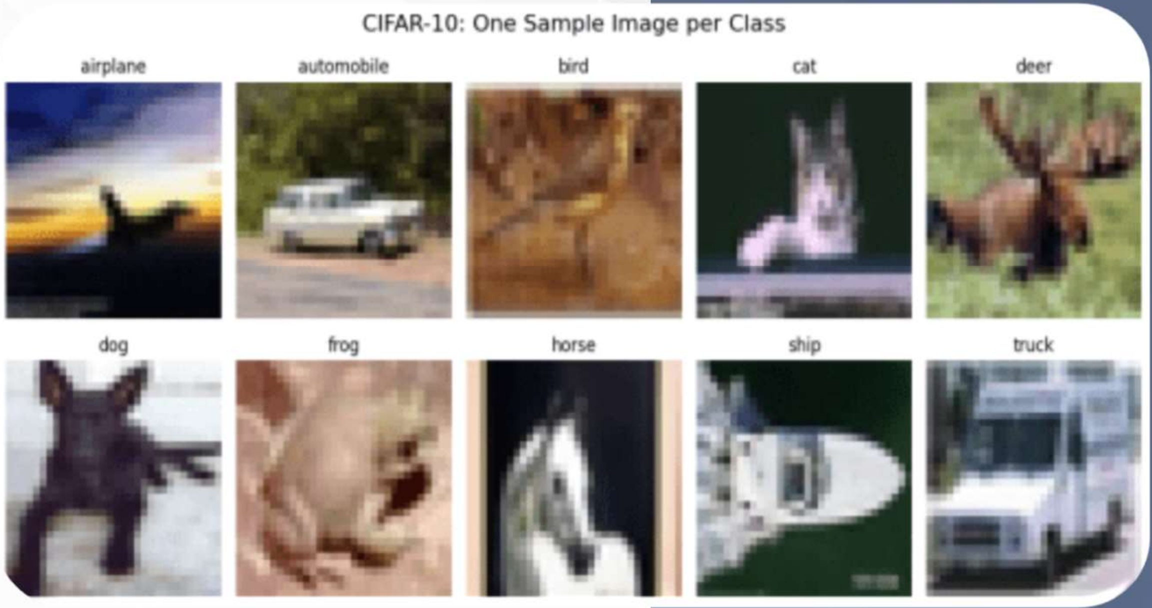
Deep Learning for Object Recognition

Track 2: Deep Learning (CNNs & Transfer Learning)

Introduction

1. Exploring the CIFAR – 10 Dataset
2. Understanding Convolutional Neural Networks
3. Creating and Tuning the Model
4. Exploring Transfer Learning

CIFAR – 10 Dataset

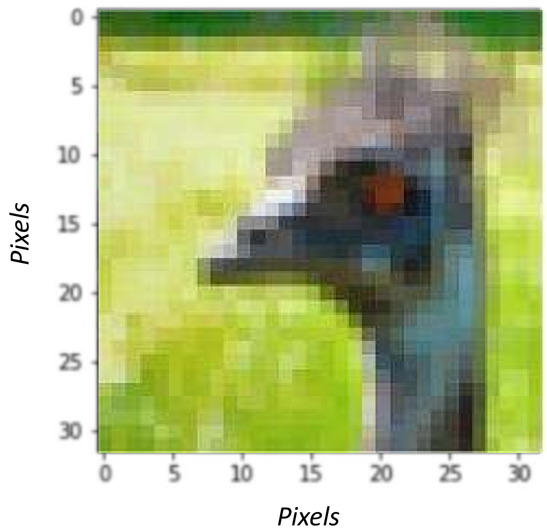


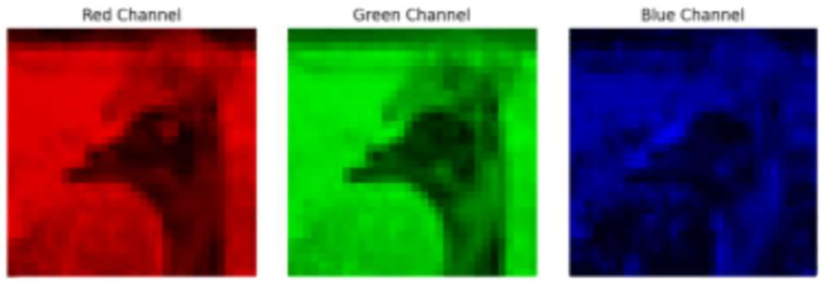
- Canadian Institute for Advanced Research (CIFAR)
- 60,000 color images
- 10 different image categories
- Common Benchmark for computer vision

CIFAR – 10 Dataset

MNIST *Dataset examples*

ImageNet *Dataset examples*

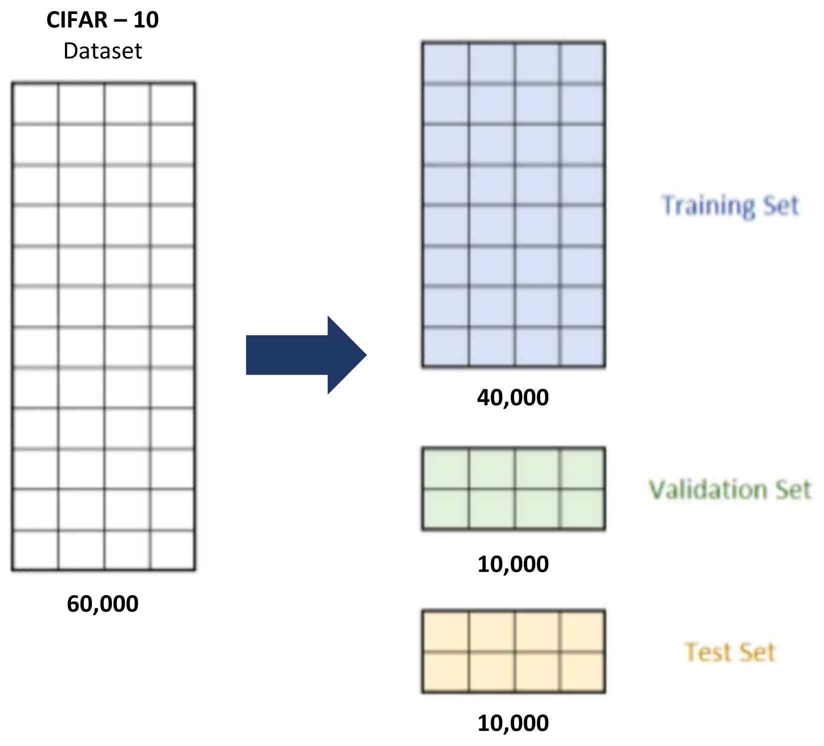




Each color image in ***CIFAR-10*** *is 32 by 32 pixels. Each pixel color is represented by its red, green and blue intensity values.*

Splitting the Dataset

How the dataset was split

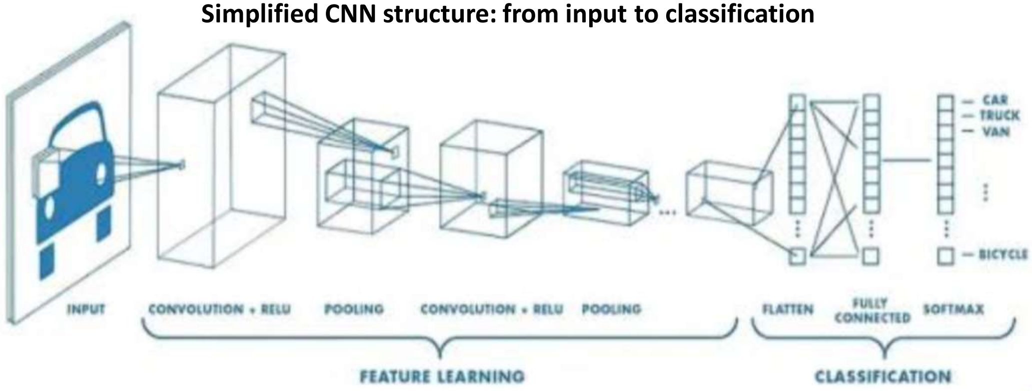


Why split the dataset?

- Prevents overfitting
- Guides parameter tuning
- Ensures fair model evaluation

What is a CNN?

Simplified CNN structure: from input to classification



A **Convolutional Neural Network (CNN)** is a deep learning model that automatically learns and detects patterns within image data.

Uses of a CNN include:

Facial Recognition

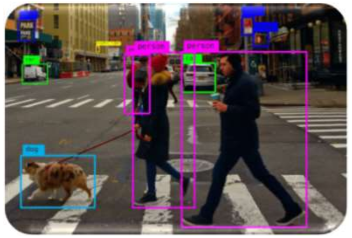
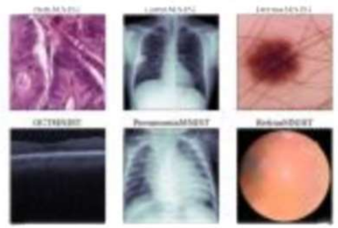


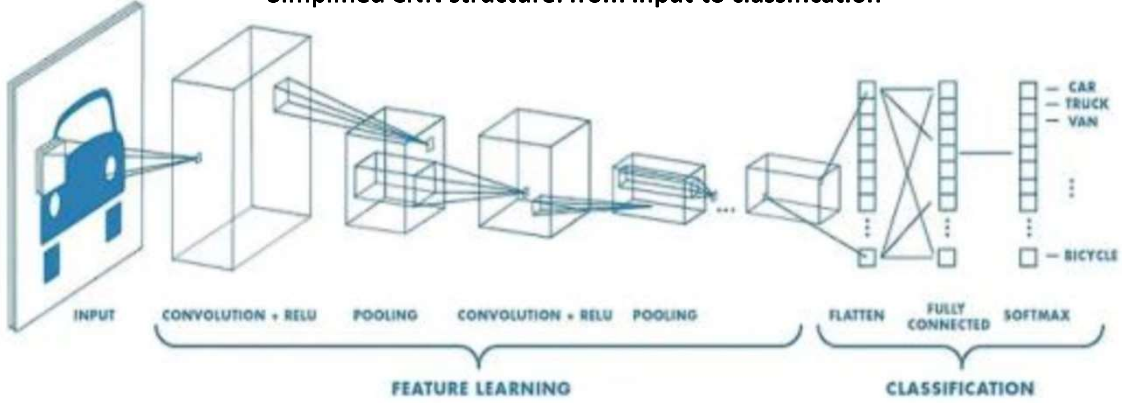
Image Detection



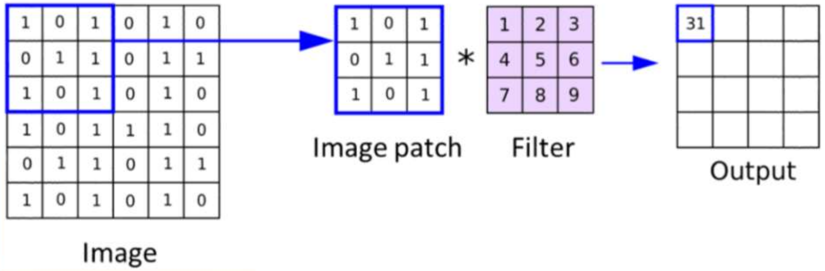
Medical Imaging

How does a CNN work?

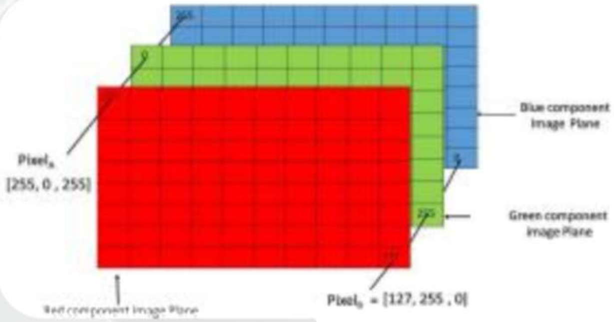
Simplified CNN structure: from input to classification



Convolutional Neural Network Process



Feature extraction using filters



Pixel color represented by 3D matrix

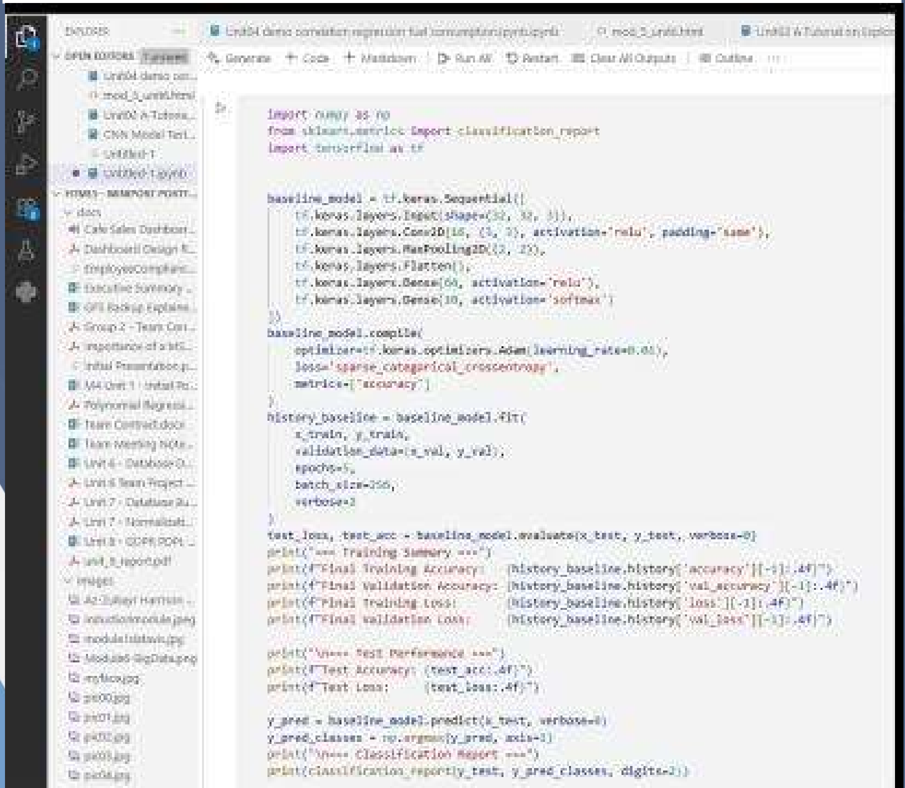
CNN Steps

- Convolution Layers
- Activation Functions
- Pooling Layers
- Flattening
- Fully Connected Layers

Baseline CNN Model

Model was implemented in **python** using **Tensor Flow** and **Keras**

Video of the Initial training and review of the baseline model in python and Visual Studio Code



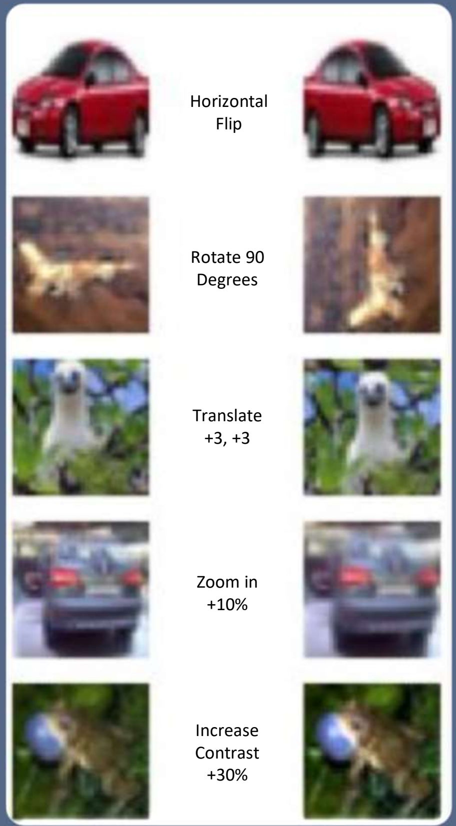
Initial Model review

```
=== Training Summary ===
Final Training Accuracy:   0.4271
Final Validation Accuracy: 0.4122
Final Training Loss:       1.5872
Final Validation Loss:     1.6402

=== Test Performance ===
Test Accuracy: 0.4125
Test Loss:     1.6204

=== Classification Report ===
              precision    recall  f1-score   support

           0       0.51      0.51      0.51      1000
           1       0.58      0.39      0.47      1000
...
    accuracy                           0.41     10000
   macro avg       0.41      0.41      0.40     10000
weighted avg       0.41      0.41      0.40     10000
```

Baseline mode’s most confident misclassifications

Data Augmentation

Examples of Data Augmentation



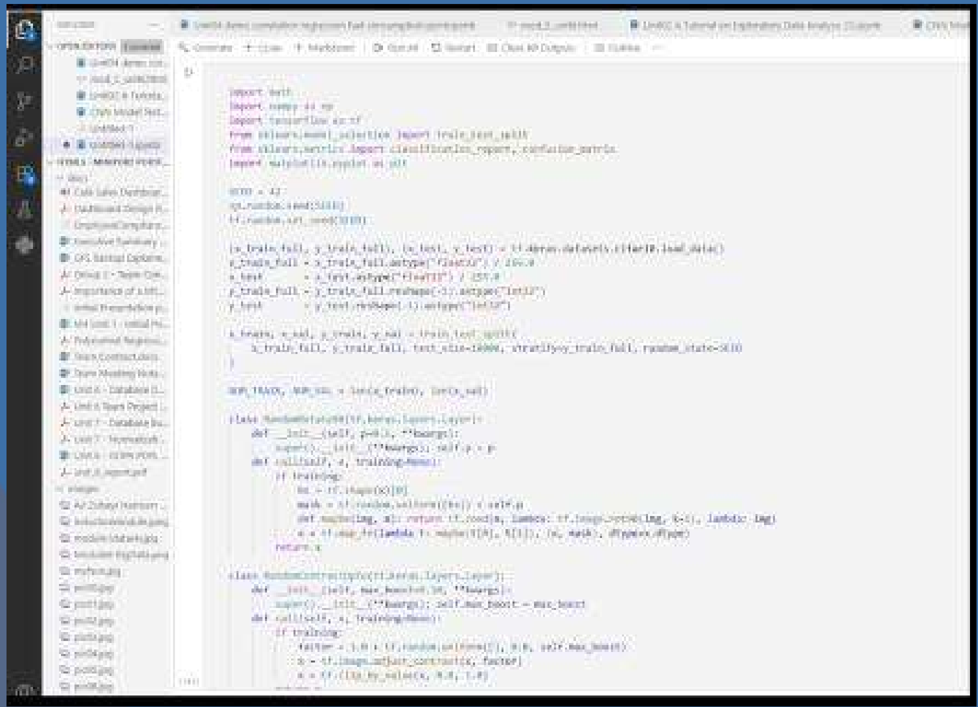
Benefits of Data Augmentation

- Increase Dataset Diversity
- Improve Model Robustness
- Reduces Overfitting
- Simulates Real-World Variations

Tuning the Model Hyperparameters

- **Kernel Size (3×3):** Captures local image patterns effectively
- **Pooling (MaxPooling):** Reduces size, keeps key features
- **Architecture (32–64–128 + Dense 128):** More layers = richer feature extraction
- **Learning Rate (0.0005):** Controls training speed and stability
- **Epochs (25):** Number of full passes through the data
- **Batch Size (25):** Smaller batches can improve generalization
- **Activation (ReLU):** Fast and effective for deep nets

Video showing the training of the new tuned model on the augmented data



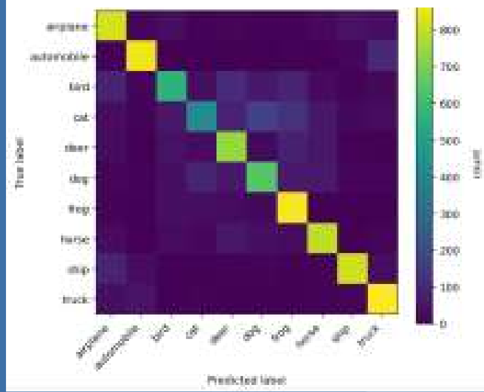
Baseline Accuracy: 41%
Tuned Accuracy: 74%

+33%

Model Test Results

accuracy			0.74	10000
macro avg	0.74	0.74	0.73	10000
weighted avg	0.74	0.74	0.73	10000

Model results Confusion Matrix



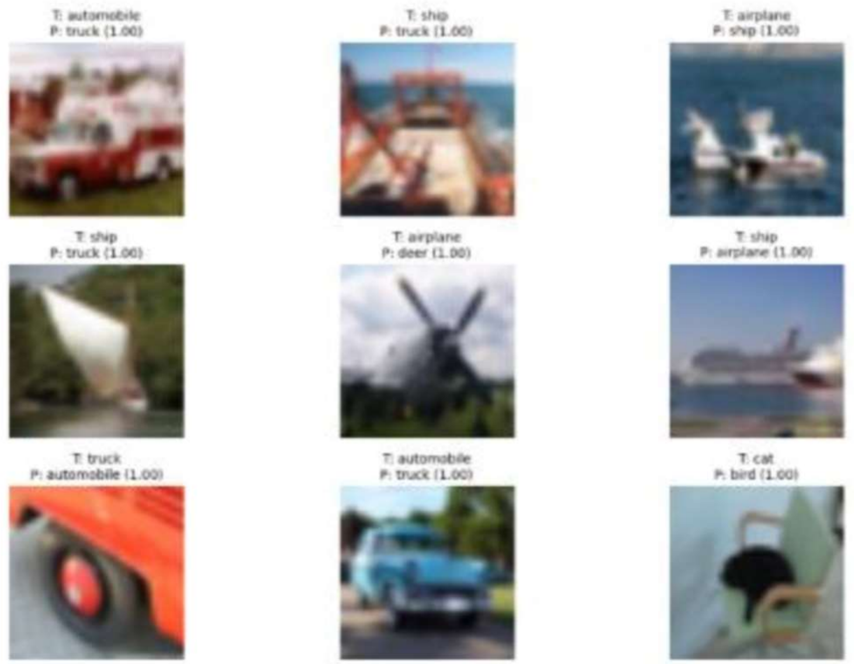
Transfer Learning

Baseline Accuracy: 41%
Tuned Accuracy: 74%
Transfer Learning Accuracy: 90%

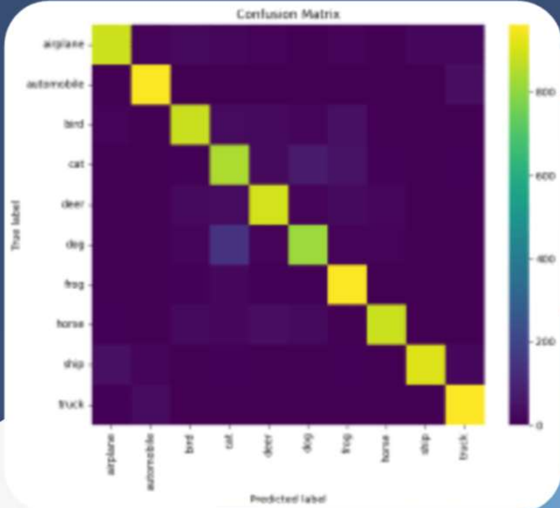
Result of using the MobileNetV2 Pretrained Model

```
=== Training Summary ===
Final Training Accuracy:    0.9991
Final Validation Accuracy:  0.9146
Final Training Loss:        0.0040
Final Validation Loss:      0.4707

=== Test Performance ===
Test Accuracy: 0.8990
Test Loss:     0.3296

=== Classification Report ===
              precision    recall  f1-score   support

    airplane       0.93      0.89      0.91      1000
  automobile       0.95      0.96      0.95      1000
        bird       0.90      0.88      0.89      1000
         cat       0.76      0.84      0.80      1000
        deer       0.89      0.89      0.89      1000
         dog       0.87      0.81      0.84      1000
        frog       0.88      0.96      0.91      1000
       horse       0.97      0.88      0.92      1000
        ship       0.97      0.91      0.94      1000
       truck       0.91      0.96      0.94      1000

    accuracy                           0.90     10000
   macro avg       0.90      0.90      0.90     10000
weighted avg       0.90      0.90      0.90     10000
```

Most Confidant Misclassifications



Confusion Matrix



Comparing ML Approaches

1 Traditional Machine Learning

Strengths:

- Simple and fast to implement
- Works with smaller datasets
- Low computational cost

Weaknesses:

- Requires manual feature engineering
- Struggles with complex patterns
- Lower accuracy compared to CNNs

2 Custom CNN

Strengths:

- Learns hierarchical features automatically
- High accuracy with tuning
- Effective for visual pattern recognition

Weaknesses:

- Data hungry for optimal performance
- Requires careful hyperparameter tuning
- High training time and computational cost

3 Transfer Learning

Strengths:

- High accuracy with less data and time
- Leverages powerful pretrained models
- Reduces overfitting, efficient training

Weaknesses:

- Less flexibility over learned features
- Must select a suitable pretrained model
- Slightly more complex setup than training from scratch

Conclusion

Summary of Project Scope

1. Understanding the CIFAR-10 dataset
2. Splitting the dataset
3. CNNs and how they work
4. Initializing a baseline CNN
5. Tunning the model's hyperparameters
6. Methods of augmenting the data
7. Transfer learning with pre-trained models
8. Comparing different ML approaches

Lessons Learned

1. **Data preparation and splitting** are essential to ensure fair and reliable evaluation.
2. **CNNs automatically learn visual features**, but performance depends heavily on hyperparameters and data diversity.
3. **Data augmentation** is crucial for improving generalisation without collecting more data.
4. **Transfer learning offers a powerful shortcut**, leveraging pretrained knowledge for excellent results with fewer resources

Thank you

For you time and attention!

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