

CIFAR-10

Photo Recognition

Applying Transfer Learning with ResNet50

Computer Vision Sprint Project

Exploring the Data

Physical visualization and problem framing

| The Challenge of Tiny Pictures



Low Resolution

Images are only 32×32 pixels. At this size, details like a cat's ears or a plane's tail are only a few colored squares. This makes identification very difficult for standard models.



Real-World Noise

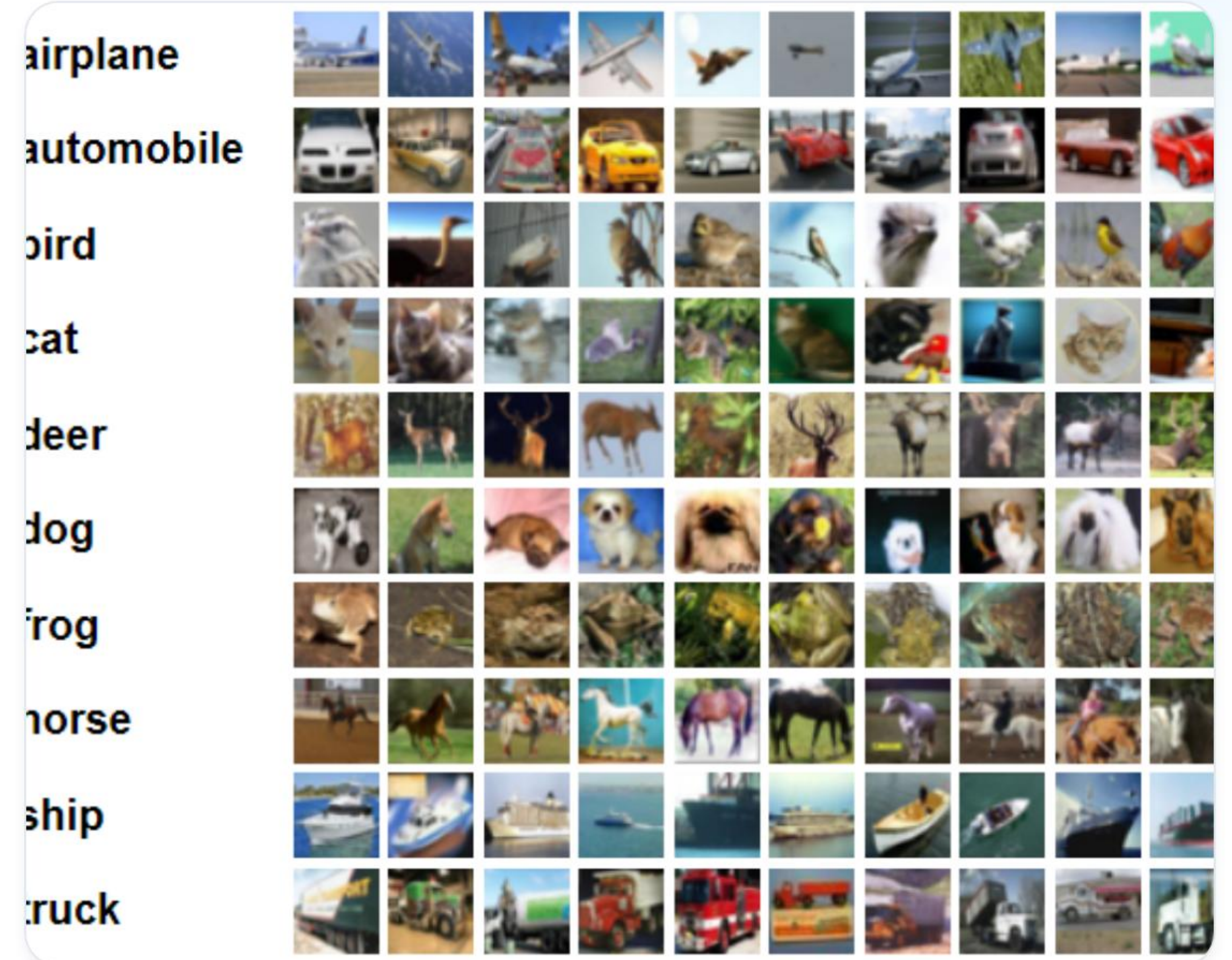
Unlike simple symbols, these are RGB color photos. They have shadows, complex backgrounds, and different angles, requiring the model to understand deep spatial patterns.

Visualizing the 10 Categories

A Balanced Dataset

The CIFAR-10 collection contains 60,000 images across 10 exclusive classes. We sampled 10,000 for training efficiency.

- **Animals:** Birds, Cats, Deer, Dogs, Frogs, Horses
- **Vehicles:** Planes, Cars, Ships, Trucks



Strategy & Logic

Why we chose ResNet50 and Preprocessing

| The Expert: ResNet50



600 × 400

Borrowing Expert "Eyes"

We used **Transfer Learning**. ResNet50 has already studied millions of photos on ImageNet. It already knows how to see shapes, edges, and textures.

Instead of teaching a "Toddler" model from scratch, we hired an "Artist" and taught them our 10 specific categories.

| Logic: Preparing the Data

preprocess_input

I chose the official ResNet50 scaling over simple $1/255$ division. This centers the colors around the "mean" that the expert brain expects to see.

Data Casting

Images were converted to **Float32**. This is essential for the math calculations in deep learning, allowing for precise adjustments during training.

| The Training Pipeline

Setup

Load 10k data & center
colors.

Phase 1

Train the Head (Expert is
Frozen).

Unfreeze

Unlock the expert's brain.

Phase 2

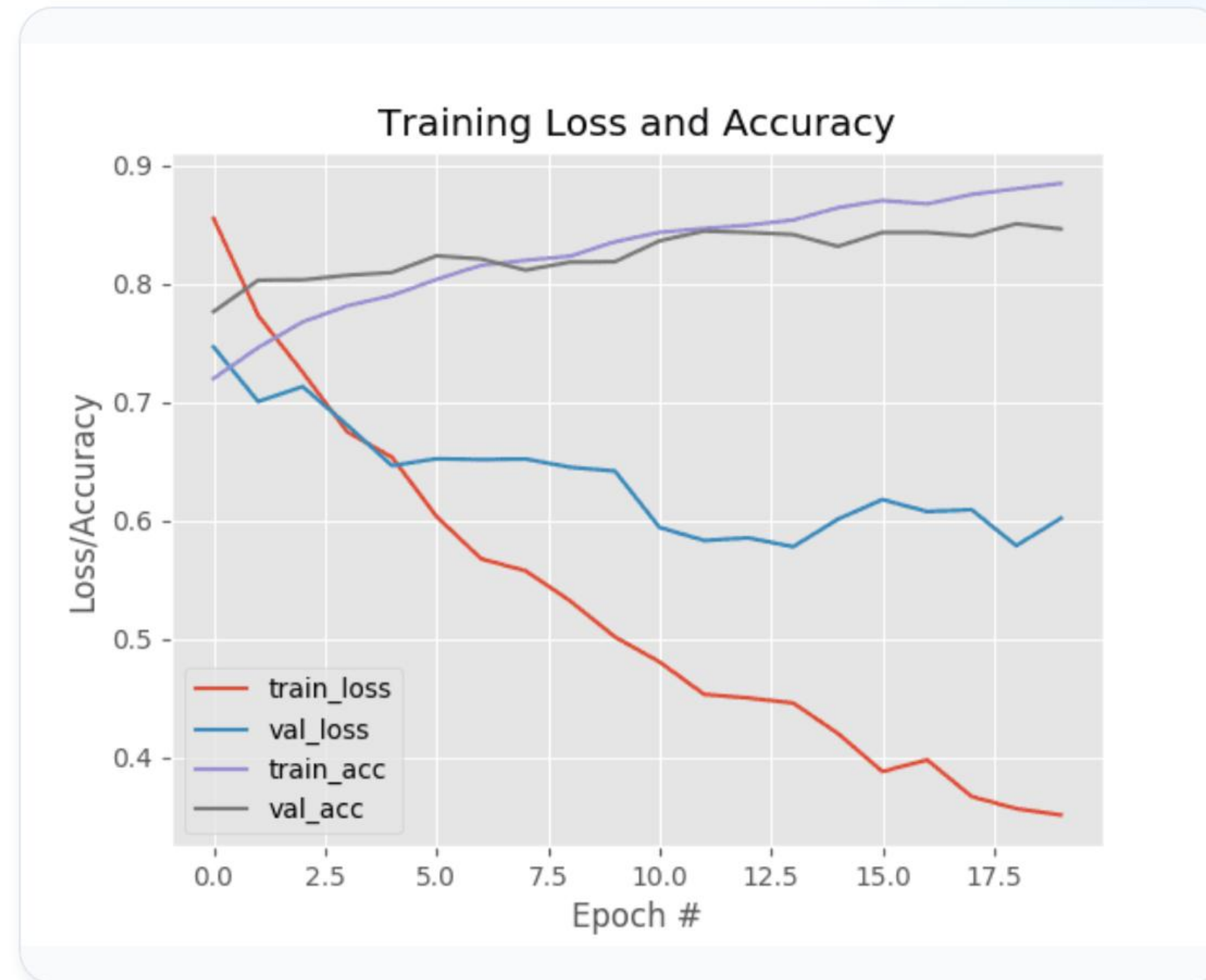
Fine-Tune at low speed
($1e-5$).

Insight: The "Accuracy Jump"

Analytical Observation

During Phase 1, accuracy grew slowly. However, as soon as we reached the **Unfreeze Point**, the accuracy jumped significantly.

This shows that letting the expert brain "squint" at our tiny photos is much more effective than just training the new head layers alone.



Judgment & Evidence

Model Predictions

The model isn't perfect, and that's an honest result. It correctly identifies many animals (Green), but sometimes confuses trucks with automobiles (Red) due to their similar metallic shapes.

Reasoning: These mistakes prove the model is learning features (like wheels) rather than just memorizing the background.



$$\text{Pixel}_B = [127, 255, 0]$$

ge Plane

age are formed from the corresponding pixel of the three c

| Constraints & Trade-offs

Decision	Impact
10,000 Sample Size	Reduced training time from hours to minutes, with a small loss in accuracy.
Dropout (0.5)	Forced the model to learn real patterns, preventing it from "memorizing" the data.
Low Learning Rate (1e-5)	Ensured stability during fine-tuning so we didn't "break" the expert weights.



Questions & Discussion

Thank you for your attention.

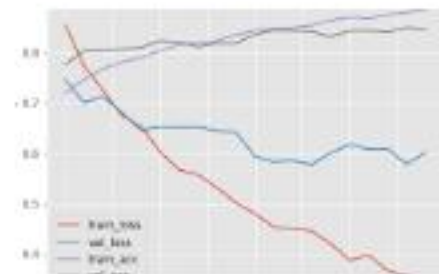
CIFAR-10 Project Artifact | Sprint Presentation

Image Sources



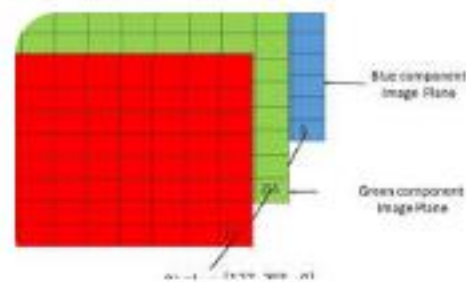
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Source: www.binarystudy.com



<https://pyimagesearch.com/wp-content/uploads/2019/06/unfrozen.png>

Source: pyimagesearch.com



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Source: medium.com