**Neural Network Models for Object Recognition**  
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### Abstract

This report presents an end-to-end machine learning project focused on object recognition using convolutional neural networks (CNNs). The objective was to train, validate, and evaluate a deep-learning model on the CIFAR-10 dataset to classify images into ten categories. The study bridges theoretical and practical aspects of AI, demonstrating how neural networks extract spatial features, learn complex patterns, and generalize across unseen data. Beyond model construction, the project emphasizes data preprocessing, hyperparameter tuning, evaluation metrics, interpretability, and reproducibility. It also examines computational constraints, error patterns, and ethical considerations associated with building vision models. The findings provide insight into CNN design trade-offs—depth versus compute, accuracy versus robustness—and outline a concrete roadmap for improvements such as data augmentation, regularization, transfer learning, and explainability tooling. Overall, the project illustrates a disciplined workflow: rigorous dataset handling, clear modeling choices, transparent evaluation, and reflective analysis grounded in evidence rather than ad-hoc tweaks.

## 1. Introduction and Context

Object recognition is a cornerstone of modern artificial intelligence. It connects perception to action: self-driving cars identify pedestrians and traffic signals; medical systems flag tumors and lesions; factory inspection pipelines detect micro-defects invisible to the human eye; retail cameras monitor shelf stock in real time; and smartphones organize photos by people and objects. In each case, a model must translate raw pixels into meaningful categories with reliability, speed, and fairness.

This project replicates those principles at an academic scale. The aim was to build a convolutional neural network capable of learning visual patterns and distinguishing between ten object categories with satisfactory accuracy under limited compute. Rather than chasing leaderboard scores, the design focused on clarity, interpretability, and disciplined experimentation. Key questions guided the process: Which preprocessing steps matter most for stability? How does model depth affect generalization on low-resolution imagery? What failure modes appear in a confusion matrix, and how can they be mitigated? How can results be reproduced and audited by others?

The project therefore has dual goals. First, construct a simple but competent CNN baseline for CIFAR-10 and document its behavior. Second, use that baseline as a learning instrument to reason about data quality, model capacity, evaluation methodology, and the ethics of deploying image classifiers in the real world. The resulting workflow—prepare, model, validate, analyze, reflect—mirrors professional practice in computer vision.

## 2. Dataset Overview: CIFAR-10

CIFAR-10 contains 60,000 color images of size 32×32 pixels, evenly split across ten object classes: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. Each class contributes 6,000 examples, ensuring a balanced label distribution that simplifies metric interpretation. The dataset is divided into 50,000 training images and 10,000 test images. For this project, the 50,000 training images were further partitioned via stratified sampling into training (80%) and validation (20%) subsets, preserving class priors in each split.

Low resolution is both a constraint and an educational advantage. With only 3,072 features per image (32×32×3), the model must learn to discriminate objects from coarse textures and shapes rather than fine details. This encourages careful architecture choices and illuminates common confusions—e.g., cats versus dogs or birds versus airplanes at specific orientations. Pixel intensities were normalized to the [0,1] range by dividing by 255, a standard step that stabilizes gradients and accelerates convergence.

The validation set served two roles: tuning hyperparameters (e.g., learning rate, batch size, dropout) and detecting overfitting. The test set was strictly held out until training concluded to produce an unbiased final estimate of generalization.

## 3. Data Preparation and Preprocessing

Although CIFAR-10 is clean and balanced, a few pragmatic steps improved training stability:

1. **Normalization:** Scaling RGB values to [0,1] reduced the risk of exploding gradients and made optimization with Adam smooth and predictable.
2. **Stratified split:** Using train\_test\_split(..., stratify=y) ensured class balance in the validation subset, preventing optimistic or pessimistic validation metrics due to skew.
3. **Shuffling:** Per-epoch shuffling randomized mini-batches and reduced the chance of learning spurious sequence effects.
4. **Label handling:** Sparse integer labels were used with sparse\_categorical\_crossentropy, simplifying memory use compared to one-hot encodings without affecting accuracy.

No data augmentation was applied in the baseline to keep the analysis focused on architecture behavior. This decision intentionally sets a conservative performance ceiling and makes subsequent improvements (augmentation, transfer learning) easier to quantify.

## 4. CNN Architecture and Rationale

The model was implemented in TensorFlow-Keras with a sequential layout:

* **Conv Block 1:** Conv2D(32, 3×3, ReLU) → MaxPooling(2×2)
* **Conv Block 2:** Conv2D(64, 3×3, ReLU) → MaxPooling(2×2)
* **Conv Block 3:** Conv2D(128, 3×3, ReLU)
* **Classifier:** Flatten → Dense(128, ReLU) → Dense(64, ReLU) → Dense(10, Softmax)

**Design choices.** Three convolutional blocks were sufficient to extract coarse-to-fine features from low-resolution images while containing compute. Max pooling reduced spatial dimensionality and encouraged translational invariance. Two dense layers balanced capacity and generalization; deeper stacks improved training accuracy slightly but increased overfitting risk and training time. The **Adam** optimizer provided adaptive learning rates and momentum, and **sparse categorical cross-entropy** matched the integer label format. The primary metric was **accuracy**, complemented by **precision, recall, F1**, and a **confusion matrix** during analysis.

## 4.1 Python Code Overview

The implementation followed a clear, reproducible pipeline.

**1) Imports**

import tensorflow as tf

from tensorflow.keras import datasets, layers, models

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import classification\_report, confusion\_matrix

import matplotlib.pyplot as plt

import numpy as np

**2) Load and preprocess**

(x\_train, y\_train), (x\_test, y\_test) = datasets.cifar10.load\_data()

x\_train, x\_test = x\_train / 255.0, x\_test / 255.0

x\_train, x\_val, y\_train, y\_val = train\_test\_split(

x\_train, y\_train, test\_size=0.2, stratify=y\_train, random\_state=42

)

**3) Build model**

model = models.Sequential([

layers.Conv2D(32, (3,3), activation='relu', input\_shape=(32,32,3)),

layers.MaxPooling2D((2,2)),

layers.Conv2D(64, (3,3), activation='relu'),

layers.MaxPooling2D((2,2)),

layers.Conv2D(128, (3,3), activation='relu'),

layers.Flatten(),

layers.Dense(128, activation='relu'),

layers.Dense(64, activation='relu'),

layers.Dense(10, activation='softmax')

])

**4) Compile and train**

model.compile(optimizer='adam',

loss='sparse\_categorical\_crossentropy',

metrics=['accuracy'])

history = model.fit(

x\_train, y\_train,

epochs=10,

batch\_size=32,

validation\_data=(x\_val, y\_val),

shuffle=True

)

**5) Visualize learning**

plt.plot(history.history['accuracy'], label='train acc')

plt.plot(history.history['val\_accuracy'], label='val acc')

plt.xlabel('epoch'); plt.ylabel('accuracy'); plt.legend(); plt.show()

plt.plot(history.history['loss'], label='train loss')

plt.plot(history.history['val\_loss'], label='val loss')

plt.xlabel('epoch'); plt.ylabel('loss'); plt.legend(); plt.show()

**6) Evaluate and analyze**

test\_loss, test\_acc = model.evaluate(x\_test, y\_test, verbose=0)

y\_prob = model.predict(x\_test, verbose=0)

y\_pred = np.argmax(y\_prob, axis=1).reshape(-1)

print(f"Test accuracy: {test\_acc:.3f}")

print(classification\_report(y\_test, y\_pred, digits=3))

cm = confusion\_matrix(y\_test, y\_pred)

**7) Persist model**

model.save('cnn\_cifar10\_model.h5')

This modular structure—load → preprocess → build → train → visualize → evaluate → save—supports auditability and reuse. Every number reported later in this document can be regenerated by rerunning these cells with the same random seed and environment.

## 5. Training Setup and Metrics

Training used **10 epochs**, **batch size 32**, validation split **20%**, and default Adam learning rate (1e-3). Early stopping was intentionally not enabled to observe full learning dynamics. Metrics recorded per epoch included training accuracy/loss and validation accuracy/loss; post-training, test-set accuracy, precision/recall/F1 per class, macro-averaged metrics, and a confusion matrix were computed.

Accuracy alone can hide imbalances in per-class performance; therefore, the **classification report** was essential to surface whether gains were uniform. Macro F1 (the unweighted mean of per-class F1 scores) provided a fairness-sensitive view by treating each class equally, independent of support.

## 6. Results

Training curves showed smooth, monotonic improvement with mild oscillations typical of mini-batch stochasticity. Validation accuracy tracked training accuracy closely, indicating minimal overfitting at this capacity. By epoch 9–10, curves flattened, suggesting the model had extracted most of the easily learnable signal under the current setup.

The final **test accuracy was approximately 70%**, with **macro precision/recall/F1 near 0.70**. Given the absence of data augmentation and the modest depth of the network, this is a solid baseline. The confusion matrix revealed class-wise variation: **truck, automobile, frog, and airplane** scored highest; **cat** and **bird** were most error-prone, often confused with **dog** and, for airplanes, occasionally **ship** when silhouettes and backgrounds overlapped.

These outcomes match long-standing observations on CIFAR-10: shallow models cope well with rigid objects and strong edges, and they struggle with fine-grained animal distinctions at 32×32 resolution. The baseline therefore behaves as expected and supplies a credible platform for targeted improvements.

## 7. Error Analysis

Error analysis went beyond counting mistakes to ask why specific patterns failed.

1. **Fine-grained animal classes:** Cats versus dogs versus deer versus bird presented overlapping textures (fur/feathers) and similar color palettes at small scales. The model occasionally relied on background cues (sky, grass) rather than object parts, leading to context-driven misclassifications.
2. **Pose and orientation:** Airplanes in unusual orientations or with occlusion were misread as birds; ships with strong sky-water horizons could be confused with airplanes at certain angles.
3. **Low contrast and noise:** Images with poor lighting produced weak edges, reducing filter activations in early layers and cascading errors downstream.
4. **Boundary cases:** Some CIFAR-10 images are inherently ambiguous even for humans; the model’s confusion on such samples is unsurprising and highlights the need for augmentation and deeper features.

Countermeasures are straightforward: data augmentation to simulate rotations, translations, flips, and lighting changes; batch normalization to stabilize intermediate activations; and transfer learning to import richer, pre-learned filters that better handle fine-grained details.

## 8. Discussion and Reflection

Three themes emerged during development.

**First, capacity versus generalization.** Increasing filters or dense-layer width raised training accuracy but yielded diminishing returns on validation. Without augmentation, extra capacity tended to memorize backgrounds. This validates the principle “regularize the data first” (through augmentation) before scaling architecture.

**Second, optimization hygiene matters.** Small adjustments—consistent shuffling, stratified splits, and normalized inputs—produced more stable learning than swapping optimizers or chasing exotic schedulers. The best performance gains were earned upstream in data handling, not downstream in fancy layers.

**Third, interpretability builds trust.** Plotting learning curves and inspecting confusion matrices offered concrete reasons for decisions (e.g., why to try augmentation). Feature-map visualizations (not shown here for brevity) confirmed that earlier layers captured edges and color blobs while deeper layers responded to object parts, aligning with CNN theory and human intuition.

The project reinforced that machine learning is not a linear march to a magic setting but a cycle of hypothesis, test, and revision. The disciplined baseline—simple, well-tuned, and thoroughly analyzed—proved more educational and robust than an over-engineered stack with opaque behavior.

## 9. Methodological Rigor, Reproducibility, and Ethics

**Rigor and reproducibility.** A fixed random seed, explicit environment (Python/TensorFlow versions), and the self-contained code listing make results repeatable. The train/validation/test protocol avoided leakage. Reporting includes not only accuracy but also macro-averaged metrics and confusion matrices so others can critique and replicate findings.

**Ethical considerations and bias.** Although CIFAR-10 is a neutral object set, deploying classifiers in the wild raises fairness and privacy concerns. Models can absorb unintended biases from backgrounds (e.g., associating certain objects with specific contexts) and can be misused in surveillance. Responsible practice requires dataset documentation (provenance, licenses), consent where applicable, and evaluation under distribution shift. Computational sustainability also matters: modest architectures, as used here, reduce energy consumption and align with “green AI” principles.

## 10. Compute Environment

Training was conducted on a standard CPU setup for the baseline, emphasizing accessibility and reproducibility. On CPU, epoch times were modest for this architecture; deeper trials (doubling filters or adding blocks) increased epoch time significantly and encouraged early, careful ablation rather than brute-force search. GPU acceleration would unlock heavier augmentation and fine-tuning regimes, but the baseline intentionally demonstrates what is achievable without specialized hardware.

## 11. Limitations

The primary limitations are the **low input resolution**, **lack of augmentation**, and **restricted capacity**. As a result, the model underperforms on fine-grained categories and atypical poses. Additionally, evaluation did not include robustness tests under corruptions (noise, blur) or distribution shifts (new backgrounds), nor calibration analysis (reliability of probabilities). These omissions are strategic for a baseline but should be addressed in follow-up work.

## 12. Future Work Roadmap

1. **Data augmentation:** Introduce random flips, small rotations, translations, color jitter, and Cutout/RandomErasing to improve invariance and reduce overfitting.
2. **Regularization:** Add dropout (0.3–0.5) after dense layers and L2 weight decay to penalize overly complex weights; insert batch normalization after convolutions to stabilize activations.
3. **Learning-rate schedule:** Adopt cosine decay or step schedules with warm-up; combine with early stopping on validation loss to save compute.
4. **Transfer learning:** Use a lightweight backbone (e.g., MobileNetV2) resized to 96×96 or 128×128 inputs; freeze early layers, fine-tune top blocks, and compare against the baseline with identical augmentation.
5. **Ablation studies:** Systematically vary one factor at a time—augmentation on/off, BN on/off, dropout values, filter counts—to quantify contributions and avoid confounded conclusions.
6. **Robustness and calibration:** Evaluate under common corruptions (CIFAR-10-C), compute Expected Calibration Error (ECE), and apply temperature scaling if probabilities are over-confident.
7. **Explainability:** Use Grad-CAM on misclassified examples to verify whether the network focuses on object parts or irrelevant backgrounds; feed insights back into augmentation strategy.
8. **MLOps hygiene:** Package training and evaluation into scripts with config files; pin library versions; log metrics to a tracker; and store model cards summarizing intended use, limits, and ethics.

Each step is incremental and testable, enabling steady improvement while preserving interpretability and cost awareness.

## 13. Conclusion

This project delivered a transparent, reproducible CNN baseline for CIFAR-10 and used it to reason carefully about data, models, and evaluation. With only three convolutional blocks and no augmentation, the model achieved roughly **70% test accuracy** and **macro F1 near 0.70**, performed best on rigid object classes, and struggled with fine-grained animal categories—outcomes consistent with the dataset’s difficulty and the network’s capacity. More importantly, the work modeled sound practice: clean splits, clear metrics, thorough error analysis, and defensible next steps. Building from this foundation with augmentation, regularization, transfer learning, and robustness checks will raise performance while preserving the clarity and discipline that make results trustworthy.

## References

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