IMAGE CLASSIFICATION USING CNN AND TRANSFER LEARNING

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Overview

PROJECT OVERVIEW

Goal:

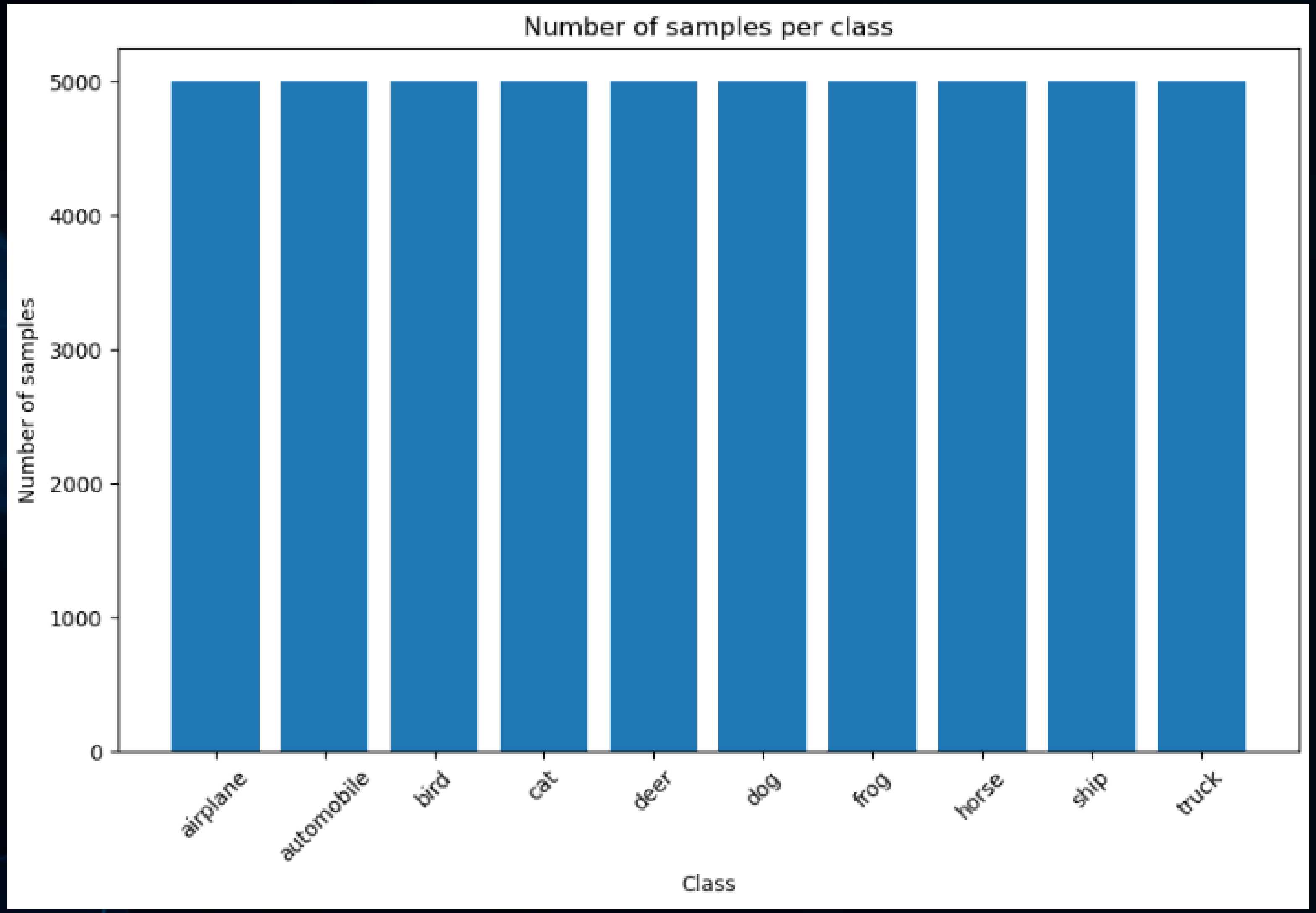
- Classify images from the CIFAR-10 dataset into 10 categories.

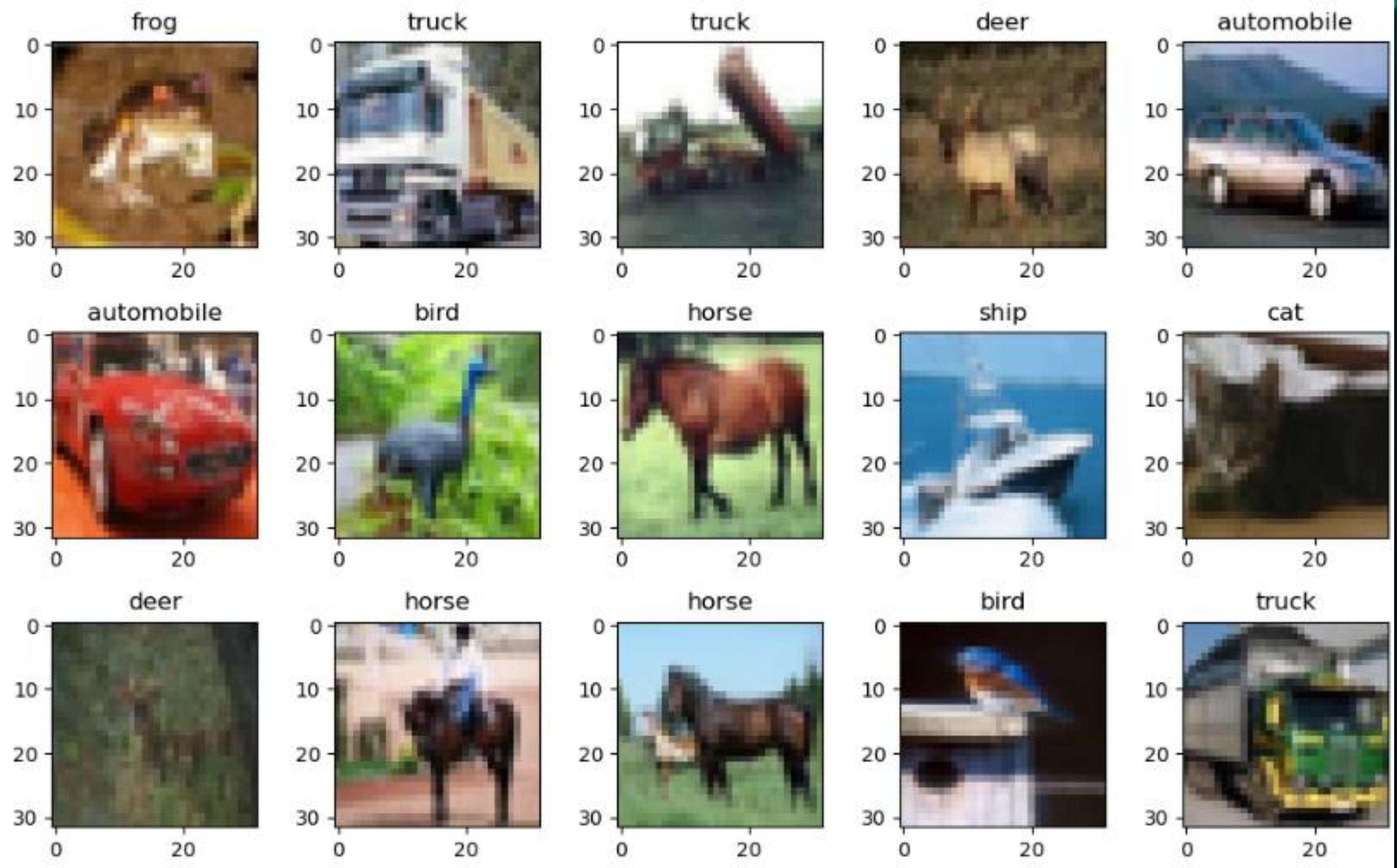
Approaches:

- Custom CNN built from scratch.
- Transfer Learning using pre-trained models.

DATASET DESCRIPTION

- Dataset: CIFAR-10
- Size: 60,000 color images (32×32 pixels).
- Classes: 10 categories





DATA PREPROCESSING

Before training, the dataset must be prepared to fit the model:

1. Reshape: Adjust input images to include the channel dimension required by CNNs.
2. Normalize: Scale pixel values to the [0, 1] range to improve training efficiency.
3. Encode: Convert class labels into one-hot vectors for multi-class classification.

Implementation uses Keras utilities:

- Rescaling for normalization
- to_categorical for label encoding

CUSTOM CNN

ARCHITECTURE & TRAINING

Model Architecture:

- Convolutional layers with ReLU activations
- MaxPooling layers for feature reduction
- Flatten layer → Fully Connected dense layers

Model Training:

- Optimizers: Adam
- Loss function: Categorical Crossentropy

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_1 (Conv2D)	(None, 13, 13, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten (Flatten)	(None, 2304)	0
dense (Dense)	(None, 128)	295,040
dense_1 (Dense)	(None, 10)	1,290

Total params: 315,722 (1.20 MB)

Trainable params: 315,722 (1.20 MB)

Non-trainable params: 0 (0.00 B)

CUSTOM CNN
EVALUATION & IMPROVEMENTS

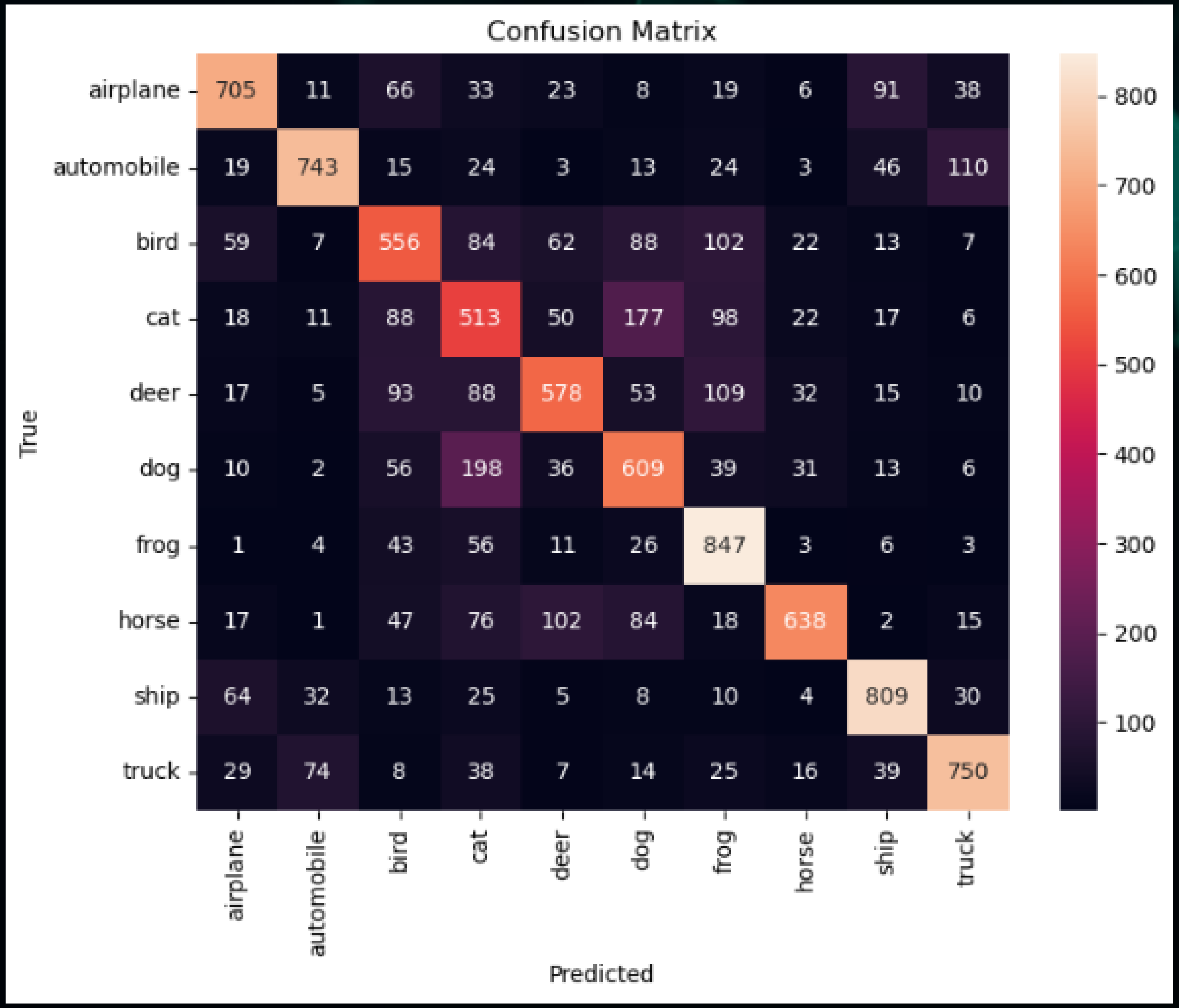
Model Evaluation:

- Metrics: Accuracy, Precision, Recall, F1-score
- Confusion matrix to analyze class-level performance

Test

```
Accuracy: 0.6748
Precision: 0.6841
Recall: 0.6748
F1 Score: 0.6761
```

Training accuracy: 0.82



CUSTOM CNN

EVALUATION & IMPROVEMENTS

Improving the Model:

- Added more convolutional layers for deeper feature extraction
  - Added 1 more layer (previously only had 2) + Dropout

```
Test accuracy with more layers: 0.7343
```

Training accuracy: 0.85

  - Added BatchNormalization + GlobalAveragePooling2D

```
Test accuracy with more layers: 0.7313
```

Training accuracy: 0.91

  - Added Regularizer

```
Test accuracy with more layers: 0.7249
```

Training accuracy: 0.93

- Added Hyperparameter turning - Earling Stopping

```
Test accuracy with early stopping: 0.7293
```

Training accuracy: 0.94

- Applied data augmentation (rotations, flips, shifts) to improve generalization

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Test accuracy with data augmentation: 0.7694
```

Training accuracy: 0.74

TRANSFER LEARNING APPROACH

Instead of evaluating multiple architectures, our approach focused exclusively on MobileNetV2 (pre-trained on ImageNet). The model was tested in three different configurations, varying which layers were frozen and the extent of fine-tuning, in order to compare performance and training time.

METRICS & EVALUATION

	Key Features	Results
MobileNetV2.1	• Simple dense head: GlobalAveragePooling → Dense(128, ReLU) → Dense(10, softmax) • Training: 5 epochs, batch size 64	`Test accuracy: 0.8658`
MobileNetV2.2	• Dense head with dropout: GlobalAveragePooling → Dropout(0.3) → Dense(10, softmax) • Training: Frozen base first phase, 10 epochs, default batch size	`Test accuracy: 0.8562`
MobileNetV2.3	• Same architecture as V2.2 • Training: Frozen base first phase, 10 epochs, batch size 64	`Test accuracy: 0.8557`

CONCLUSIONS

Custom CNN (with Data Augmentation):

- Solid baseline model.
- Achieved moderate performance with accuracy = 0.7694.
- Requires longer training time since all weights are learned from scratch.

Transfer Learning (MobileNetV2.1):

- Achieved higher accuracy = 0.8658.
- Faster convergence by leveraging pre-trained features.
- Better generalization compared to training from scratch.

Takeaway:

- Transfer learning is the recommended approach for similar image classification tasks.

FUTURE STEPS

- Test other pre-trained models (e.g., EfficientNet, ResNet).
- Fine-tune more layers for better feature learning.
- Apply advanced data augmentation techniques.
- Optimize hyperparameters for higher accuracy.