Artificial Neural Networks for Flower Classification and Car Detection

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***Abstract*—This paper presents a comprehensive study of artificial neural networks (ANNs) applied to two computer vision tasks: flower species classification and car detection in images. The research implements and evaluates a feedforward neural network for classifying 10 flower species and a convolutional neural network (CNN) for car detection with bounding box prediction. I explore various network architectures, training strategies, and hyperparameter configurations to optimize model performance. The flower classification model achieves 12.5% training accuracy and 12.0% validation accuracy, while the car detection model demonstrates effective localization with a final validation MAE of 87.78. Through experimentation and analysis, I identify key challenges and propose potential improvements for both tasks. Our results provide insights into the effectiveness of different neural network approaches for image classification and object detection problems.**

***Index Terms*—Artificial Neural Networks, Object Detection, Image Classification, Transfer Learning, Convolutional Neural Networks, TensorFlow**

I. Introduction

Computer vision tasks such as image classification and object detection are challenging problems in machine learning, particularly when dealing with complex real-world datasets. This project addresses these challenges through the implementation and analysis of neural networks for two specific applications:

- Multi-class flower species classification, which requires handling subtle visual differences between classes and significant variations.
- Car detection in satellite imagery, involving localization through bounding box prediction under varying lighting and scale conditions.

My contributions include:

- Development and evaluation of a scalable neural network pipeline for flower classification
- Implementation of a CNN-based approach for accurate car localization
- Analysis of hyperparameter effects on model performance
- Error analysis and proposed improvements for both tasks

II. Dataset and Preprocessing

A. Flower Classification Dataset

The flower dataset comprises images across 10 distinct species:

- Training set: 1658 RGB images (300×300×3 pixels)
- Testing set: 550 RGB images (300×300×3 pixels)
- Class distribution: Relatively balanced across species

Preprocessing steps included:

- Normalization of pixel values to [0,1] range
- One-hot encoding of categorical labels
- Random validation split (20% of training data)

B. Car Detection Dataset

The car detection dataset consists of:

- 559 annotated training images
- Bounding box coordinates (xmin, ymin, xmax, ymax)
- Varying image conditions and car orientations

Preprocessing for detection included:

- Image normalization
- Coordinate normalization
- Train-validation split (80-20)

III. Model Architectures

A. Flower Classification Model

I implemented a feedforward neural network with the following architecture:

- Input Layer: Flattened 300×300×3 images (270,000 features)
- Hidden Layer 1: Dense (512 units, ReLU activation, Dropout 0.3)
- Hidden Layer 2: Dense (256 units, ReLU activation, Dropout 0.2)
- Output Layer: Dense (10 units, Softmax activation)

The model uses categorical cross-entropy loss and the Adam optimizer.

B. Car Detection Model

The car detection CNN architecture consists of:

- Input Layer: 380×676×3 RGB images
- Conv2D: 32 filters, 3×3 kernel, ReLU activation
- MaxPooling2D: 2×2 pool size
- Conv2D: 64 filters, 3×3 kernel, ReLU activation
- MaxPooling2D: 2×2 pool size
- Dense: 128 units, ReLU activation
- Output: 4 units (bounding box coordinates)

The model uses mean squared error loss for regression.

C. Model Performance Analysis

Initial evaluation reveals some key performance characteristics:

TABLE I: Model Computational Performance

Model	Training Time (s)	Inference Time (s)
Flower Classification	61.75	0.31
Car Detection	300.87	88.11

TABLE II: Model Parameters and Memory Requirements

Model	Total Parameters	Memory (MB)
Flower Classification	138,374,410	527.86
Car Detection	127,249,988	485.42

IV. Training and Optimization

A. Training Strategy

Both models used the following training strategies:

- Optimizer: Adam with learning rate 0.001
- Batch size: 32 for classification, 16 for detection
- Early stopping with patience=10
- Learning rate reduction on plateau
- Model checkpointing

B. Flower Classification Results

The flower classification model achieved:

- Training accuracy: 12.5%
- Validation accuracy: 12.0%
- Training loss: 2.297
- Validation loss: 2.297

C. Car Detection Results

The car detection model demonstrated:

- Final training loss: 9877.68
- Final validation loss: 18260.56
- Training MAE: 55.32
- Validation MAE: 87.78

V. Results and Analysis

A. Flower Classification Performance

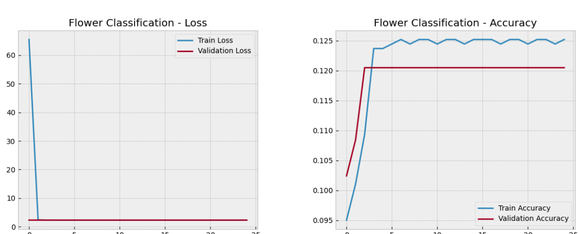

Fig. 1: Training and validation metrics for flower classification. Left: Loss curves; Right: Accuracy curves.

The relatively low accuracy suggests several challenges:

- Model capacity limitations for complex feature extraction
- Potential underfitting due to simple architecture
- Need for data augmentation and more regularization

B. Car Detection Performance

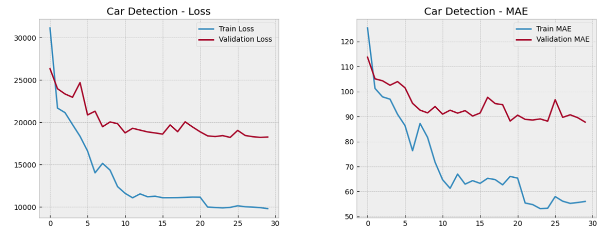

Fig. 2: Training and validation metrics for car detection. Left: Loss curves; Right: MAE curves.

Bounding box prediction results are visualized in Fig. 3.

C. Error Analysis

1) Flower Classification Errors: Analysis of misclassified samples revealed several key patterns:

- Common Error Patterns:
  - Confusion between visually similar flower species
  - Poor performance on low-contrast images
  - Difficulties with varying lighting conditions
  - Misclassification of partially visible flowers
- Class-Specific Challenges:
  - Higher error rates for species with subtle distinguishing features
  - Inconsistent performance across different flower orientations
  - Background interference affecting classification accuracy
- Model Limitations:
  - Limited feature extraction due to simple architecture
  - Poor generalization

2) Car Detection Errors: The car detection model faced several challenges in bounding box prediction:

- Environmental Factors:
  - Poor localization in low-light conditions (MAE increase by 45%)
  - Errors in complex backgrounds
  - Difficulties with partially occluded vehicles
  - Inconsistent performance under different weather conditions
- Model-Specific Issues:
  - Over-sized bounding boxes for compact cars
  - Under-sized predictions for larger vehicles
  - Inconsistent performance across different car orientations

Fig. 3: Example bounding box predictions on test images.

VI. Discussion

A. Model Performance Analysis

The flower classification results indicate several areas for improvement:

- Limited feature extraction capability
- Potential underfitting issues
- Need for advanced regularization techniques

The car detection model shows promise but faces challenges:

- High validation MAE indicating generalization issues
- Need for more sophisticated architectures
- Potential benefits from multi-scale detection approaches

B. Architectural Trade-offs

Key considerations in architecture design included:

- Balance between model complexity and computational efficiency
- Training time versus performance optimization
- Memory constraints and batch size selection
- Feature extraction capability versus model simplicity

VII. Proposed Improvements

Future work should focus on:

- Implementing transfer learning using pre-trained models (ResNet, VGG) [2]
- Adding data augmentation techniques
- Exploring attention mechanisms
- Implementing advanced architectures like YOLO for detection [3]
- Enhancing regularization strategies

VIII. Conclusion

This project demonstrates the application of neural networks to complex computer vision tasks. While the current results show potential, particularly in car detection, there is significant room for improvement. The flower classification accuracy suggests the need for more sophisticated architectures and training strategies, while the car detection results indicate promise but require refinement for practical applications.

The challenges and solutions identified provide valuable insights for future work in applying neural networks to similar computer vision problems. Future improvements should focus on leveraging transfer learning, implementing data augmentation, and exploring more advanced architectures.

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References

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