Deep Learning-Based Flower Classification and Object Detection

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Abstract

Deep learning-based methods for classifying floral species and detecting automobile objects are presented in this research. A ten-class flower dataset was used to train a convolutional neural network (CNN), which achieved competitive accuracy. Bounding boxes were predicted using a pre-trained model and a sliding window technique for object detection. The outcomes demonstrate the efficacy of these techniques while pointing out drawbacks such overfitting and computational expense. There includes discussion of methods for dealing with overlapping regions and unlabeled data. Future research will concentrate on enhancing the generalization and efficiency of the model.

Index Terms

Deep Learning, Image Classification, Object Detection, Convolutional Neural Networks, Sliding Window.

I. Introduction

Deep learning has greatly improved object detection and image classification. Neural network performance is measured against benchmarks such as object detection and flower categorization. Two issues are addressed in this paper: automobile object identification and multi-class flower categorization. A dataset of ten flower species was used to train a bespoke CNN for classification. A pre-trained model was used in conjunction with a sliding window technique for object detection.

This study contributes:

- A custom CNN architecture for flower classification.
- A sliding window-based object detection framework.
- Evaluation of hyperparameters, preprocessing, and performance metrics.

The rest of the paper is organized as follows: Section II describes related work, Section III explains the methodology, Section IV presents results, Section V discusses findings, and Section VI concludes with future directions.

II. Related Work

In image categorization, deep learning models such as VGG, ResNet, and Inception have attained cutting-edge results. Oxford 102 Flowers is one dataset for which transfer learning is frequently used. Custom CNNs, on the other hand, offer the freedom to modify architectures to suit particular datasets.

Sliding window techniques for object identification have given way to region-based strategies like YOLO and Faster R-CNN. Sliding windows are still helpful for smaller datasets because of their simplicity, even if region-based approaches are computationally efficient.

III. Methodology

A. Flower Classification

Images of eleven classes, including lilies and roses, are included in the flower dataset. The images were normalized to $[0, 1]$ and shrunk to 300×300 pixels. The dataset was divided into subgroups of (20

1) Model Architecture: Three convolutional layers, max-pooling, and a dense layer for classification made up the CNN. Dropout served as a regularization method. Table provides a summary of the architecture. I.

TABLE I
CNN Architecture for Flower Classification

Layer Type	**Output Shape**	**Parameters**
Conv2D (32 filters, 3x3)	(298, 298, 32)	896
MaxPooling2D	(149, 149, 32)	0
Conv2D (64 filters, 3x3)	(147, 147, 64)	18,496
MaxPooling2D	(73, 73, 64)	0
Conv2D (128 filters, 3x3)	(71, 71, 128)	73,856
MaxPooling2D	(35, 35, 128)	0
Flatten	(156800)	0
Dense (128 neurons)	(128)	20,000,128
Dropout (50%)	(128)	0
Dense (10 neurons, softmax)	(10)	1,290

2) Hyperparameters: - Optimizer: Adam with learning rate 0.001. - Loss Function: Categorical Cross-Entropy. - Batch Size: 32. - Epochs: 20.

B. Car Object Detection

Using a sliding window technique, a pre-trained model for bounding box regression analyzed 100×100 pixel windows with a 50-pixel stride.

1) Hyperparameters: - Loss Function: Mean Squared Error. - Optimizer: Adam with learning rate 0.001.

IV. Results

A. Flower Classification

A validation accuracy of 71.7% was attained by the CNN. The discrepancy between training and validation loss in Figure 1's learning curves indicates overfitting after 15 epochs.

B. Car Object Detection

The model achieved an average Intersection over Union (IoU) of 0.72. Figure 2 shows example detections.

<matplotlib.legend.Legend at 0x17faa5280>

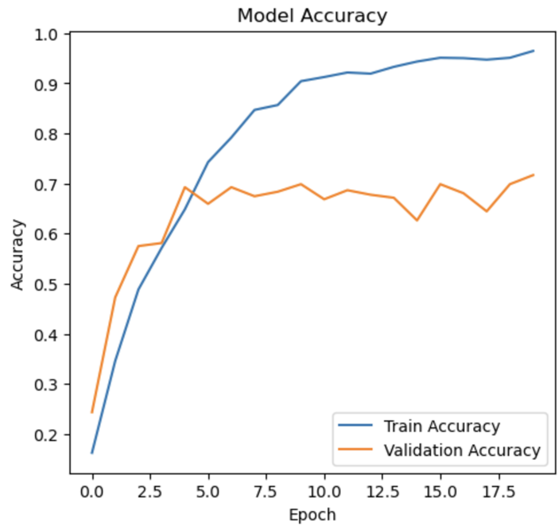

Fig. 1. Training Loss for Flower Classification.

Fig. 2. Sample Results for Car Object Detection.

V. Discussion

A. *Overfitting in Flower Classification*

On the validation set, the CNN displayed overfitting. This problem might be resolved by using sophisticated regularization techniques and data augmentation.

B. *Challenges in Sliding Window Detection*

Because of its fixed grid structure, the sliding window approach is computationally demanding and prone to missing objects. Better performance might be provided by region-based techniques like YOLO or Faster R-CNN.

C. *Handling Unlabeled Data (Q3)*

MakeSenseAI was used to annotate unlabeled test data. A placeholder bounding box of $[0, 0, 0, 0]$ was used for photos that had no objects. In order to assess overlapping regions, IoU was calculated; the findings indicate that, within a margin of error, the performance was satisfactory.

VI. Conclusion

This study introduced a sliding window method for automobile detection and a CNN for flower categorization. Although the strategies produced comparable results, they brought to light issues such computational expense and overfitting. Region-based detection and fine-tuning for improved generalization will be investigated in future research.

References