Deep learning classifier for tornado damage assessment.

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Pretrained convolutional neural networks (CNNs) outperform non-pretrained ones in **post-event building damage classification**. Furthermore, pretraining on **specialized classification tasks** can yield, in some cases, **similar level of improvement** compared to pretraining on general classification tasks.

Introduction

Accurate and fast tornado damage assessment is critical to create adequate post-disaster response and recovery strategies. Deep learning could facilitate these damage assessments. However, large datasets are often required to extract the full potential of deep learning networks.

By leveraging the knowledge gained from other tasks, transfer learning can reduce the data demand required to train deep learning networks. In this study, transfer learning is adopted to enhance network performance. Furthermore, the benefits of pretraining on different datasets is explored.

Methodology

Transfer learning:

1. CNNs are pretrained on general or specialized tasks (See Figure 1)
2. The pretrained CNN backbone is extracted and transferred to a new CNN
3. The new CNN is retrained

Evaluation metrics:

Accuracy on testing dataset

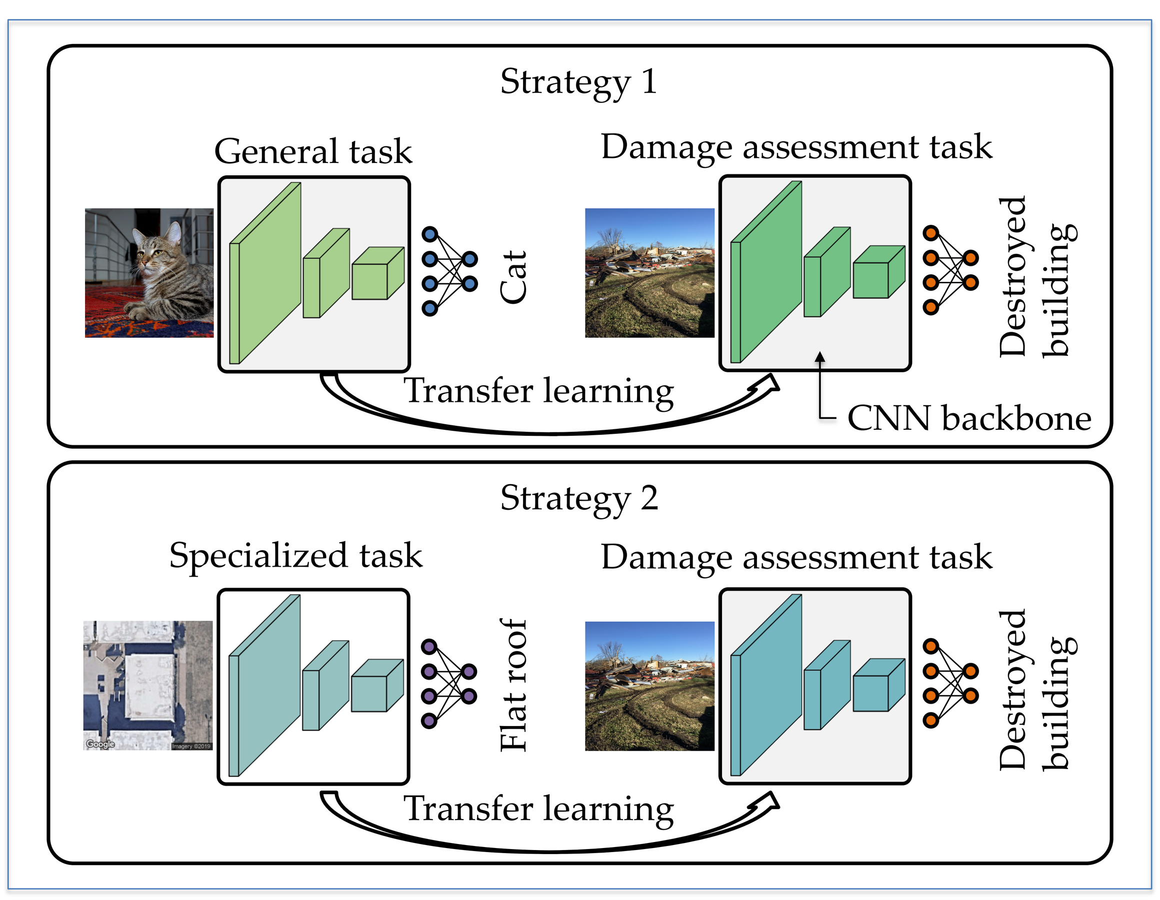

Figure 1: Transfer learning strategies in this study

Experiments

CNNs:

Different CNNs from the BRAILS framework are adopted in this study (see Table 1) [1].

Datasets for pretraining:

Datasets collected by BRAILS for the specialized tasks, and ImageNet [2] and COCO [3] for general tasks.

Damage assessment dataset:

Post-event building damage dataset with 634 images and three classes (see Table 2).

Table 1: CNN backbones in BRAILS

Task	CNN backbone
Foundation Classification	Resnet50
Roof Type Classification	Efficientnetv2-S
Occupancy Classification	Efficientnetv2-S
Chimney Detection	Efficientnet-b4
Garage Detection	Efficientnet-b4
Number of Floors Detection	Efficientnet-b4

Table 2: Building damage dataset

Classes	Images
1. Non or minor damage	197
2. Moderate damage	267
3. Severe damage or destroyed building	170

Results

- Tables 3-5 show the performance on the damage assessment testing dataset.
- Pretraining on general tasks leads to an improvement of up to 22%.
- Pretraining on specialized tasks leads to an improvement of up to 20%.

Table 3: Resnet50 performance

Pretraining dataset	Accuracy (%)
N/A	63.3
ImageNet	79.5
Foundation (BRAILS)	67.3

Table 4: Efficientnetv2-S performance

Pretraining dataset	Accuracy (%)
N/A	61.3
ImageNet	83.7
Roof Type (BRAILS)	77.8
Occupancy (BRAILS)	81.9

Table 5: Efficientnet-b4 performance

Pretraining dataset	Accuracy (%)
N/A	67.2
ImageNet	76.6
COCO	80.6
Chimney (BRAILS)	80.7
Garage (BRAILS)	76.9
Number of Floors (BRAILS)	81.2

Figure 2: Predictions using best Efficientnetv2-S

Conclusions

- Pretraining improves the accuracy of CNNs for post-event building damage classification.
- Pretraining on specialized classification tasks provides, in some cases, similar improvement compared to pretraining on general classification tasks.

References

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