Super-Resolution of Low-Quality Images for Realtime Pothole Detection

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Introduction

- Publicly available pothole detection datasets largely consist of high-resolution dashcam footage.
- Given the expensive nature of high-resolution dashcams, drivers instead opt for cheaper, low-resolution alternatives.
- As such, object detection models do not perform well for use with a majority of dashcams due to the domain mismatch between the high-resolution training data and the low-resolution test data.
- We present a novel approach to address this issue for real-time automated pothole detection through the use of Super-Resolution Generative Adversarial Networks (SRGANs).

Related Works

- Past approaches for automated pothole detection involved accelerometers, gyroscopes, wireless IoT sensors, thermal imaging cameras, etc.
  - High cost / complexity for setting up equipment
- Modern approaches leverage deep learning + dashcam footage
  - Various YOLOv3 architectures achieved the quickest and most reliable pothole detection
- However, no past work evaluated the effects of super-resolution on dashcam images
  - Kim et al. used SRGAN on images from CCTV cameras before feeding into CNN-based vehicle model classifier; upscaling from 224x224px to 896x896px led to significant increases in classification accuracy

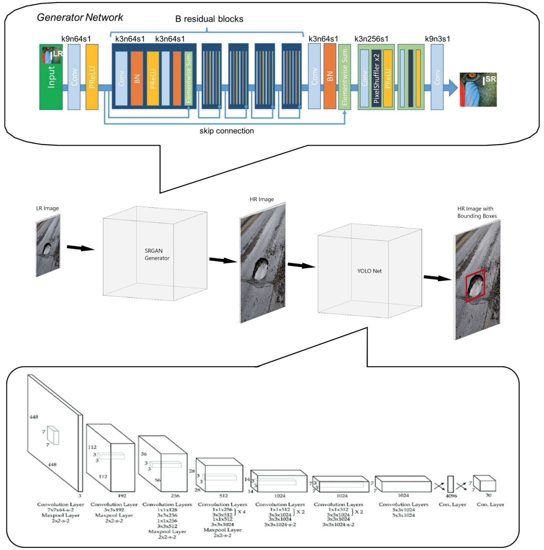
Dataset

3,888 RGB images (from Stellenbosch University)

- 2,634 images in train set (68%); 627 in val set (16%); 627 in test set (16%)
- Originally 3680x2760 pixels
- 3 versions of dataset:
    - Rescaled to 4K (3840x2160px)
    - Downscaled to 720p (1280x720px)
    - Downscaled to 360p (640x360px)

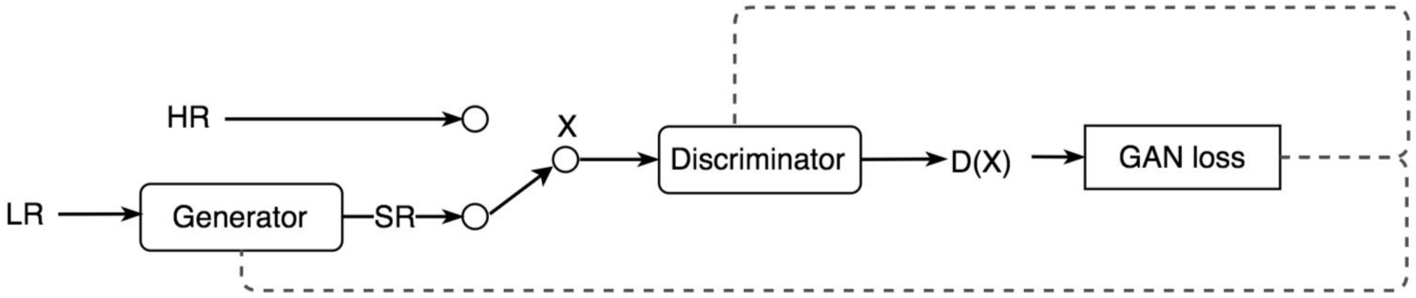
Methods

- The pothole detection pipeline consists of an SRGAN followed by a YOLOv4 model where the SRGAN performs super-resolution on the incoming stream of low-resolution dashcam frames and the YOLO model performs object detection.



SRGAN

- The SRGAN consists of a generator, which upscales the low-resolution (LR) images to super-resolution (SR) images, and a discriminator, which distinguishes between the HR and SR images and backpropagates the GAN loss to train the discriminator and generator.



YOLO

- YOLO network splits input image into grid of cells
  - each cell predicts whether center of a pothole is inside of it
  - outputs vector w/ confidence scores of all cells + bounding boxes
- Using YOLOv4 (April 2020) for this project
  - Trained on 3 versions of the training set
    - 360p
    - 720p
    - 4K

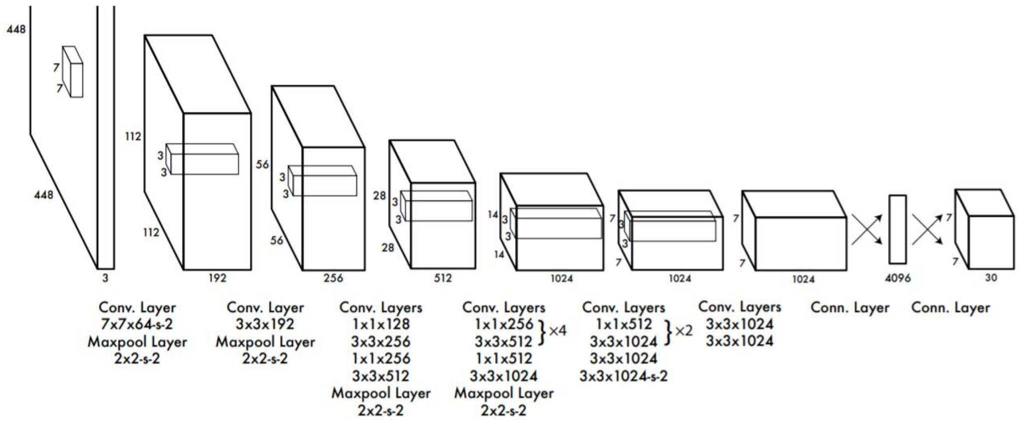


Image source: https://arxiv.org/pdf/1506.02640.pdf

Experiments and Results (Quantitative)

Model	Training set	Test set	Evaluation Metrics	
			mAP (%)	F1-score
YOLOv4 (baseline)	720p	720p	64.01	0.67
YOLOv4	4K	720p	60.67	0.64
YOLOv4	4K	**4K (SRGAN)**	**65.84**	**0.68**
YOLOv4 (upper benchmark)	4K	4K (original)	68.79	0.70
YOLOv4 (baseline)	360p	360p	28.49	0.39
YOLOv4	720p	360p	31.09	0.42
YOLOv4	720p	**720p (SRGAN)**	**60.06**	**0.65**
YOLOv4 (upper benchmark)	720p	720p (original)	64.01	0.67

Experiments and Results (Qualitative): SRGAN

Experiments and Results (Qualitative): YOLO

Demo: SRGAN-to-YOLO Output

Conclusion

Low-resolution dashcams can be used for more accurate real-time pothole detection

Dashcams can record at low resolutions to save memory

Can apply SRGAN for tougher object detection problems

Image sources: Bottom left: https://en.wikipedia.org/wiki/Hard_disk_drive Bottom right: https://www.mentalfloss.com/article/51292/night-sky-6-hours-stars

Future Work

- Assess how pothole detection speed and performance changes with different / newer models
  - SRResNet
  - FaSTGAN
  - YOLOv5
  - PP-YOLO

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