Remote Sensor Design for Automated Visual Recognition

DSI Workshop Presentation

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August 7-8th, 2018

LLNL-PRES-XXXXXX
This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract DE-AC52-07NA27344. Lawrence Livermore National Security, LLC

LLNL-PRES-755028

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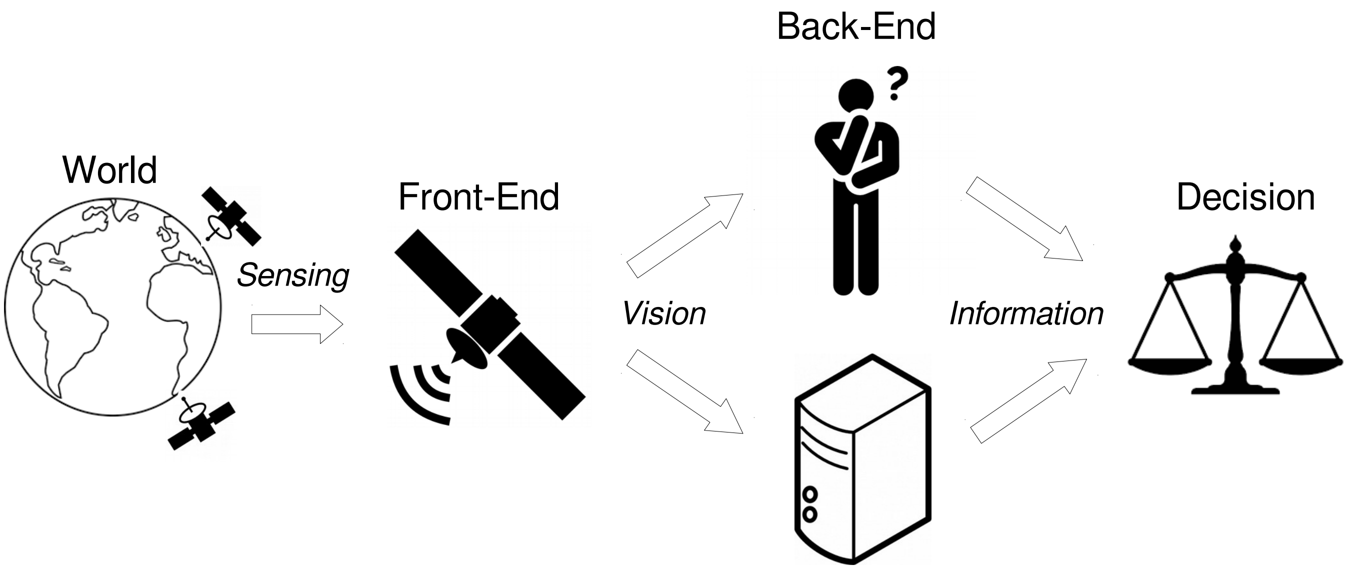
Problem: Image Systems Are Designed for Human Vision

- Current sensor models optimize for human vision (NIIRS)
- Modern systems use automated recognition for remote sensor data
- **Need:** optimize sensor models for computer vision



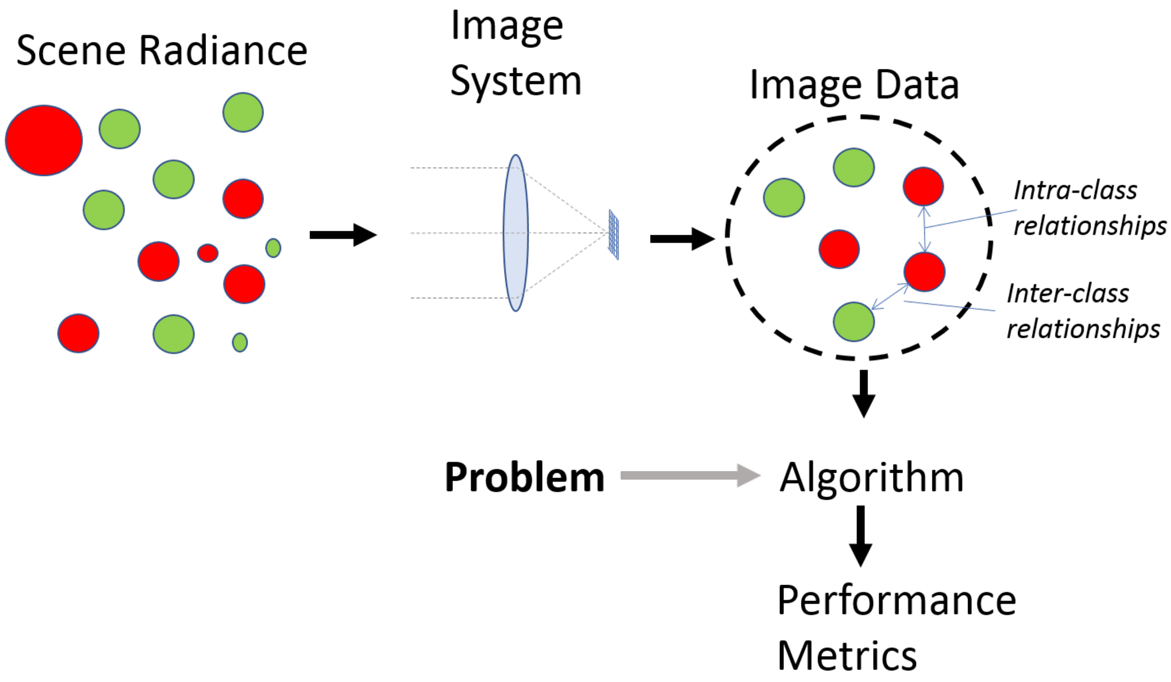
Holistic model of human and machine vision for satellite imaging.

Approach: Measure Sensor Parameter vs. Algorithm Performance (1)

1. **Simulate** an image sensor system: view existing imagery as seen through the sensor

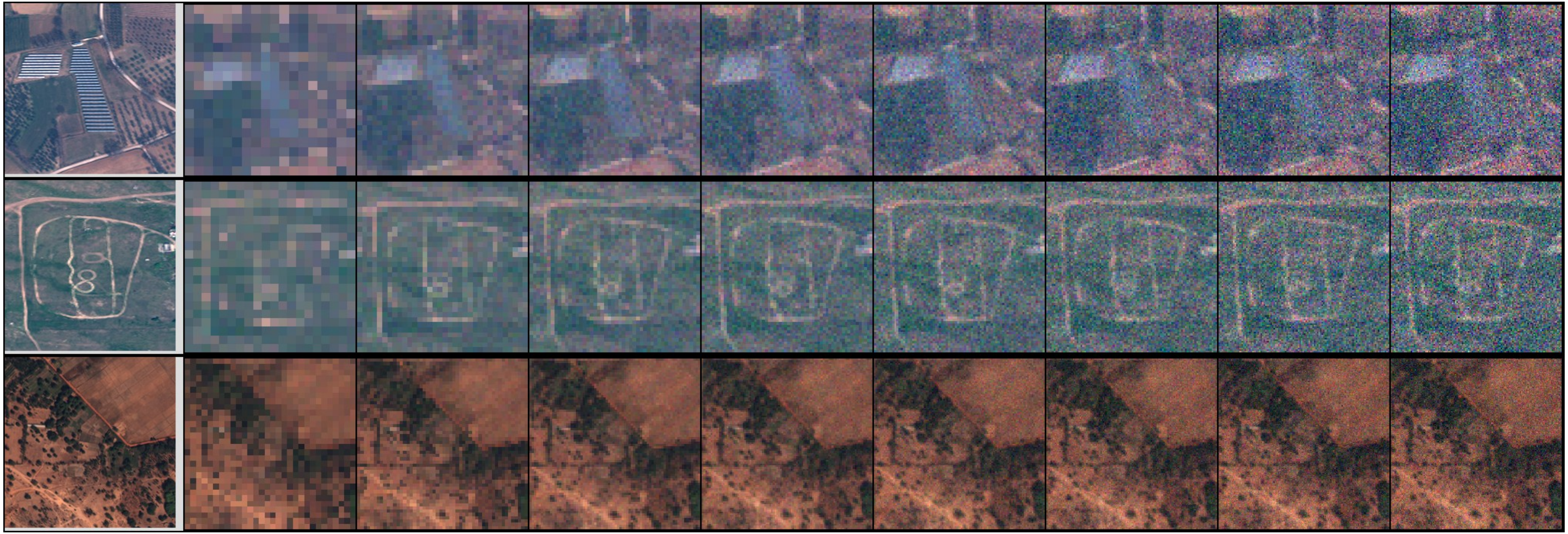
2. Vary a parameter of the sensor system and **transform** an existing dataset for each parameter value increment

3. **Measure** change in ML performance with respect to sensor parameter value



The problem to be solved and relationships between the data are critical to system performance.

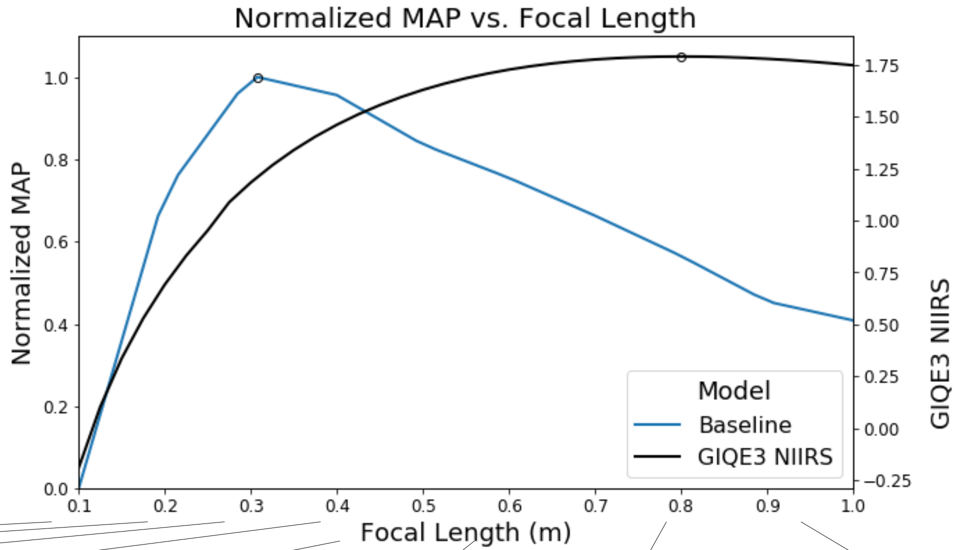
Approach: Measure Sensor Parameter vs. Algorithm Performance (2)



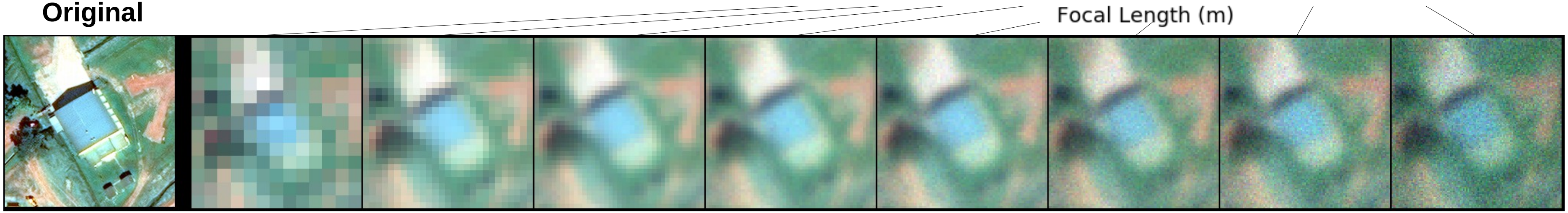
Three classes (solar farm, race track, crop field), are simulated with varying focal length (increasing from left to right). Original image is on the left of each row.

Approach: Measure Sensor Parameter vs. Algorithm Performance (3)

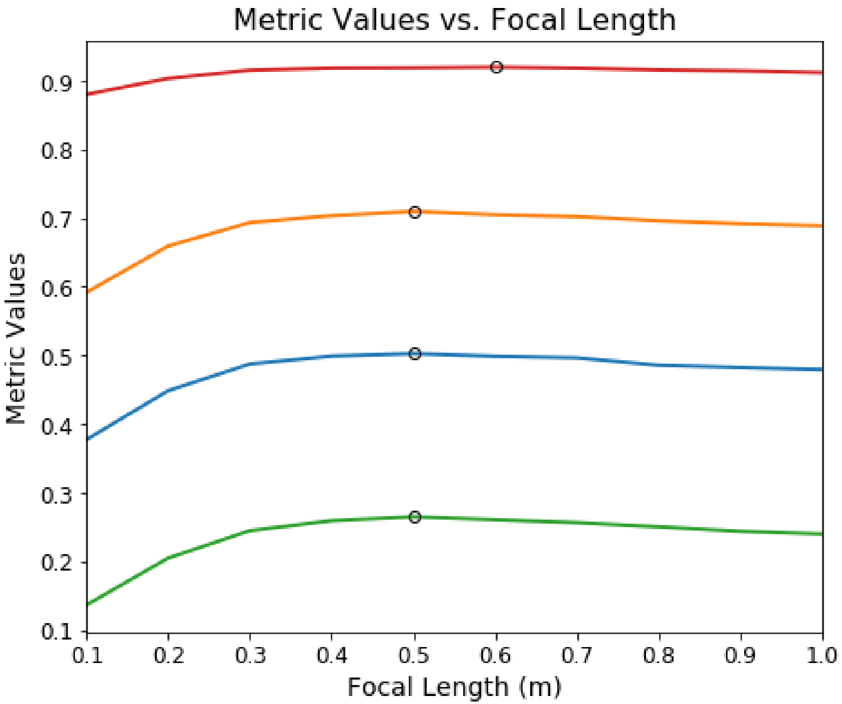
- In a satellite image dataset with 35 classes, predict which images are most similar to the target image
- How does Mean Average Precision (MAP) of a neural network change as focal length increases?
- How does this relationship compare to human interpretability (NIIRS)?

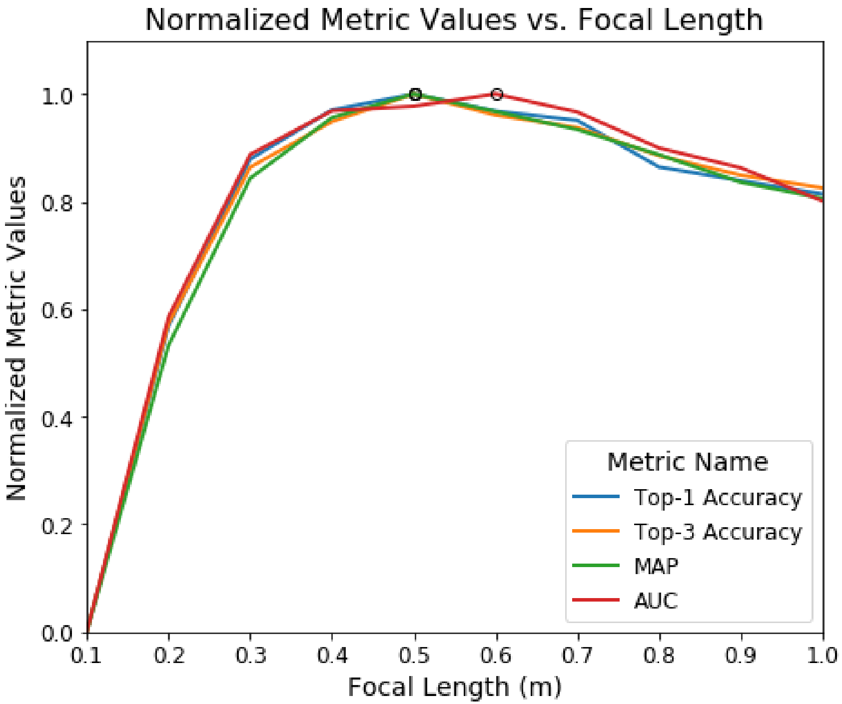


Original



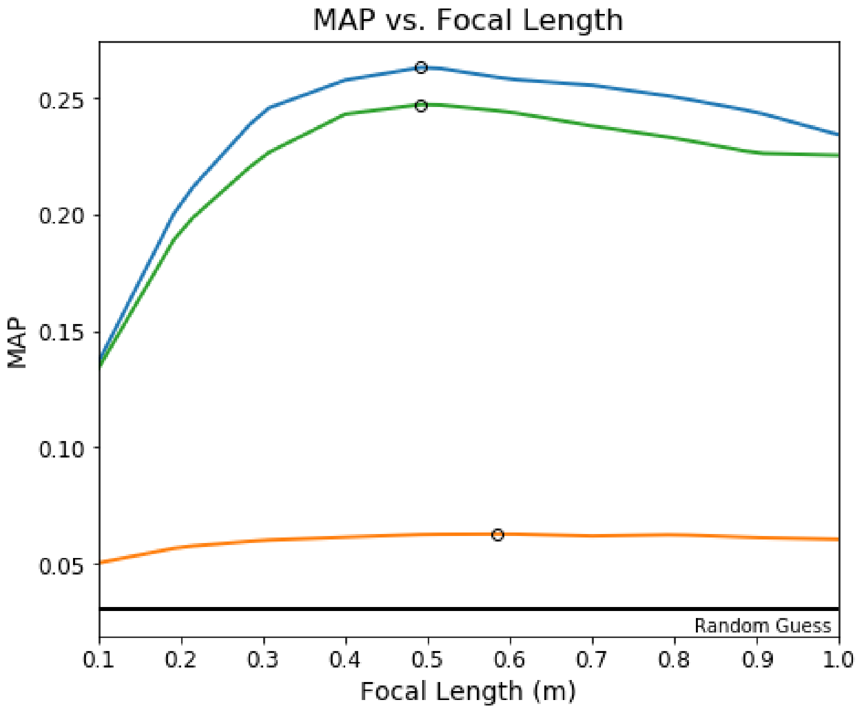
Analysis: Compare Performance Metrics

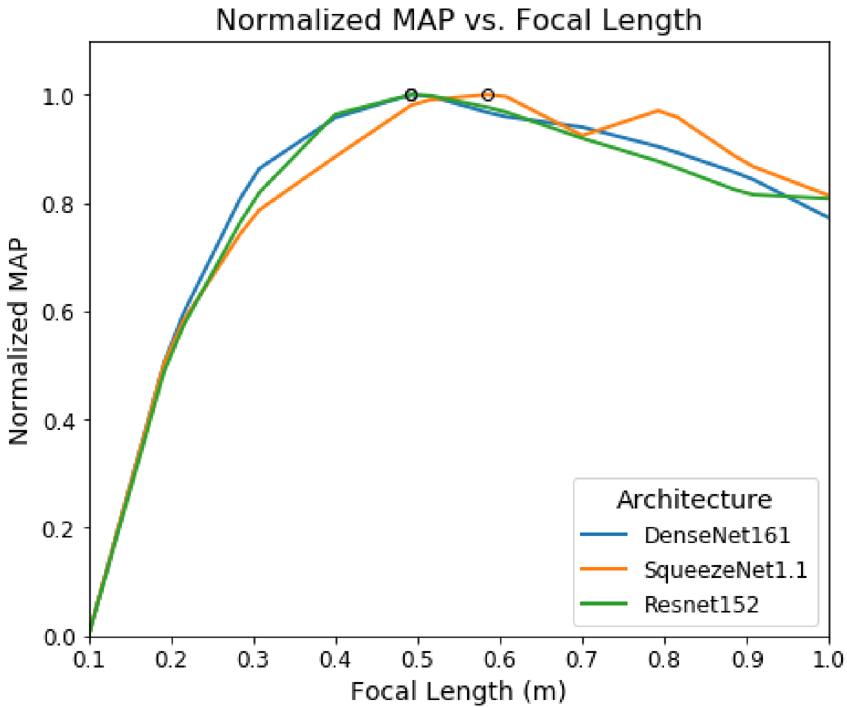




Four recognition metrics are compared as a function of system focal length. Area Under the ROC Curve (AUC) differs most.

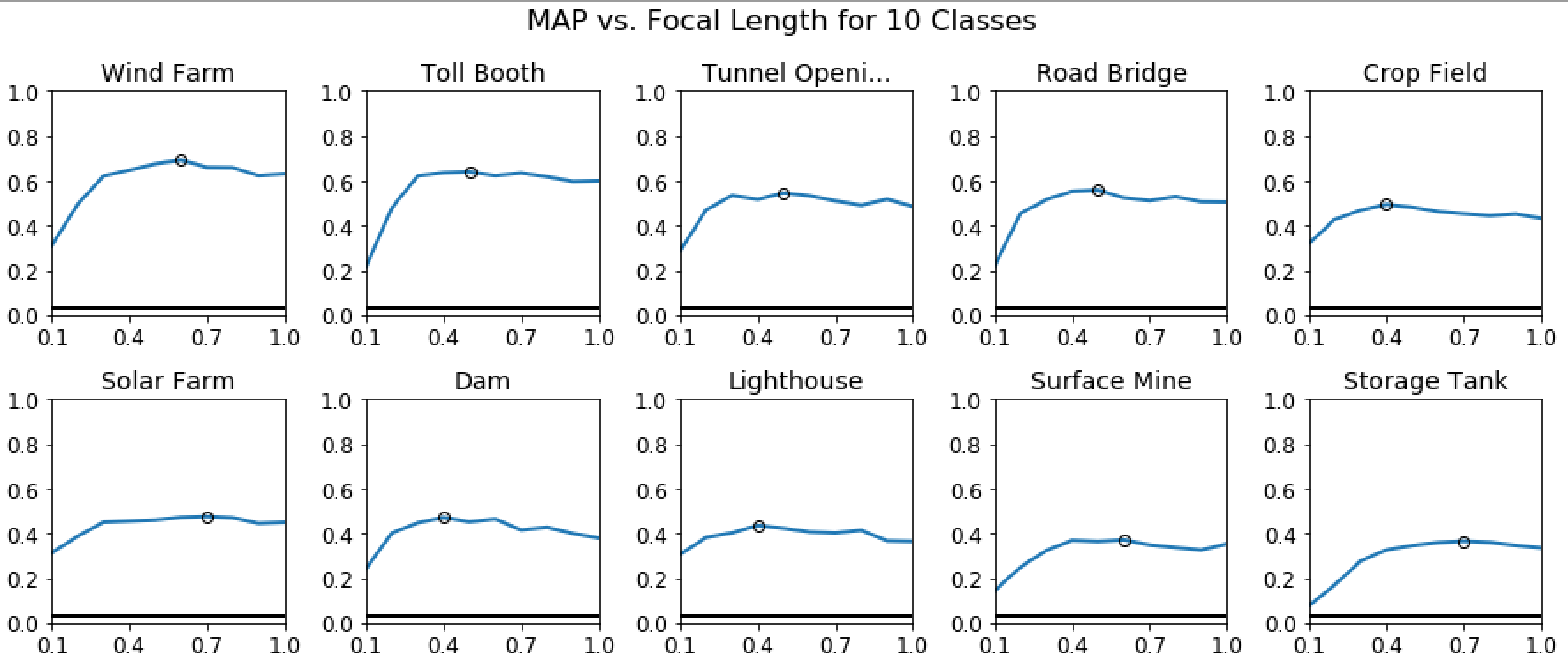
Analysis: Compare CNN Architectures





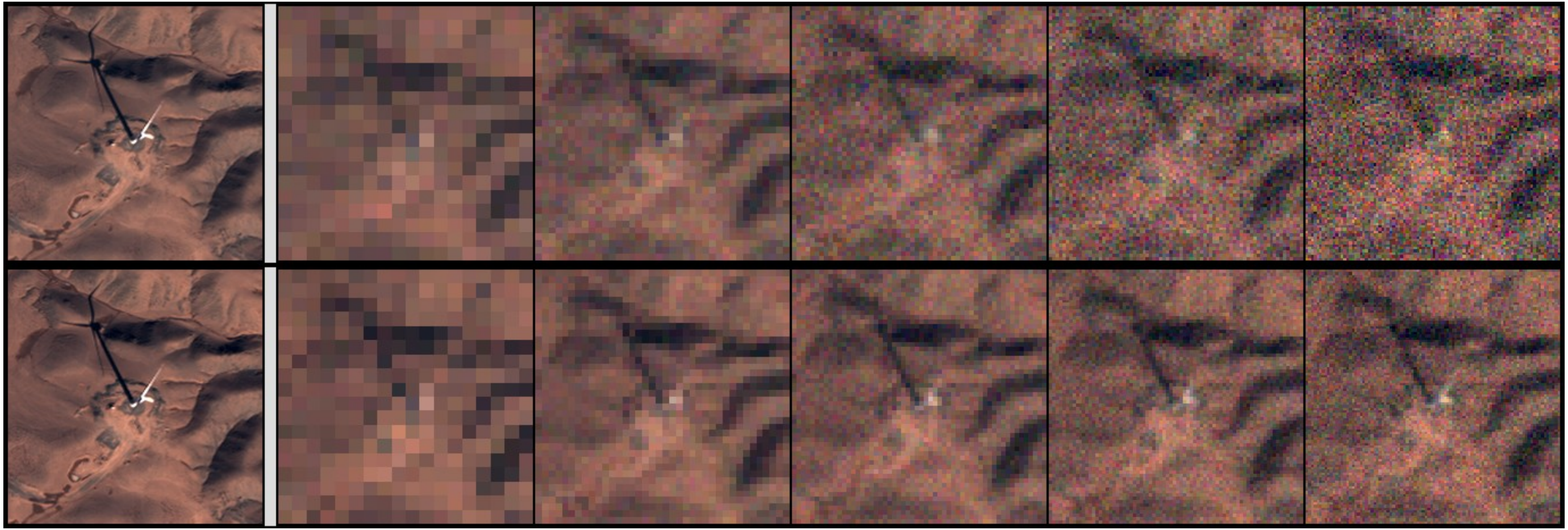
Three architectures are compared for MAP vs. focal length. SqueezeNet differs most because of poor (high-d) features.

Analysis: Compare Image Classes



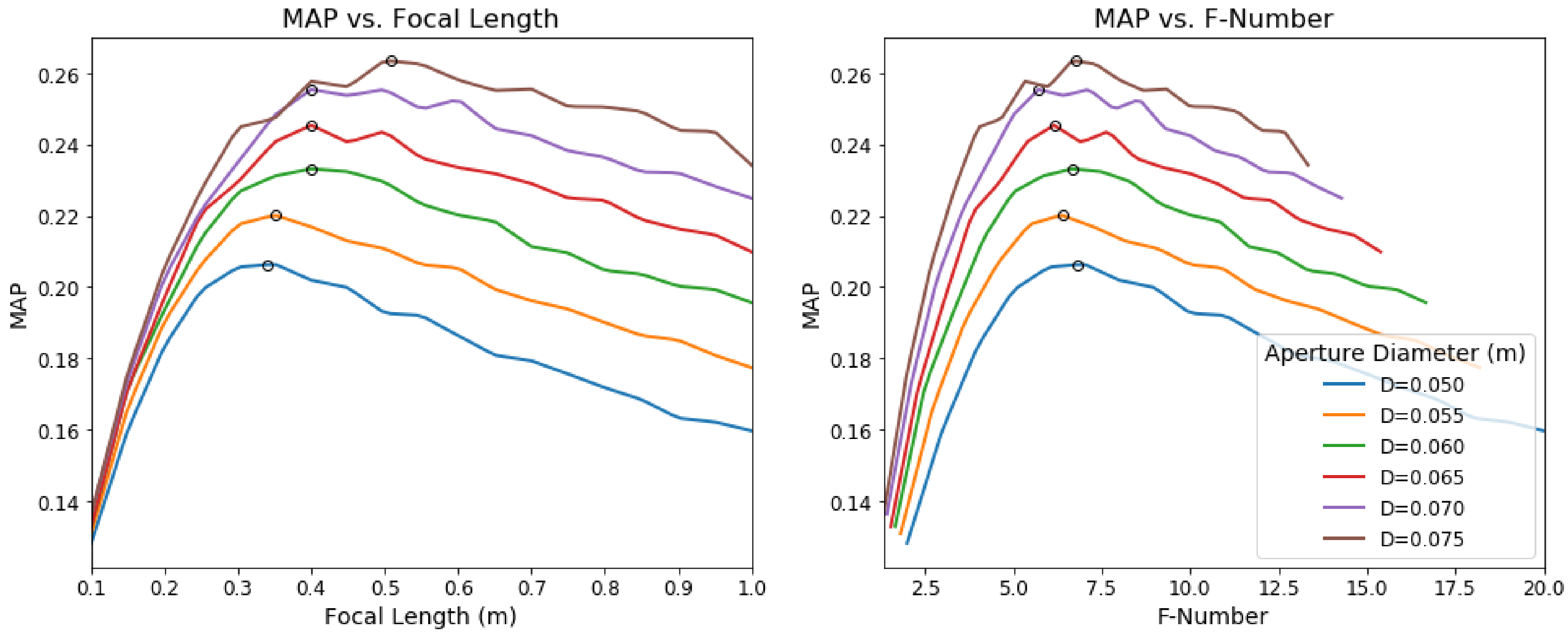
Notice that different image classes exhibit similar trends but have different absolute performance and different peaks.

Analysis: Measure Relationship with Aperture Diameter (1)



Simulation of changing focal length for two aperture diameter values (low top, high bottom). Notice that the lower aperture diameter system has considerably more noise than the greater one, as focal length increases.

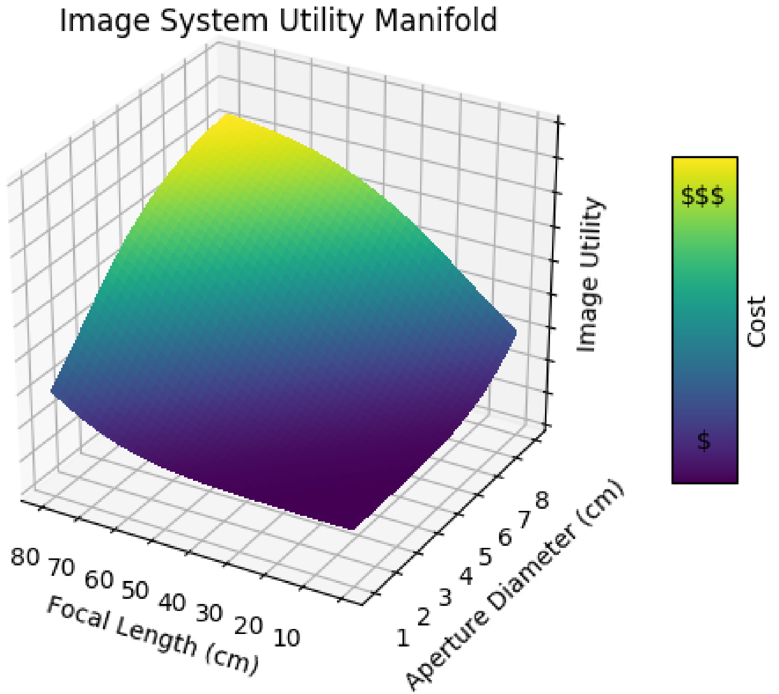
Analysis: Measure Relationship with Aperture Diameter (2)



MAP peaks align well for different aperture diameters when plotting against f-number instead of focal length.

Conclusions

- We develop a methodology for optimizing remote sensing parameters with respect to deep learning
- Human and machine visual recognition performance can differ significantly
- Find optimal point in the Image System Utility Manifold for cost vs. performance
- **Benefit:**
  - Design cost-effective satellites
  - Solve more recognition problems



Find optimal cost/performance tradeoff.

References

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Appendix A: Convolutional Neural Networks

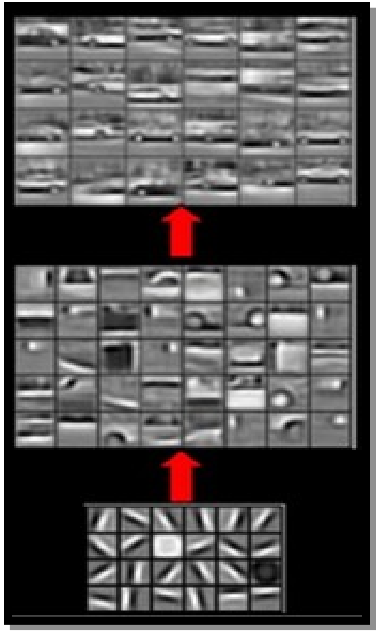


Figure 1: *CNN features hierarchy for cars [2]*

- Neural networks are data structures which allow efficient learning of complex non-linear functions
- CNNs utilize spatial locality and hierarchical representations to learn salient features
- CNNs are state-of-the-art, exceed human performance on challenging recognition tasks

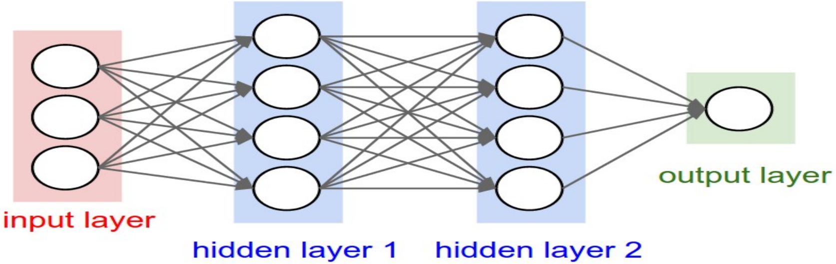
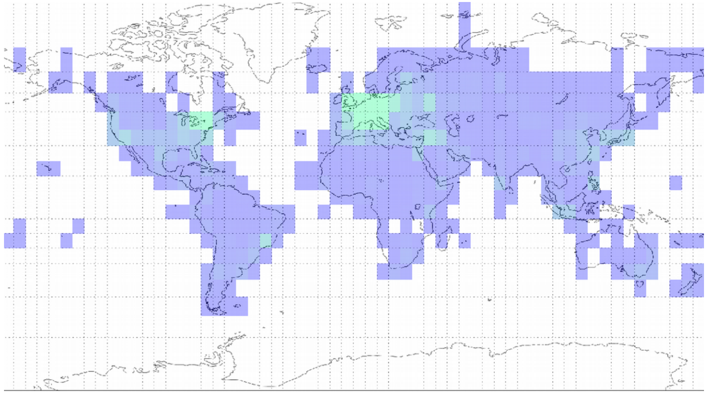


Figure 2: *Simple neural network diagram [5]*

Appendix B: Functional Map of the World (fMoW)

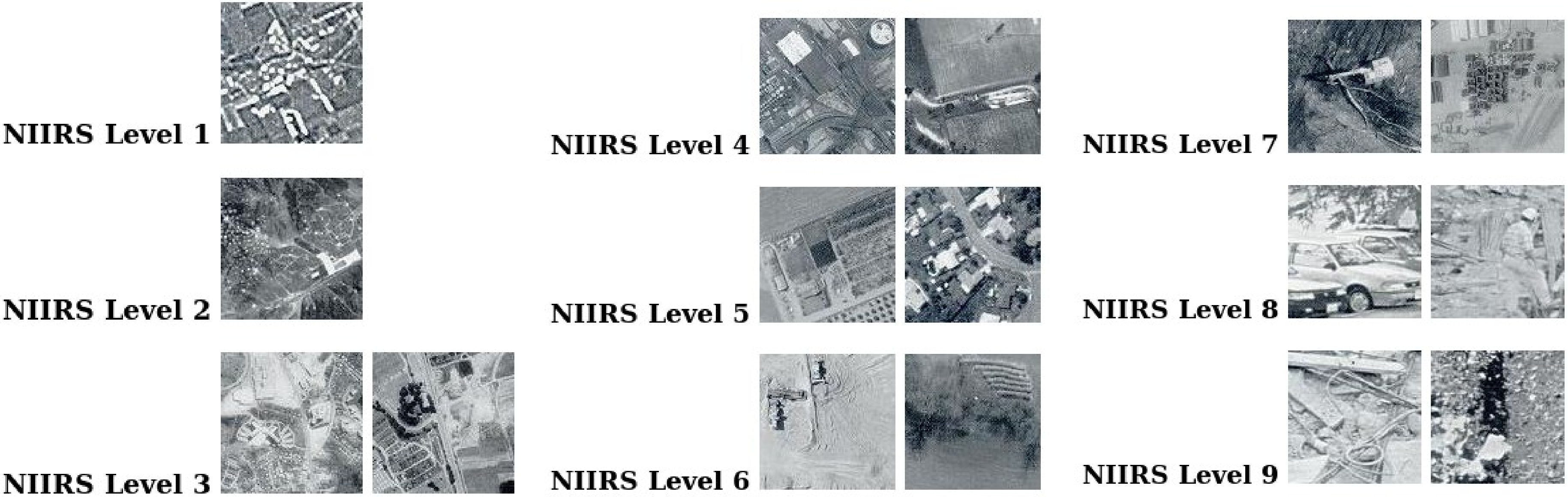
- Public Digital Globe satellite images
- RGB + 8-band MS, metadata
- GSD around 0.5 m/p
- 62 classes
  - e.g., airport hangar, nuclear powerplant, space facility, military facility, storage tank
- Multiple images per instance
  - e.g., one airport in the world has many images taken at different times

Example images from 16 FMOW classes.



Geographic diversity of FMOW data [1].

Appendix C: National Imagery Interpretability Rating Scale



Example images for each NIIRS rating. From: https://fas.org/irp/imint/niirs_c/append.htm