Thermal Imagery Based Instance Segmentation for Energy Audit Applications in Buildings

Youness Arjoune, Sai Peri, Niroop Sugunaraj, Debanjan Sadhukhan, Michael Nord, David Flynn, Gautham Krishnamoorthy, Prakash Ranganathan
School of Electrical Engineering & Computer Science, University of North Dakota, Grand Forks, ND-58202

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Abstract

This paper focuses on a machine learning pipeline to quantify heat loss in buildings using 60,000 thermal images in buildings captured from a small Unmanned Aerial System (sUAS) over the last two years to form a large thermal data repository. Annotations for multiple objects such as facades, windows, and sky were undertaken to aid in machine learning. Object detection and instance segmentation models such as Mask R-CNN, Fast R-CNN, and Faster R-CNN were trained and tested. The preliminary results indicate that Mask R-CNN has a larger mean average precision (mAP) of (83%) over R-CNN (51%), Fast R-CNN (62%), and Faster R-CNN (62%) for a threshold of 50%. The surface temperature values from these thermal images (pixel-by-pixel) were then used in the standard heat transfer coefficient (U-value in BTU/hr/Sq.ft./F) calculations.

Introduction

One way of performing the quantitative assessment of a building is by providing the overall thermal transmittance (generally known as the "U-value") of different parts of the buildings.

• The U-value is defined as the rate of heat that flows through one square meter of the wall (or the inspected part of the wall) from/to the outside air when the temperature difference between the inside and outside is one Kelvin under steady state conditions. The unit of U-value is BTU/ft²/hr/F or Wm−2K−1.

• In our analysis, we discard certain sections of images (such as the sky, the ground around the building face, or trees) using an instance segmentation process, and considered them as noise as they can result in inaccurate U-value/heat-loss calculations.

U-value

The U-value is given by:

$$U = \frac{\varepsilon\sigma(T_s^4 - T_{ae}^4) + 3.8054v(T_s - T_{ae})}{T_{ai} - T_{ae}}$$

Variable	Definition
U	Overall heat transfer coefficient [(BTU/ft^2/hr/F)]
ε	Wall emissivity, wall spectral emissivity
σ	Stefan-Boltzmann constant [W/m^{2}K^4]
v	Wind speed [m/s]
T_s	Surface temperature [K]
T_{ae}	External Air temperature [K]
T_{ai}	Internal Air Temperature [K]

Contact Information

Prakash Ranganathan,
Director of Cyber Security,
College of Engineering & Mines (CEM),
University of North Dakota
prakash.ranganathan@engr.und.edu

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Experimental Methodology

Using a sUAS equipped with a FLIR camera, and with partnerships with a local UAS company (SkySkopes Inc.) in North Dakota, more than 60,000 infrared images were taken. A guideline to acquire thermal images from buildings were developed, and followed strictly to adhere consistency in the acquisition of images. Prior to data collection, a piece of aluminum foil and black tape were placed on each building to calculate the reflected temperature and emissivity. Intense efforts are made to annotate multiple sections of the buildings (e.g. windows, doors, ground, facade, trees, and sky). Data augmentation processes are then applied to generate a large comprehensive training data set. Object detection and instance segmentation models such as Mask R-CNN, Fast R-CNN, and Faster R-CNN were trained and tested.

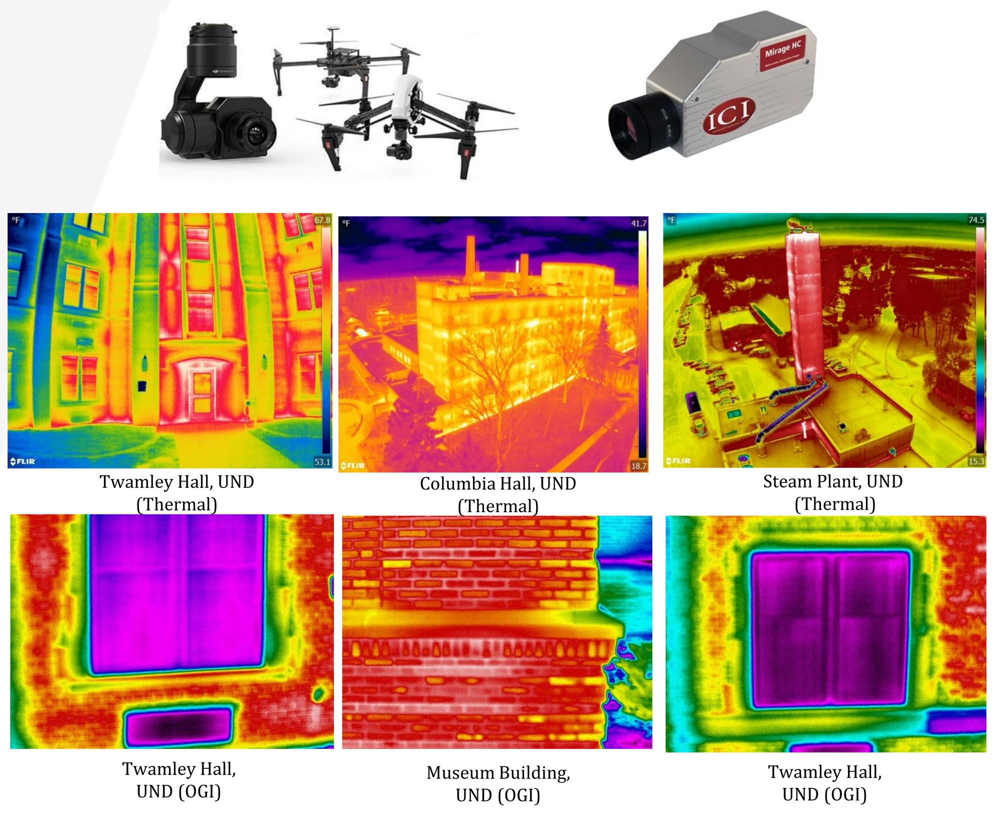

Figure 1: Equipment, FLIR & OGI images of various buildings in the University of North Dakota (UND) campus

Machine Learning Process

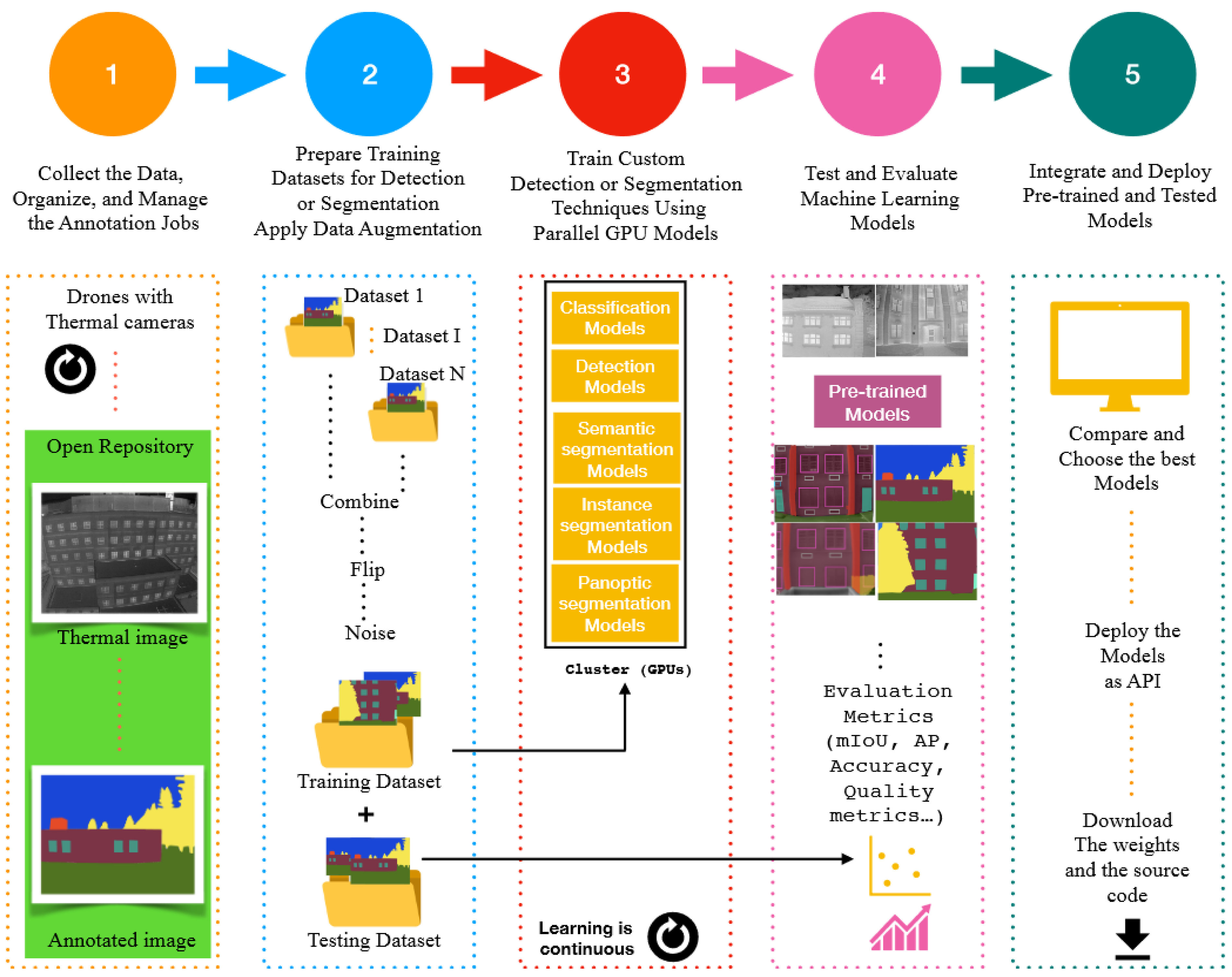

Figure 2: Machine Learning Pipeline for Building Audits

Performance Metrics

Intersection over Union (IoU) and **mean Average Precision (mAP)** are used to evaluate the object detection and instance segmentation models.

$$Precision = \frac{TP}{TP+FP} \quad [5]$$

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union} \quad [6]$$

The precision (**AP**) measures the percentage of correct predictions and the **IoU** measures the number of pixels that are common between the target and prediction masks. If the IoU is greater than a certain threshold, it is treated as TP, otherwise it is a FN.

TP: True Positive
FP: False Positive
FN: False Negative

Accuracy and U-Value Quantification Results

Average U-value (BTU/ft²/hr/F)

Building Name	Wall Sample 1	Wall Sample 2	Wall Sample 3	Windows (Face 1)	Windows (Face 2)	Windows (Face 3)
Twamley Hall	0.005	0.02	0.02	1.14	0.7	0.6
Museum	0.07	0.08	0.06	0.3	0.28	0.4

Training/Testing Results of Convolution Algorithms

Models	mAP$^{0.25}$	mAP$^{0.5}$	mAP$^{0.75}$	mIoU
RCNN	0.53	0.51	0.32	0.76
Faster RCNN	0.68	0.62	0.40	0.82
Faster RCNN ResNet 50	0.83	0.58	0.53	0.75
Faster RCNN Inception ResNetV2	0.65	0.62	0.51	0.83
Mask R-CNN	0.83	0.83	0.59	0.80

Conclusions

The preliminary findings indicate Mask R-CNN produces better mAP of (83.0%) in segmenting objects for thermal imagery. It is observed that the U-values for windows in Twamley are larger than ND Museum. This is an anticipated result as the windows in Twamley are older and are of single pane type while the windows in Museum building are new and upgraded with double pane types. It is desired to have a lower U-value for heat loss quantification.
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School of Electrical Engineering & Computer Science
UNIVERSITY OF NORTH DAKOTA