AUTOMATED BUILDING ENERGY CONSUMPTION ESTIMATION FROM AERIAL IMAGERY

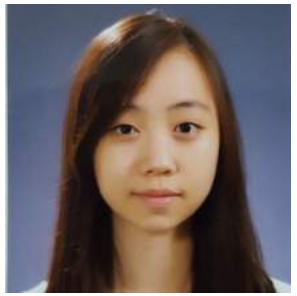
A BASS CONNECTIONS IN ENERGY PROJECT TEAM

Team Members 2016-17

Student Researchers

Mitchell Kim
Pratt '18

Sebastian Lin
Trinity '18



Sophia Park
Pratt '17

Eric Peshkin
Trinity '18

Samit Sura
Economics '17

Nikhil Vanderklaauw
Pratt '18

Hoël Wiesner
Nicholas '17

Yue Xi
Trinity '19

Faculty Advisors

Dr. Timothy Johnson
Nicholas School

Dr. Kyle Bradbury
Energy Initiative

Dr. Leslie Collins
Pratt School

AUTOMATED BUILDING ENERGY CONSUMPTION ESTIMATION FROM AERIAL IMAGERY

A BASS CONNECTIONS IN ENERGY PROJECT TEAM


What can an image
tell us about our
energy consumption?


Commercial and
Industrial Activitiy


Transportation


Buildings

Governments and policy makers

Governments and policy makers

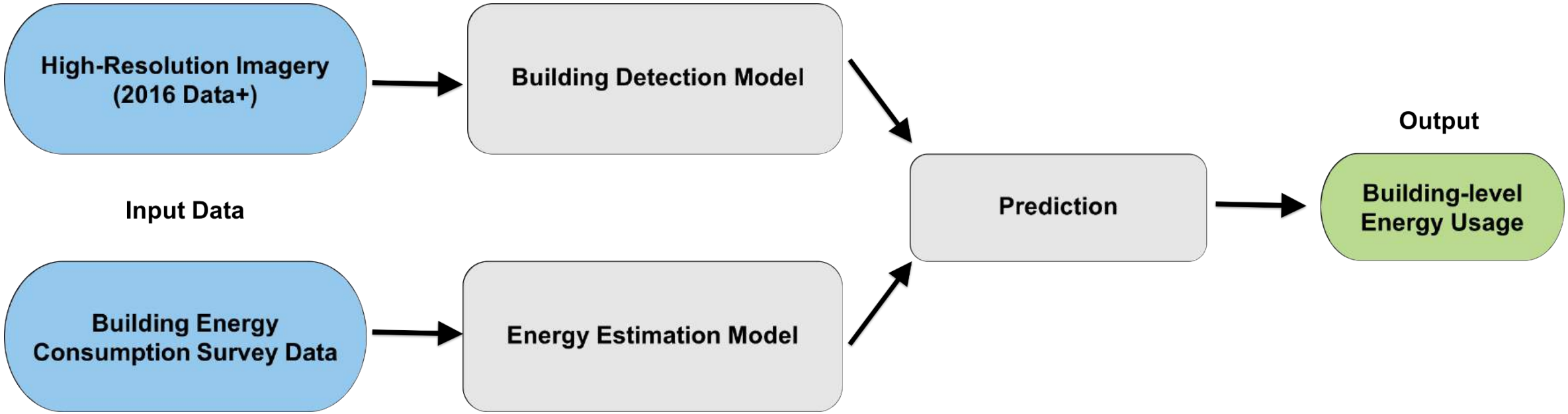
Businesses and NGOs

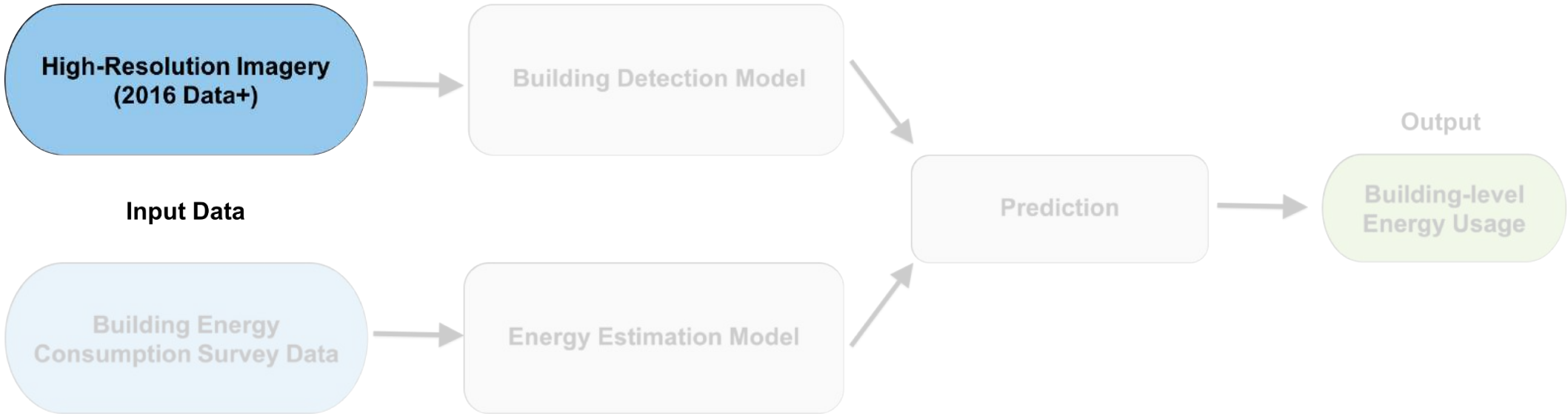
Governments and policy makers

Businesses and NGOs

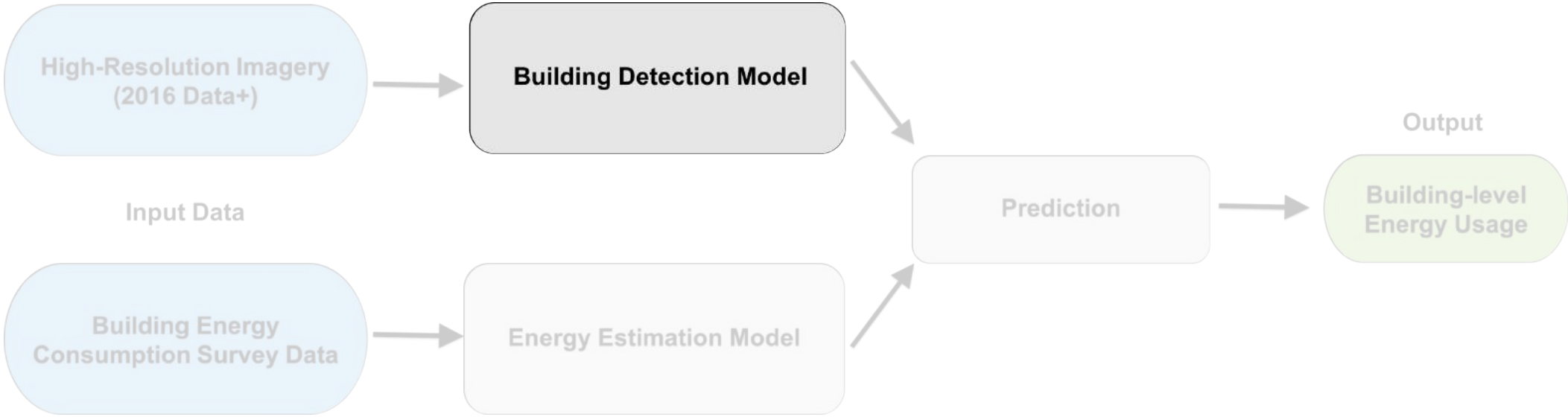
Researchers

Our Process

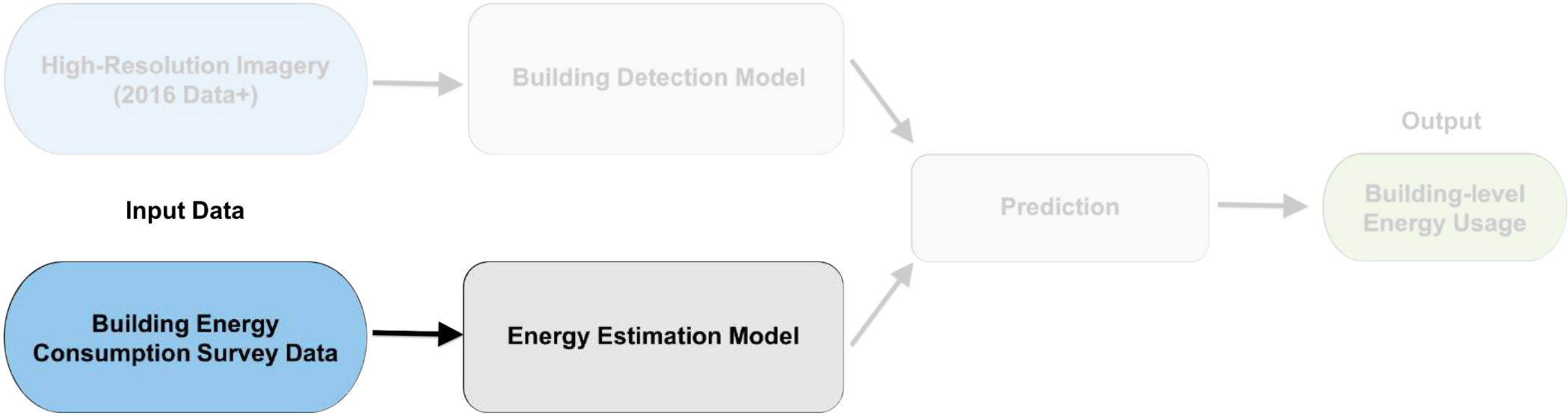

High-Resolution Imagery (2016 Data+)
Building Detection Model
Input Data
Building Energy Consumption Survey Data
Energy Estimation Model
Prediction
Output
Building-level Energy Usage



From a high resolution aerial image…



Detect building outlines and calculate their area



Data

Energy Use Estimation

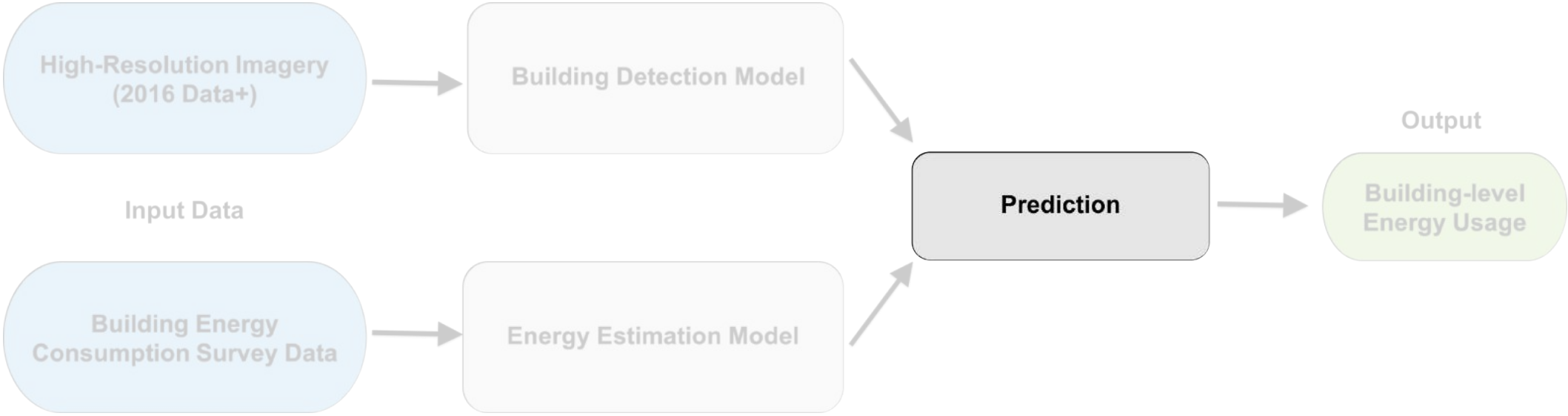
Available

Unavailable

Area (Image)	
Climate (Weather Data)	Demographic Information (Census Data)
Height (LIDAR)	
Land & House Value (Tax Data)	House Age & Materials (Commercial Database)
Consumer Preference & Plug-in Loads (Household Survey)	

Multiple Linear Regression Model

Household Energy Consumption Estimate



Use area of detected buildings for energy use estimation

Building Energy Use (yearly kWh)

- <12,000
- 12,000 - 13,000
- 13,000 - 14,000
- 14,000 - 15,000
- 15,000 - 16,000
- 16,000 - 17,000
- 17,000 - 18,000
- 18,000 - 19,000
- >19,000

High-Resolution Imagery (2016 Data+)

Building Detection Model

Input Data

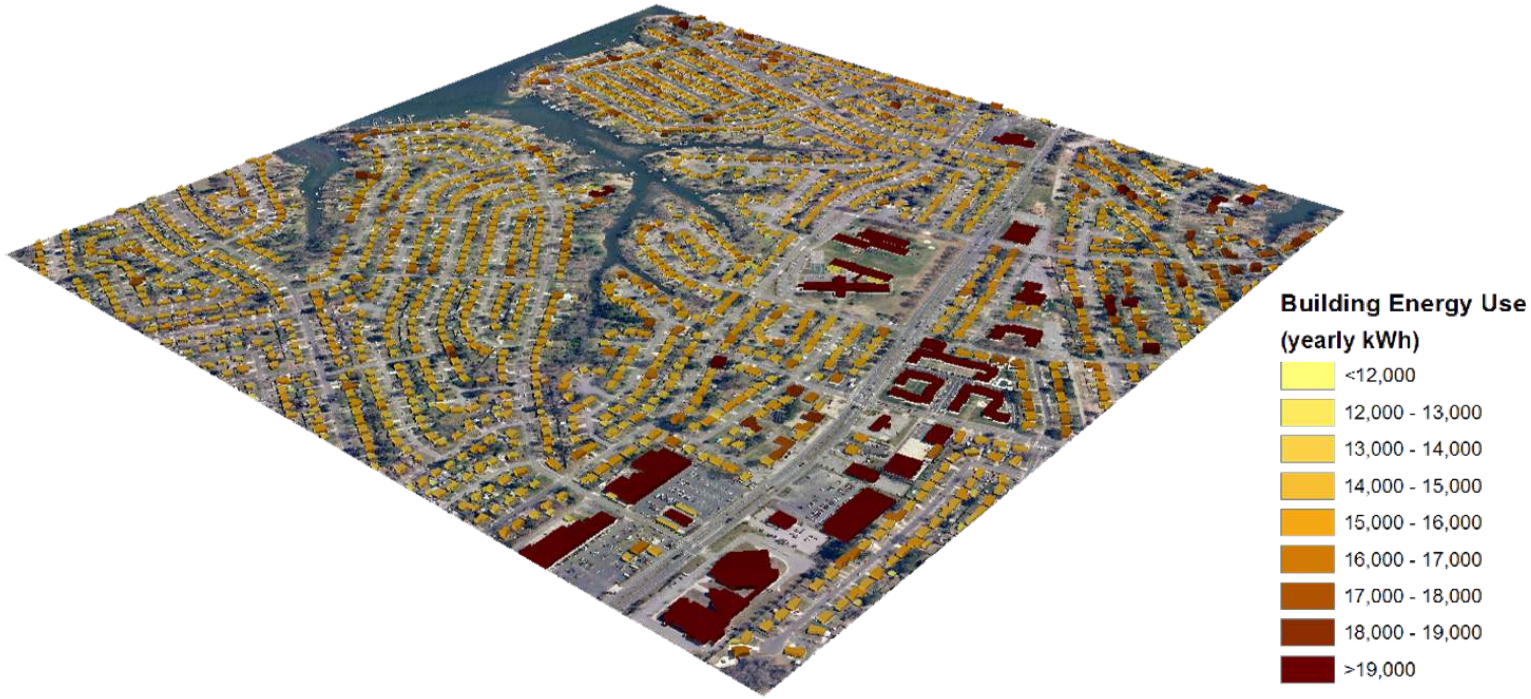
Building Energy Consumption Survey Data

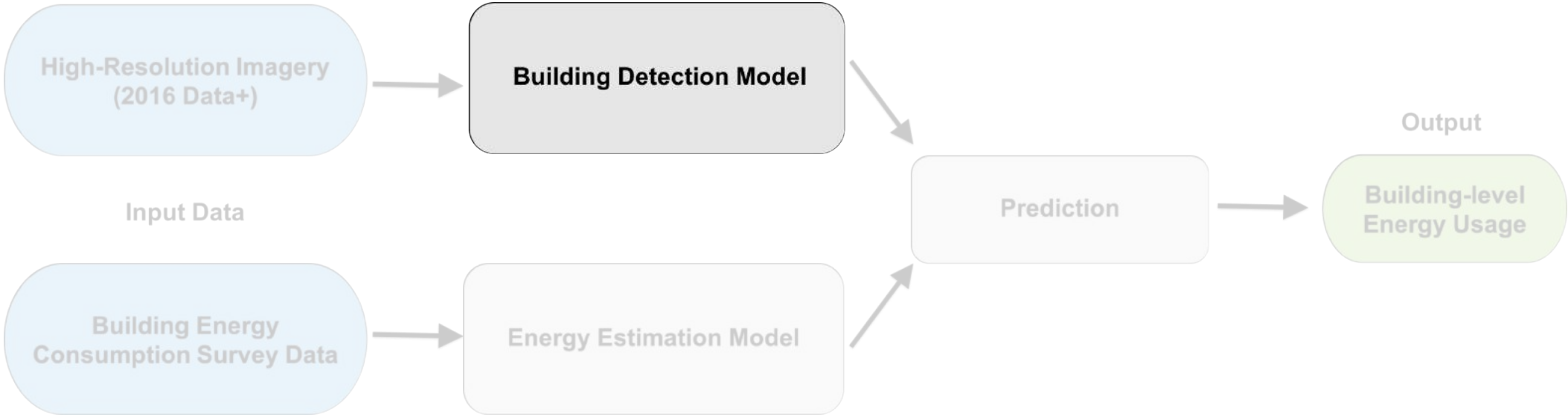
Energy Estimation Model

Prediction

Output

Building-level Energy Usage

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Building Detection Model
Input Data
Building Energy
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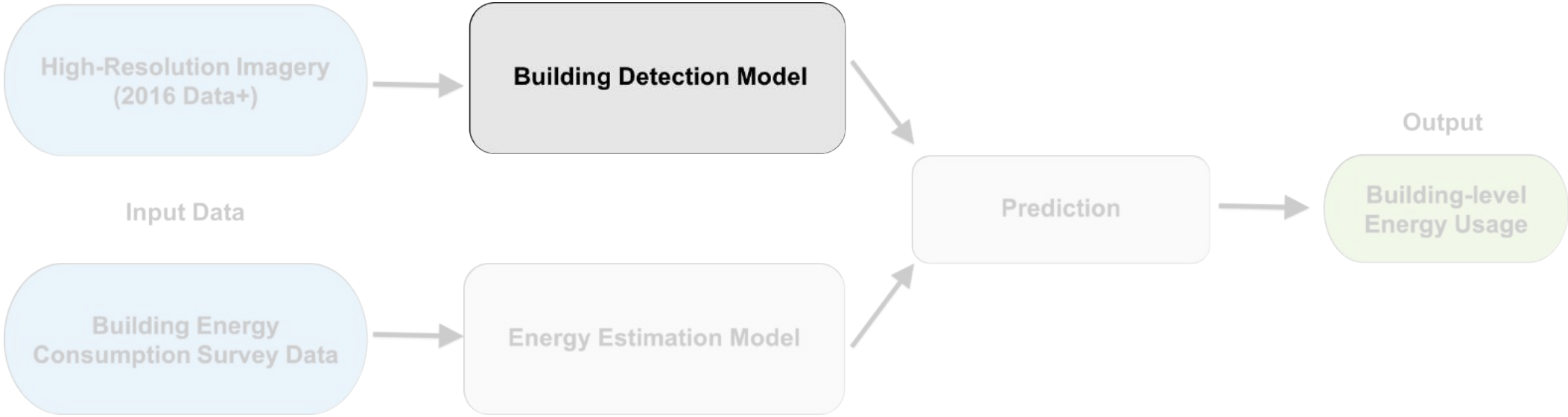
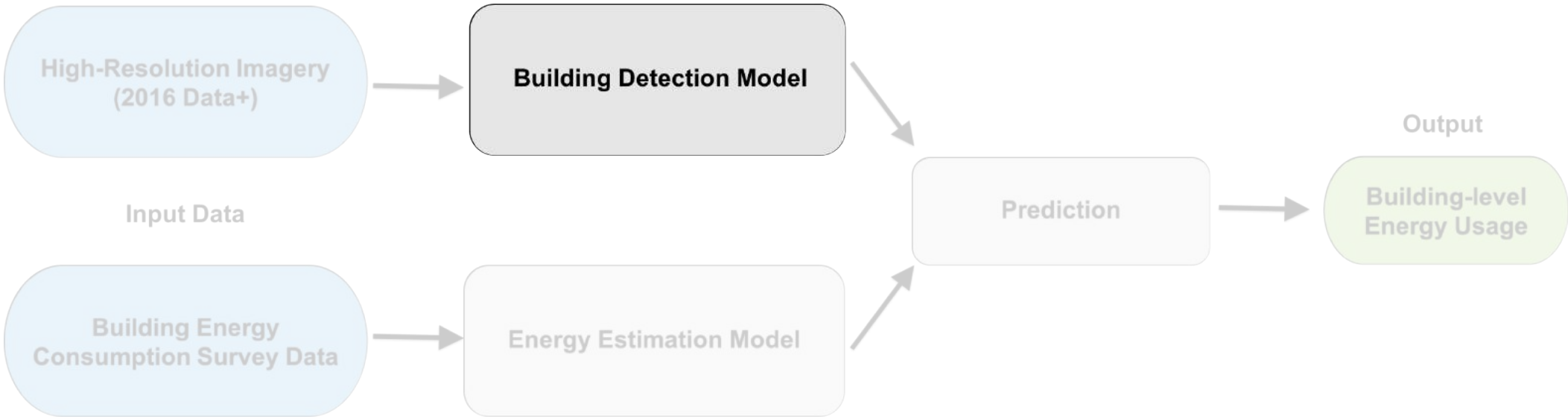
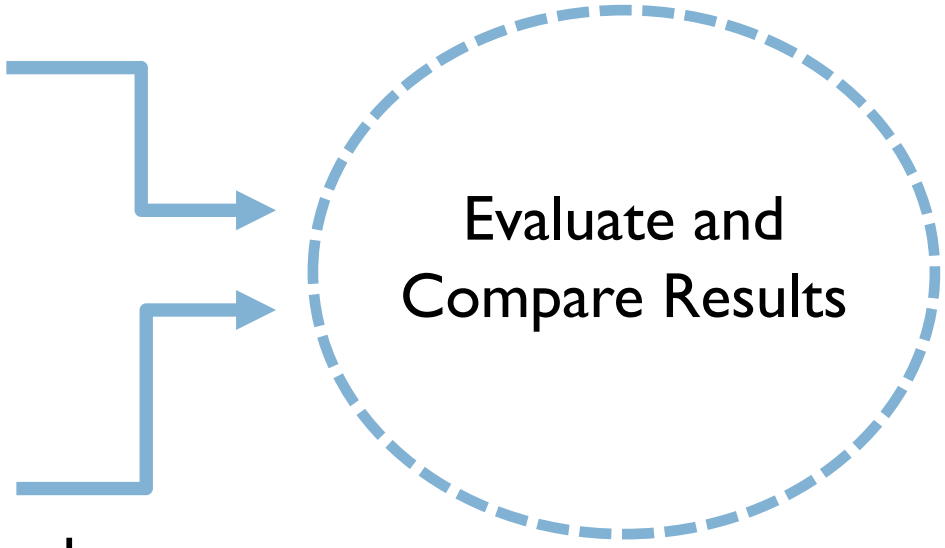


Approach 1:
Random Forests

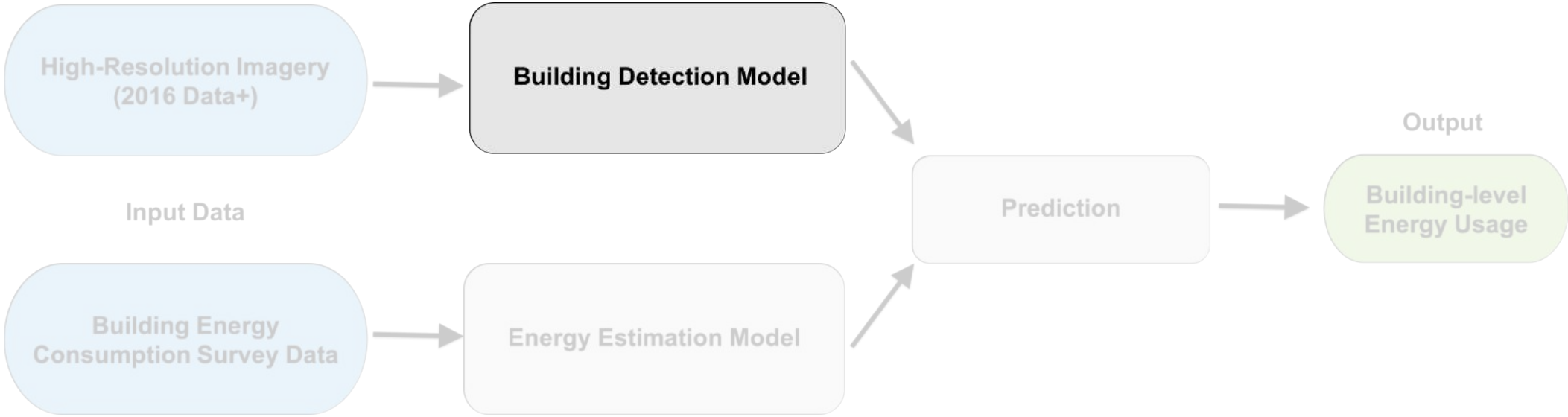
Approach 2:
Convolutional Neural Network



Approach 1:
Random Forests

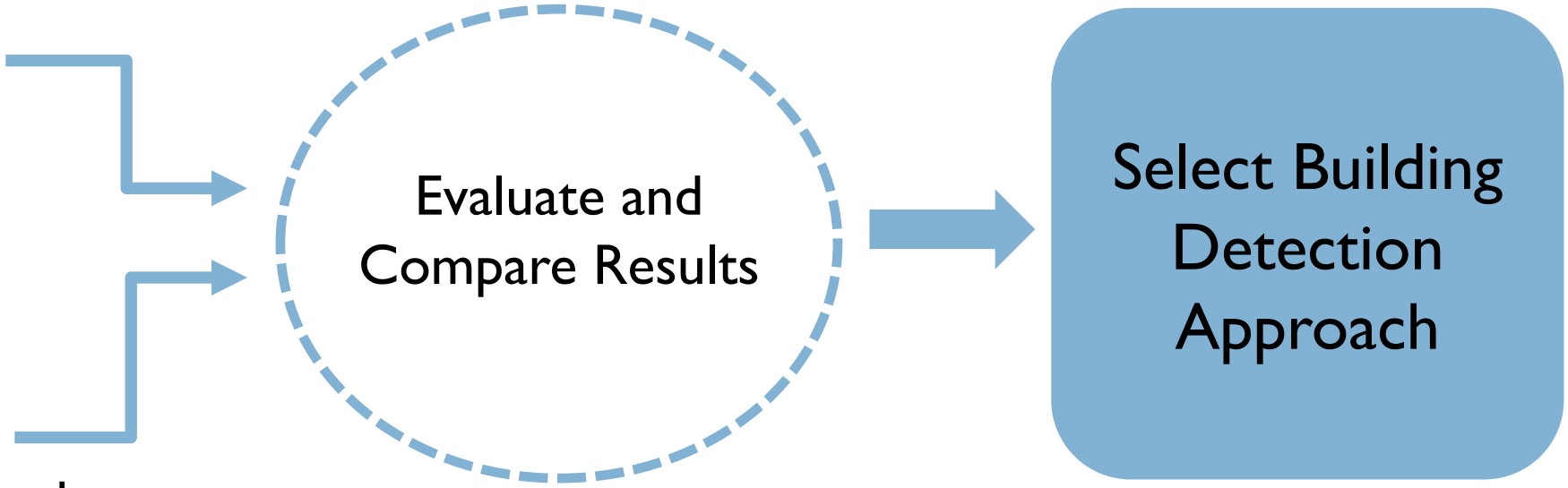


Approach 2:
Convolutional Neural Network



Approach 1:
Random Forests

Approach 2:
Convolutional Neural Network



Approach 1: Classical Machine Learning

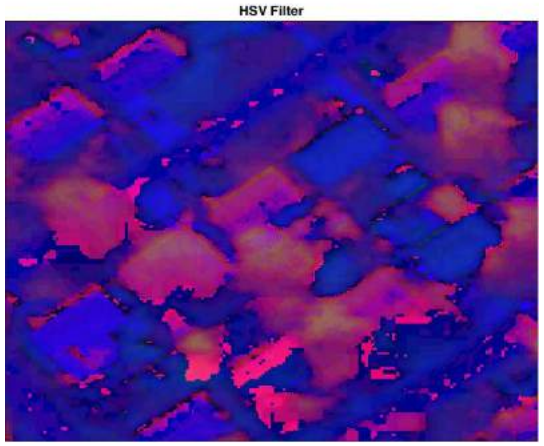
How Can We "Teach" a Computer?

Feature Extraction → Learning Algorithm (Random Forest) → Classification → Detected Buildings

Approach 1: Classical Machine Learning

Features:

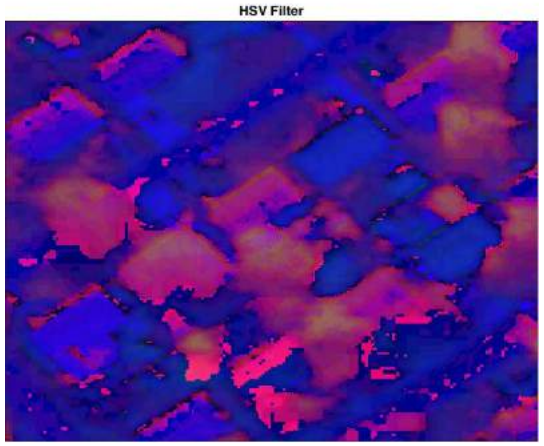
Approach 1: Classical Machine Learning

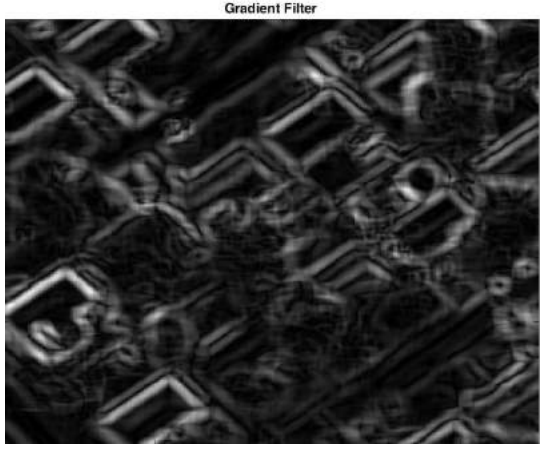


Features:

- Color Data (HSV)

Approach 1: Classical Machine Learning

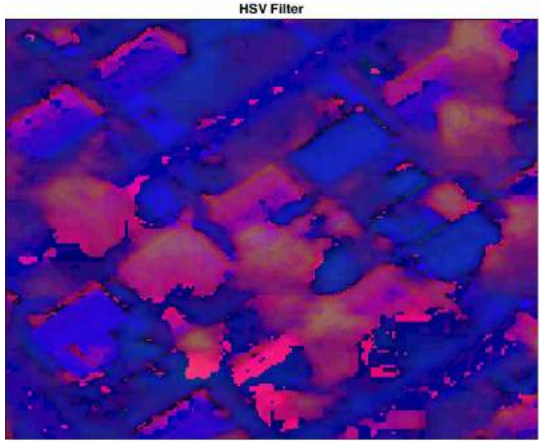


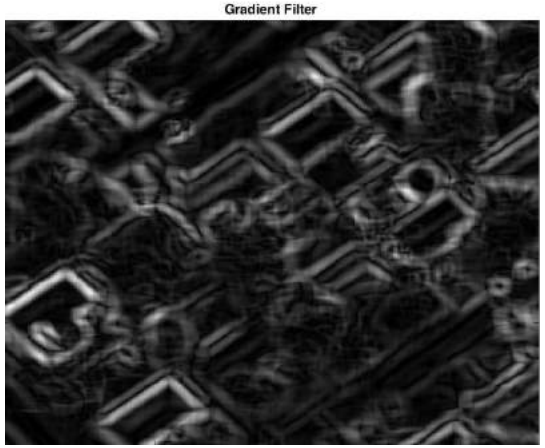


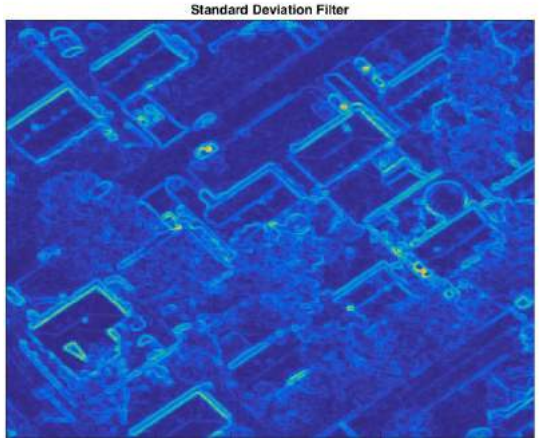
Features:

- Color Data (HSV)
- Edges (Gradient)

Approach 1: Classical Machine Learning



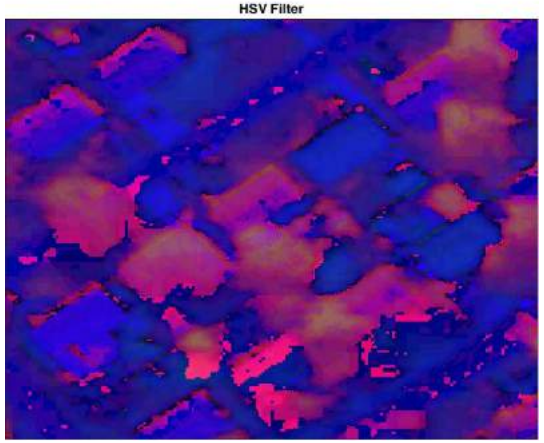


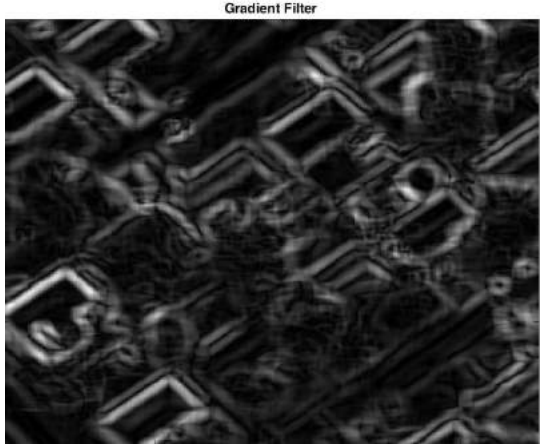


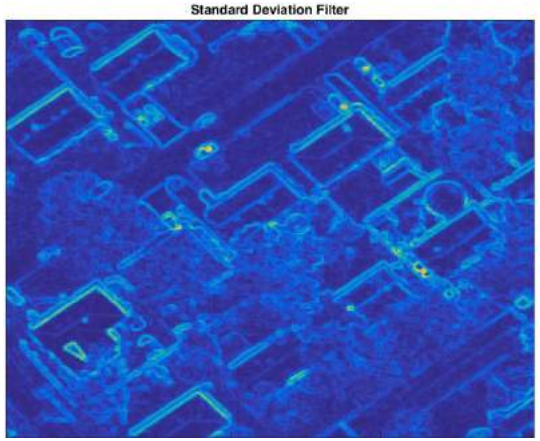
Features:

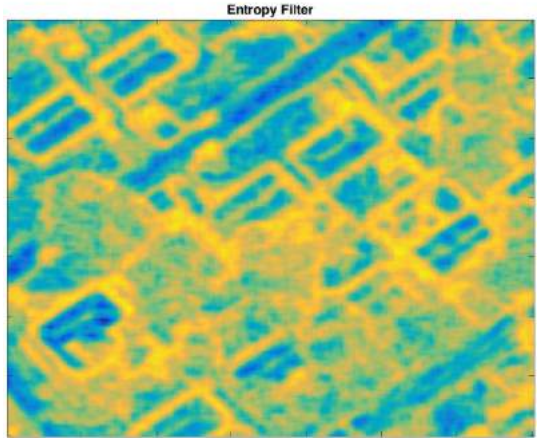
- Color Data (HSV)
- Edges (Gradient)
- Variation in Pixels (STDev)

Approach 1: Classical Machine Learning





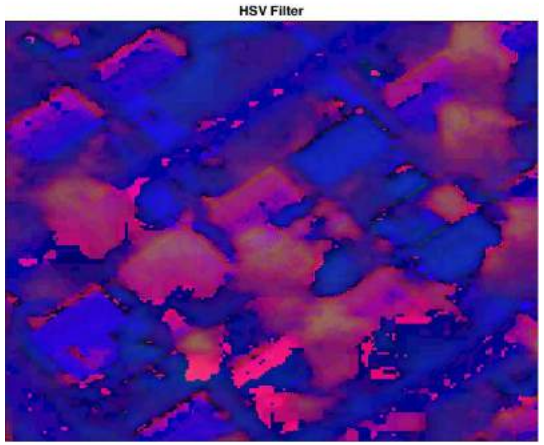


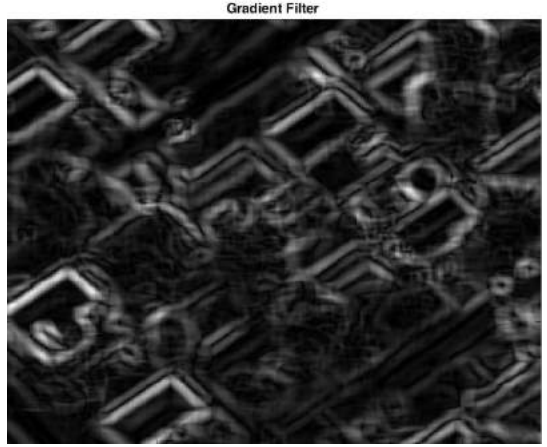


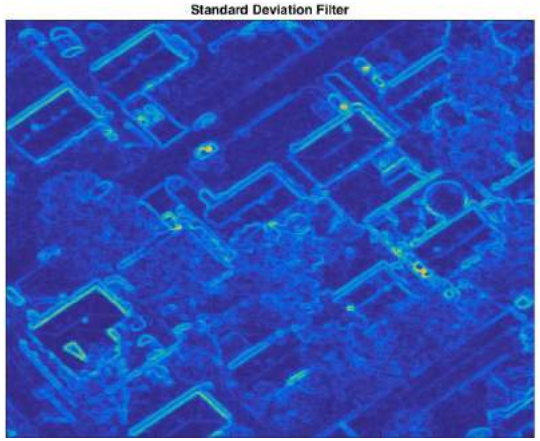
Features:

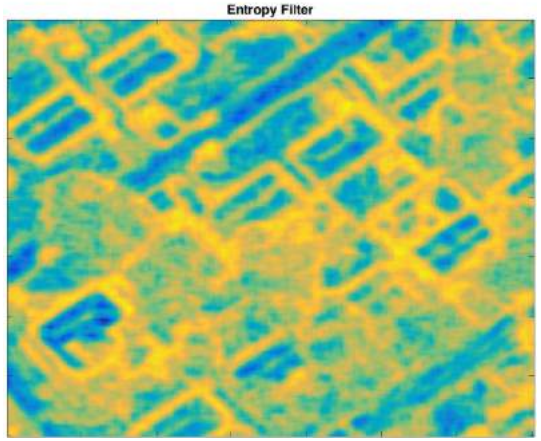
- Color Data (HSV)
- Edges (Gradient)
- Variation in Pixels (STDev)
- Texture (Entropy)

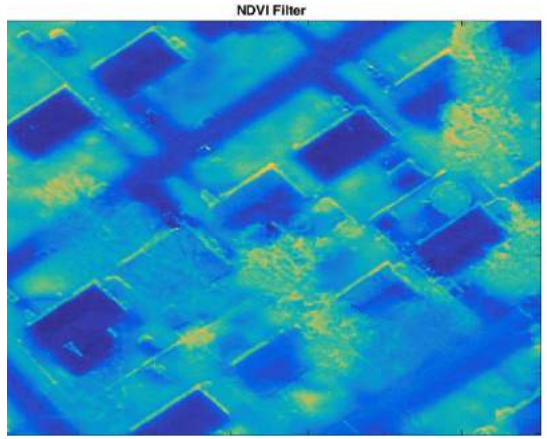
Approach 1: Classical Machine Learning











Features:

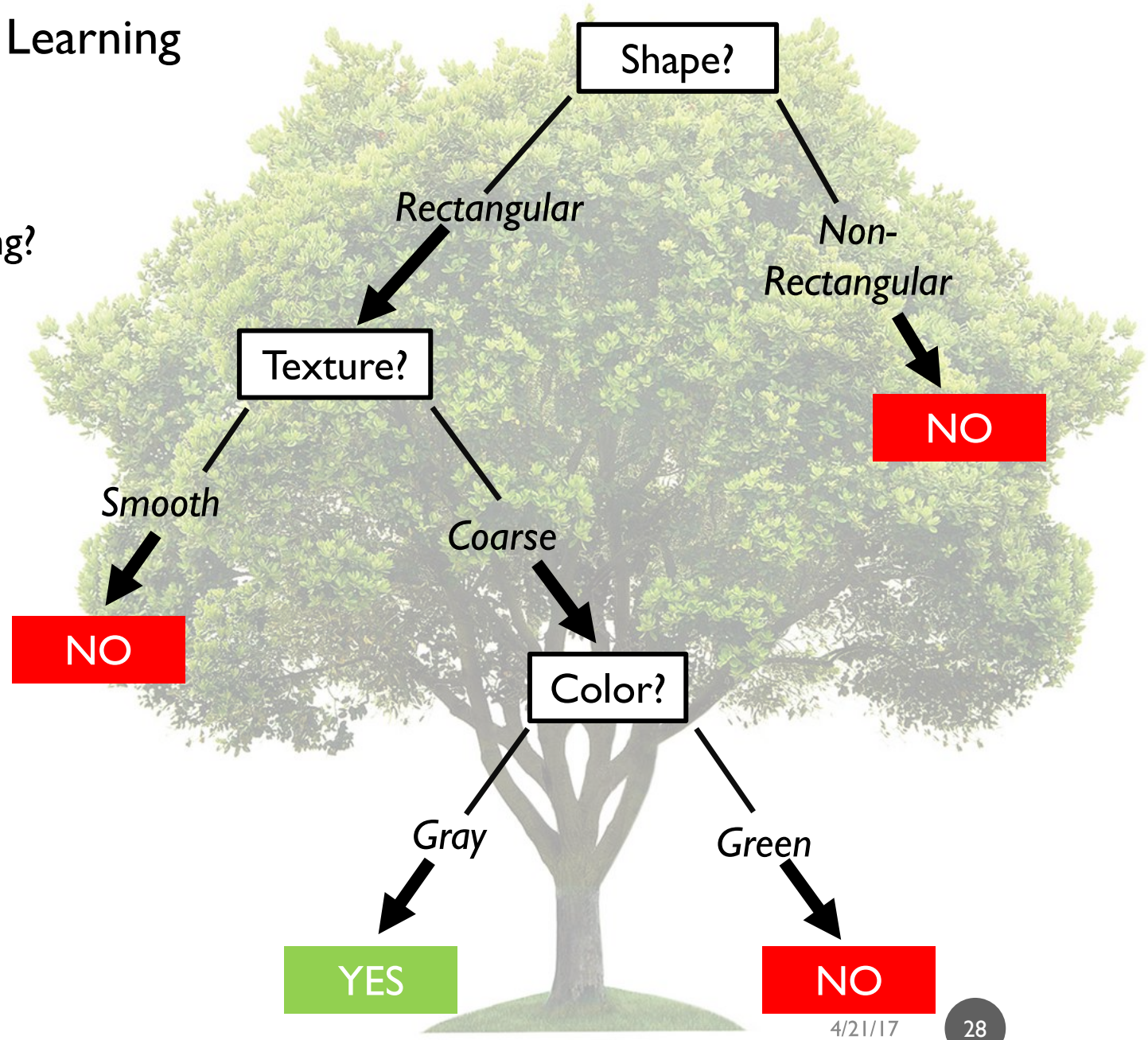
- Color Data (HSV)
- Edges (Gradient)
- Variation in Pixels (STDev)
- Texture (Entropy)
- Vegetation Detection (NDVI)

Approach 1: Classical Machine Learning

Decision Tree:

Question: Is the pixel part of a building?

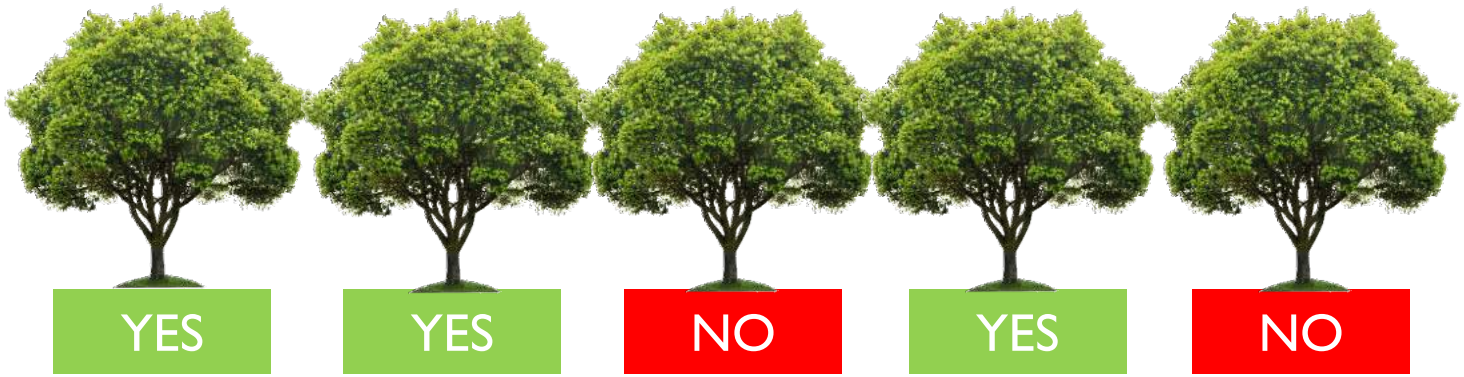
Answer: YES NO



Approach 1: Classical Machine Learning

Random Forest

Input Pixel



Vote = YES

Approach II: Convolutional Neural Network

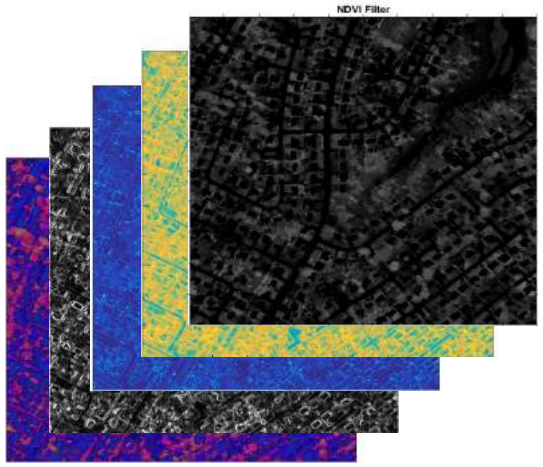
Approach II: Convolutional Neural Network

Approach II: Convolutional Neural Network

Approach II: Convolutional Neural Network

Neural Network vs. Random Forest Classifier

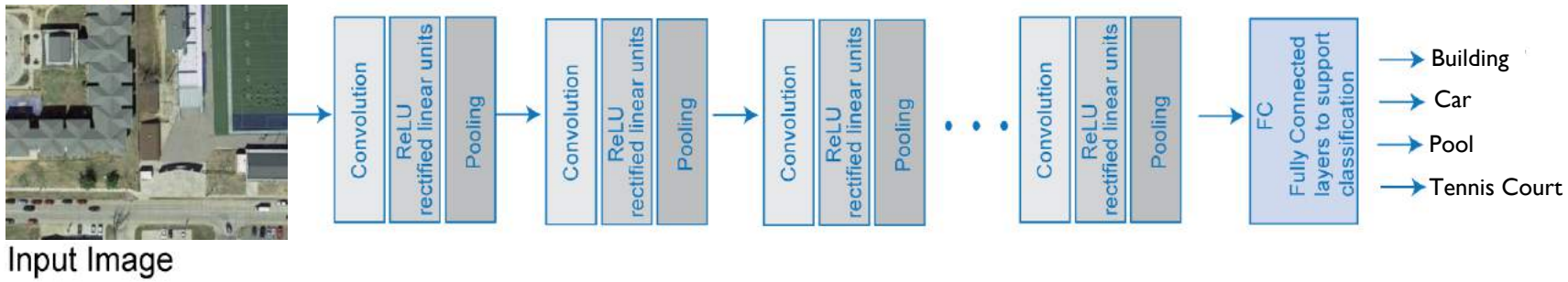
Features?

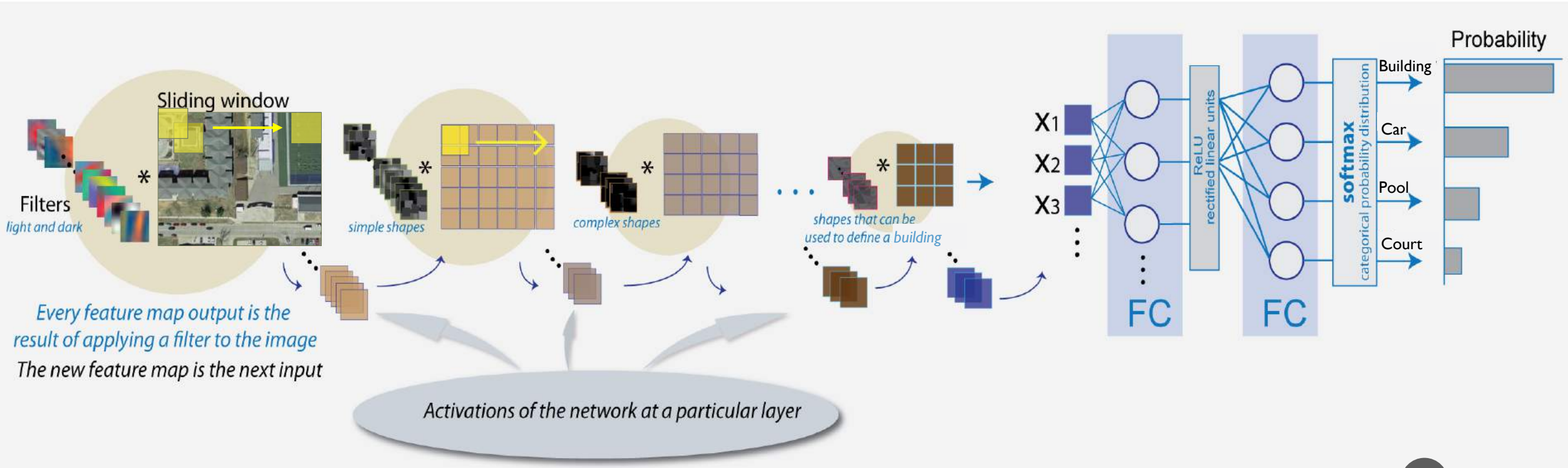


Time?

Approach II: Convolutional Neural Network

Our Neural Network: Overview



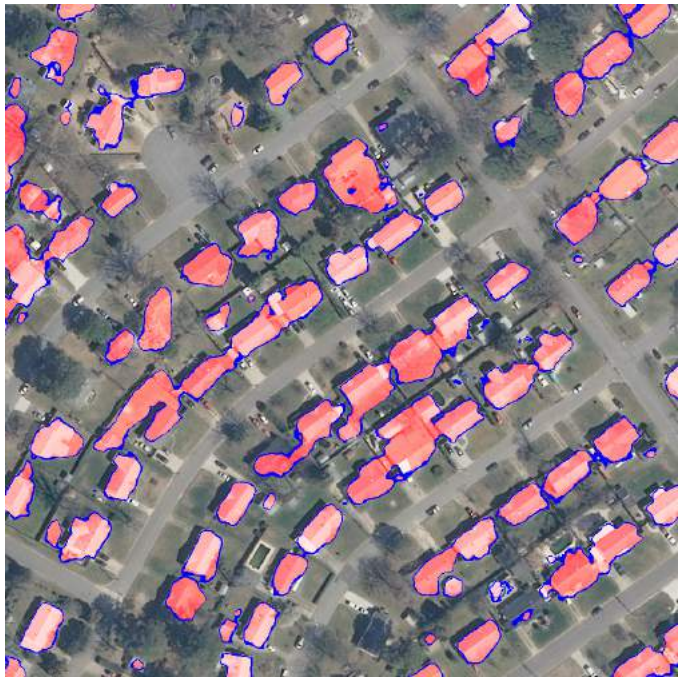


Adapted From: https://www.mathworks.com/help/nnet/convolutional-neural-networks.html

Comparing Approaches:

Ground truth building outlines, i.e., the ideal classification output

Building outlines detected by **random forest classification**

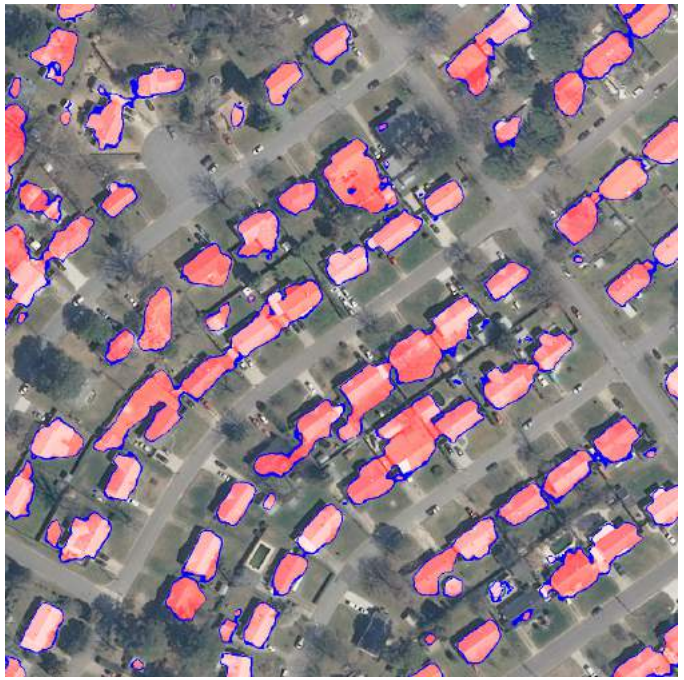


Building outlines detected by **convolutional neural network**

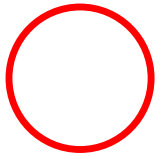
Comparing Approaches:

Ground truth building outlines,
i.e., the ideal classification output

Building outlines detected by
random forest classification



Building outlines detected by
convolutional neural network



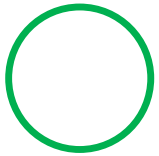
Misclassified building pixel
"islands"

Comparing Approaches:

Ground truth building outlines, i.e., the ideal classification output

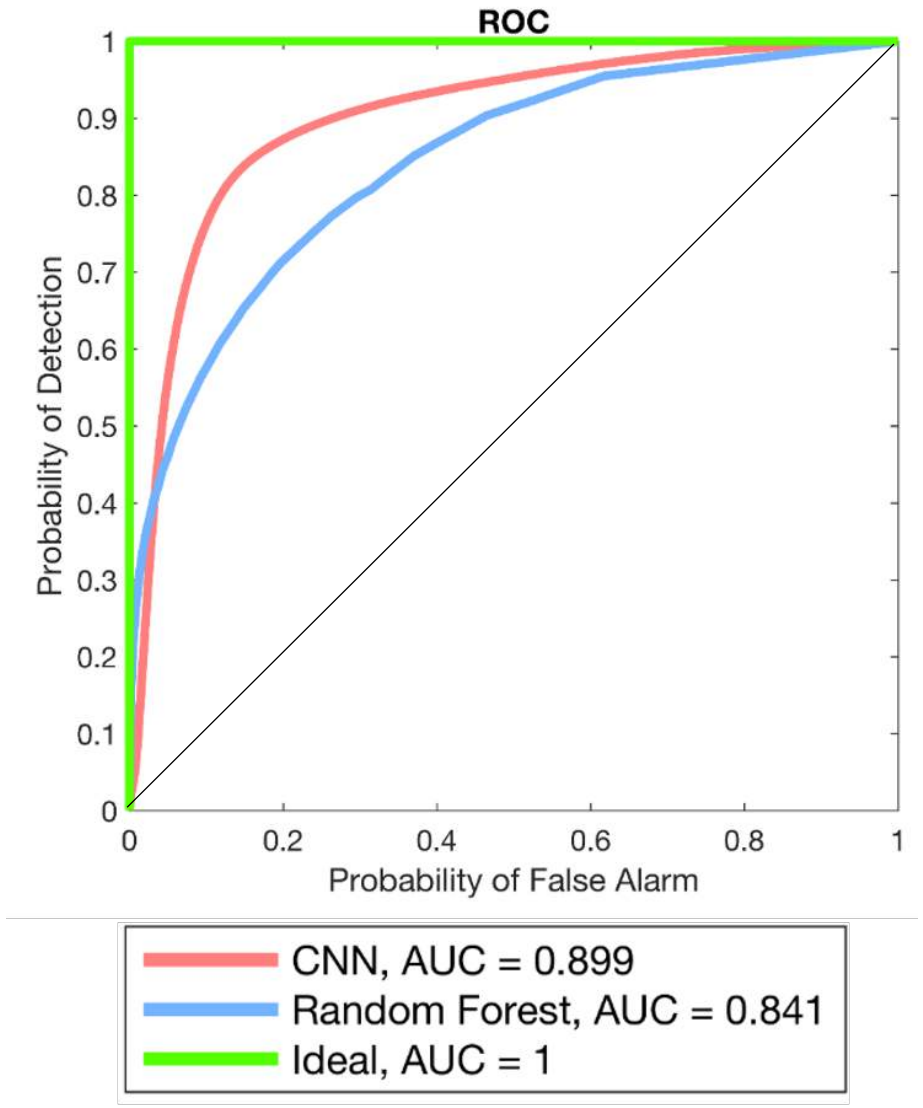
Building outlines detected by **random forest classification**

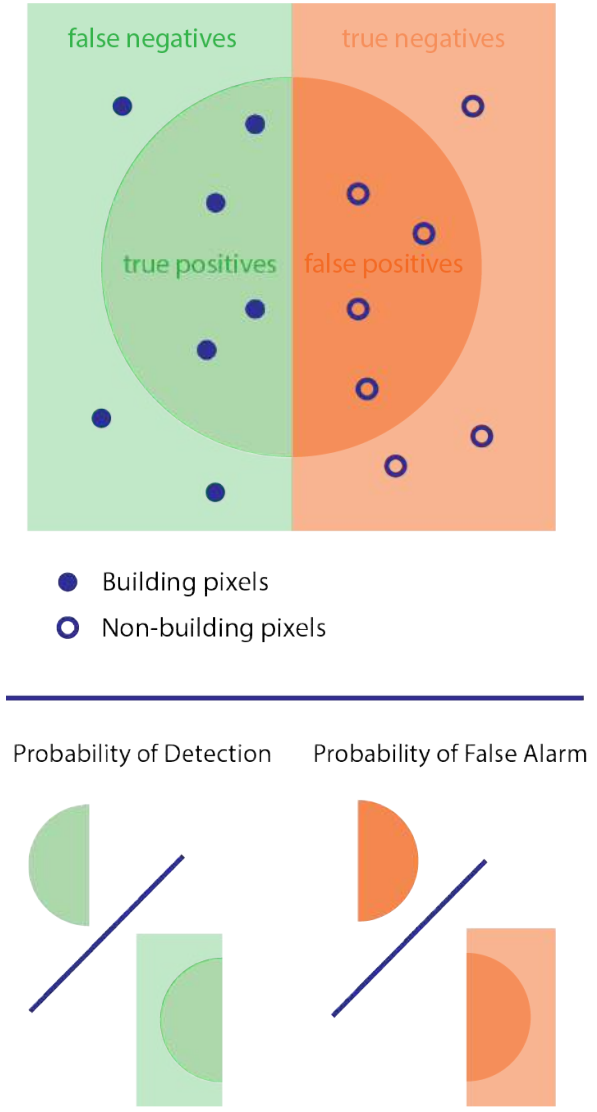
Building outlines detected by **convolutional neural network**



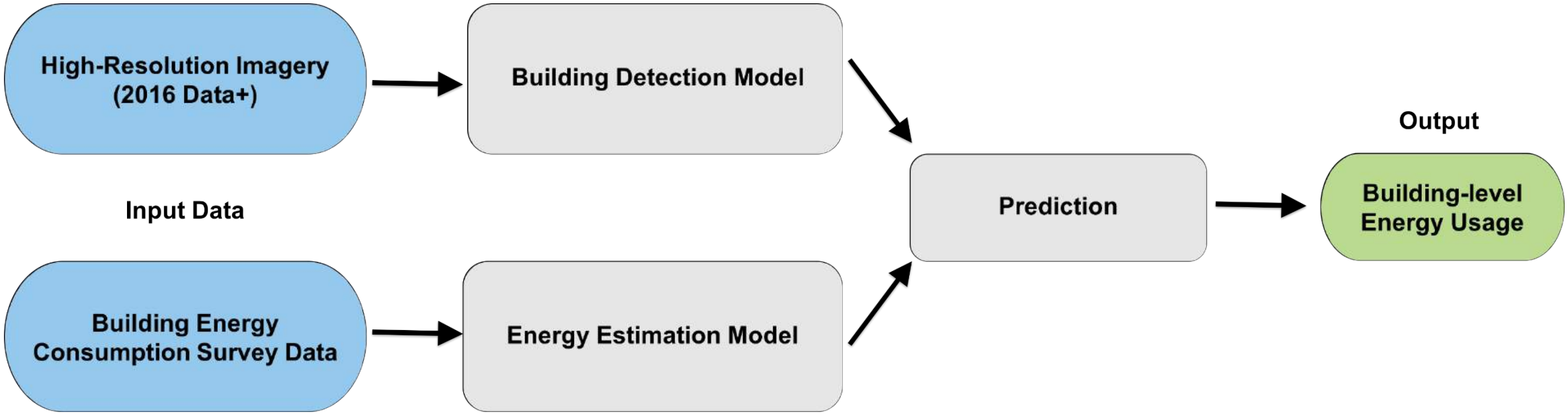
Irregular edges & merged buildings

Comparing Approaches:





Our Process


High-Resolution Imagery (2016 Data+)
Building Detection Model
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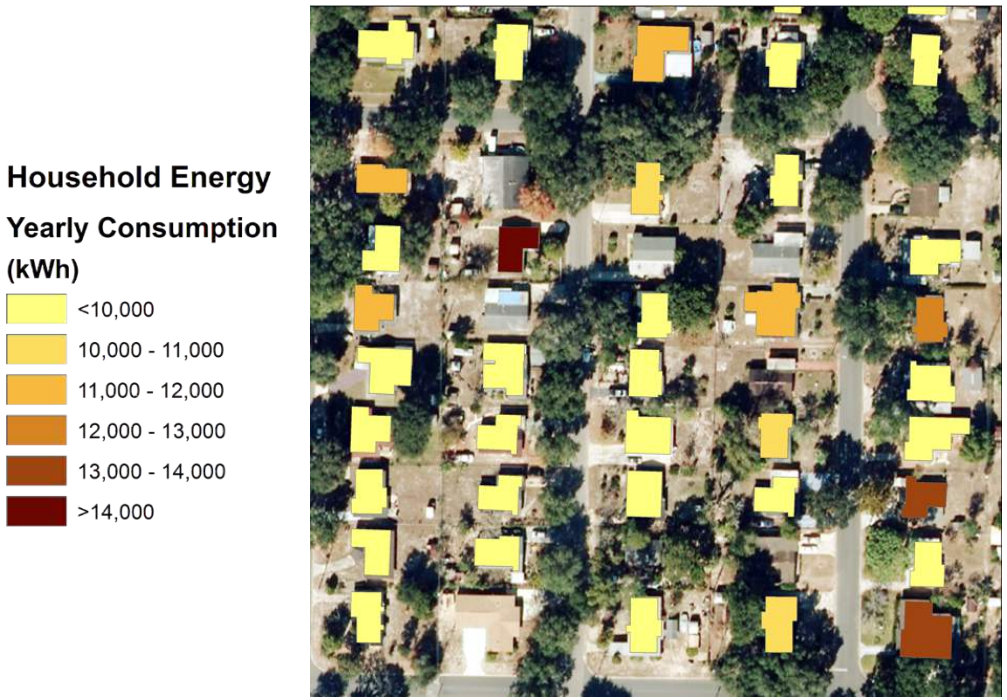
Building-level Energy Usage

How good is the model?

How good is the model?

Actual Buildings and Energy Consumption



Number of Buildings	**388**
Average Energy Use (kWh/yr)	**10,237**
Total Energy Estimation Error (%)	**-**

Household Energy
Yearly Consumption
(kWh)

- <10,000
- 10,000 - 11,000
- 11,000 - 12,000
- 12,000 - 13,000
- 13,000 - 14,000
- >14,000

Actual Buildings and Energy Consumption

Actual Buildings and Estimated Energy Consumption

Number of Buildings	**388**	**388**
Average Energy Use (kWh/yr)	**10,237**	**11,977**
Total Energy Estimation Error (%)	**-**	**17%**

Household Energy
Yearly Consumption
(kWh)

- <10,000
- 10,000 - 11,000
- 11,000 - 12,000
- 12,000 - 13,000
- 13,000 - 14,000
- >14,000

Actual Buildings and Energy Consumption

Actual Buildings and Estimated Energy Consumption

Detected Buildings and Estimated Energy Consumption

Number of Buildings	**388**	**388**	**299**
Average Energy Use (kWh/yr)	**10,237**	**11,977**	**12,405**
Total Energy Estimation Error (%)	**-**	**17%**	**-7%**

Conclusion

From a high resolution aerial image…

Conclusion

From a high resolution aerial image…

Detect building outlines and calculate their area

Conclusion

From a high resolution aerial image…

Detect building outlines and calculate their area

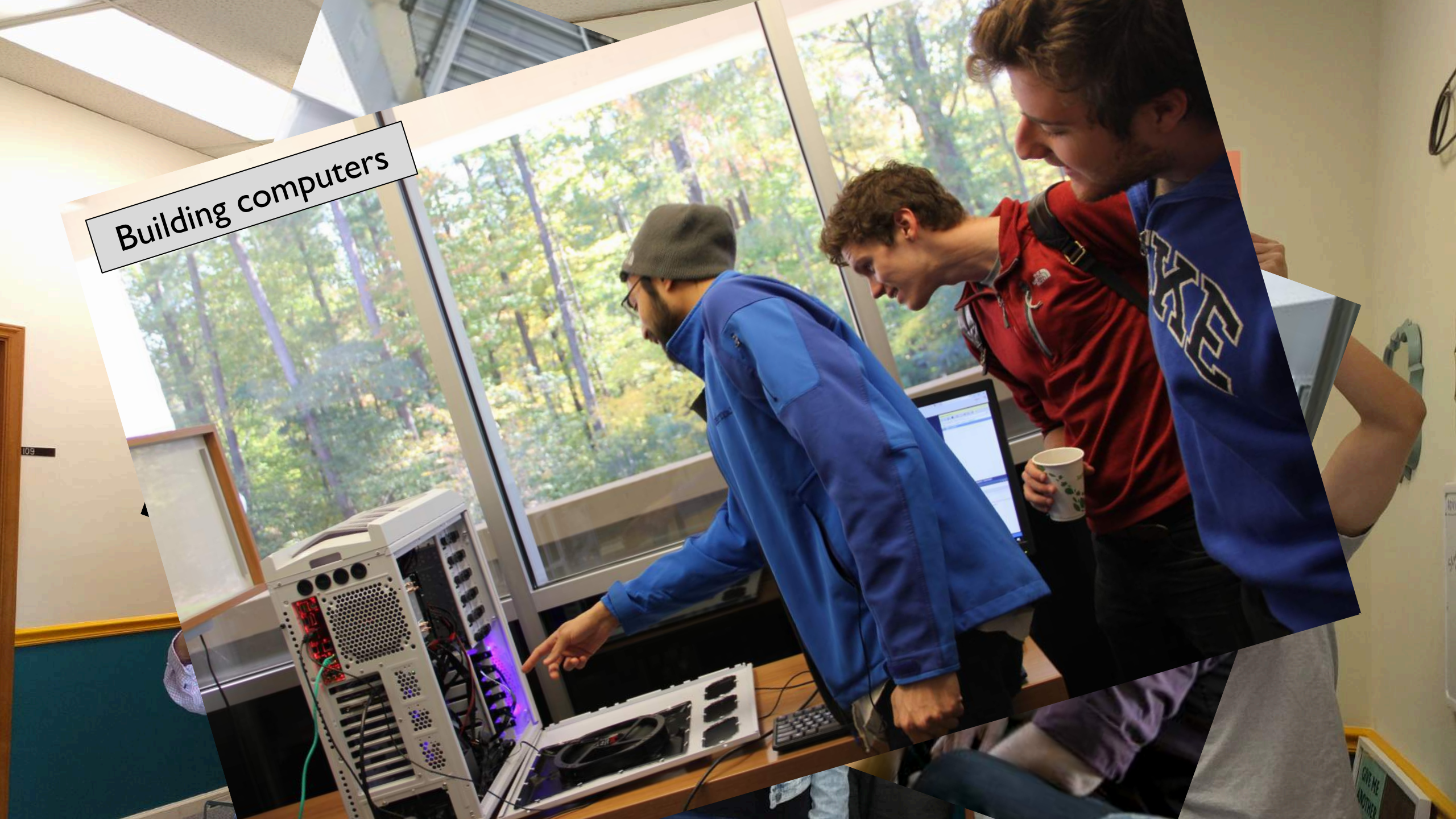
Use area of detected buildings for energy use estimation

Conclusion

Scale up to gather this data for whole cities, with thousands of buildings, anywhere in the world!

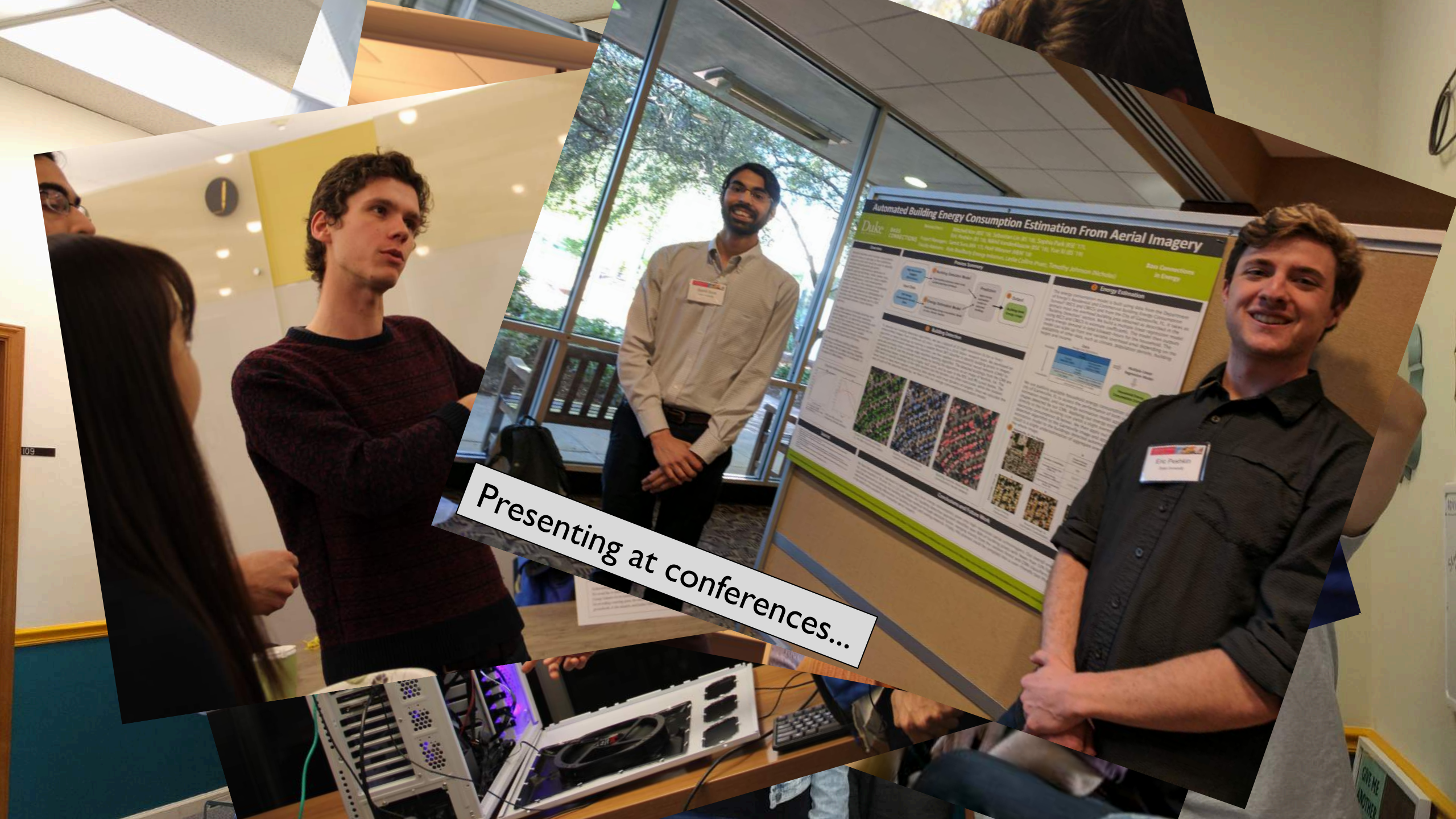
Solving Murders!


Modeling!
GENIUS


Building computers


Presenting our research
SAEEDI-ZWICK ALGORITHM
Segmented Images
Rooftop Hypotheses Generation
Local Refinement
Global Refinement
Rooftop Detection


Presenting our poster…
Object Detection for Energy Resource Asse
Duke
Introduction
Building Detection
Energy Estimation


Automated Building Energy Consumption Estimation From Aerial Imagery
Presenting at conferences...


And even winning awards for presenting!
Automated Building Energy Consumption Estimation From Aerial Imagery
Duke
BASS CONNECTIONS
Overview
Process Summary
Energy Estimation
Building Detection
Sources
Conclusions and Future Work
42
1
Imagery

THANK YOU