Comparison of Object Detection Methods on Illegal Oil Refineries in Satellite Imagery – Niger Delta

Sara Chlebecek Kenna

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About Me

- Almost 4 years GIS experience as a professional geospatial analyst
  - Oil pipeline monitoring
  - High resolution image analysis
  - Countrywide human landscape
  - High accuracy LULC
  - Wastewater networks
- 2+ years oil and gas experience
- 5 years geology experience

Overview

- Background
- Goals & Objectives
- Methodology
- Anticipated Results
- Timeline
- Conference & Takeaways
- References
- Closing

Background

- Study area
  - ~ 1300 sq km south of Port Harcourt
- Oil and gas industry in Nigeria for almost 70 years[17]
  - Accounts for ~10% of country's total GDP[15]

Background

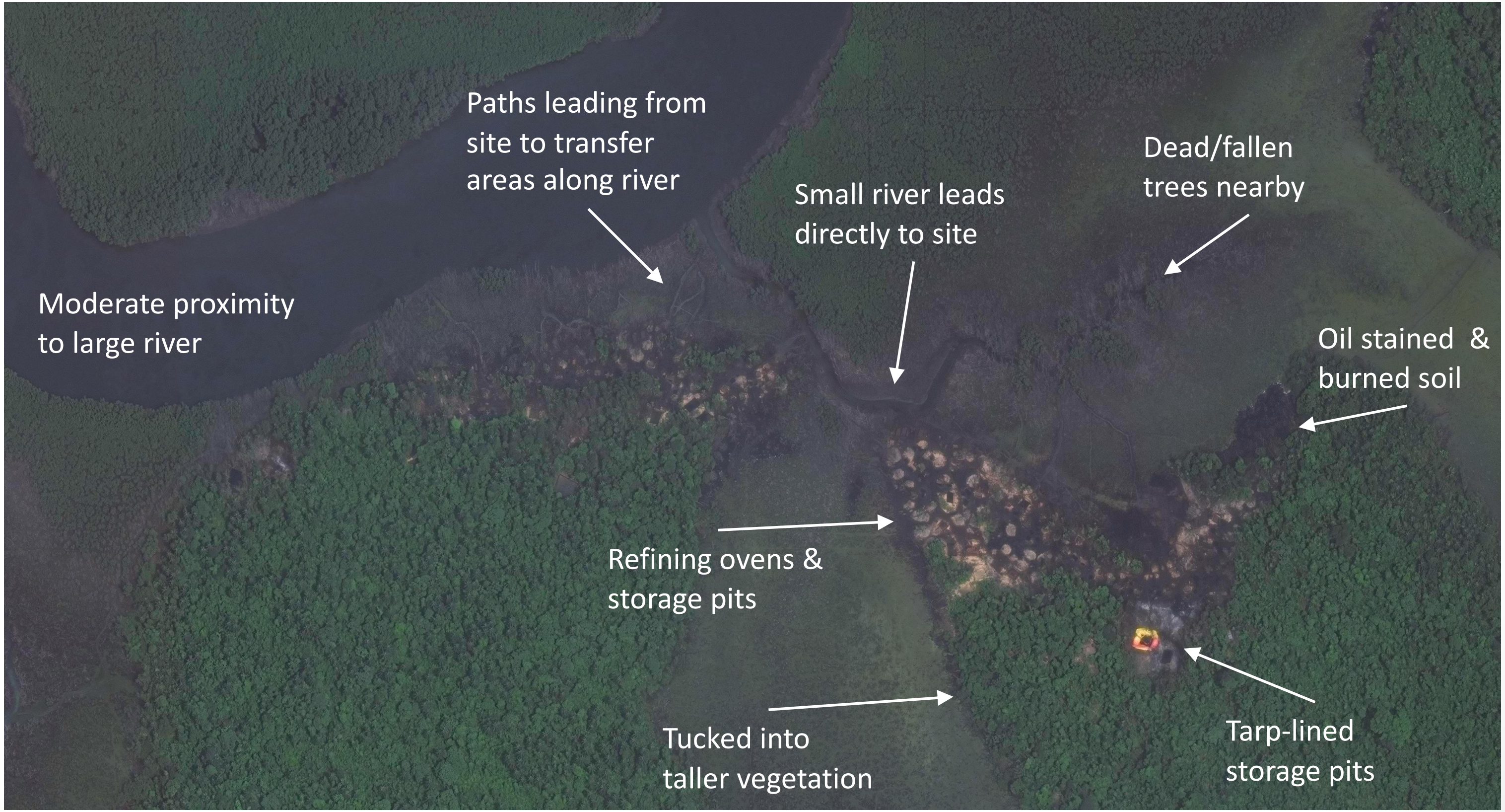
- Many oil companies in region are foreign owned
  - ~90% of their export earnings due to petroleum[20]
- Over time locals have been dealing with polluted habitats[17]
  - Majority of delta population are fishers and farmers
    - Cannot feed family due to contaminated fish and soil
    - Hard to find other means of support
  - Some turn to illegal activities
    - Oil theft amounts to 120,000 bpd or ~6% of output[8]
    - Thousands of illegal refineries exist throughout the Niger Delta

(George, 2019)

Background

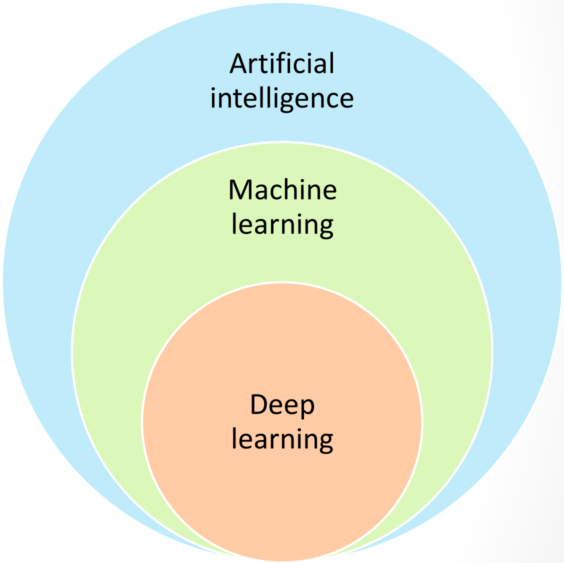
- What is object detection
  - Uses object-based view rather than field-based
  - In satellite imagery it is the recognition of target features
    - Human brain automatically interprets and understands complex relationships
- 4 methods to conduct this analysis
  - Professional image analyst
  - Machine learning algorithm
  - Crowdsourcing
  - Hybrid machine learning/crowdsourcing
- Challenges finding analogous studies in a diverse and new field include lack of standardized descriptors

How Does a Professional Identify an Illegal Refinery?



Breakdown of Machine Learning

- Artificial intelligence
  - Tries to generally apply human intelligence to machines
- Machine learning
  - Enables the computer to learn on its own
- Deep learning
  - Next step that self categorizes and labels to help in its understanding



History of Machine Learning – Amassed by Foote[5]

- In 1952 Arthur Samuel created a computer program that played checkers. It remembered moves played that were related to winning and learned to use those.
- The beginning of basic pattern recognition was conceived by the nearest neighbor algorithm in 1967. This algorithm was used to map routes by computing the travel distance to each city in an area and determining the shortest route.
- In 2006 during the Face Recognition Grand Challenge - a National Institute of Standards and Technology program – several algorithms of the time were tested and some “were able to outperform human participants in recognizing faces and could uniquely identify identical twins.”[5]

History of Crowdsourcing

- An early form of crowdsourcing in 1714 ”The Longitude Prize” offered by the British government to develop a reliable way to compute longitude[3]
- Jeff Howe brought this concept and the term back to light in 2006 with his article “The Rise of Crowdsourcing” in Wired magazine[11]
- In 2008, a pilot project began to provide damage and situation assessments for the recovery effort after an earthquake in Wenchuan, China[1]
- 8 million volunteers searched high-resolution satellite imagery for signs of Malaysia flight 370 that was lost in 2014[16]
- Category 5 hurricane Michael hit Florida in October 2018; days after the event drone imagery was collected and within 3 hours, over 7,000 buildings were assessed for damage[24]

Background – Previous Research

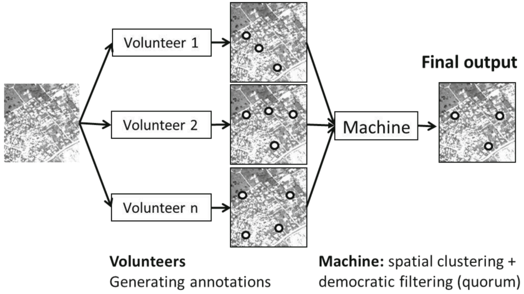
- Lee and others compared object-based extraction to deep learning (machine learning) feature extraction[12]
  - Open-source (a) and commercial (b) object-based extraction were not as accurate due to shadows
  - Deep learning (c) extraction had a problem defining narrow roads as the training dataset supplied differing road construction from the study area

(a) (b) (c)

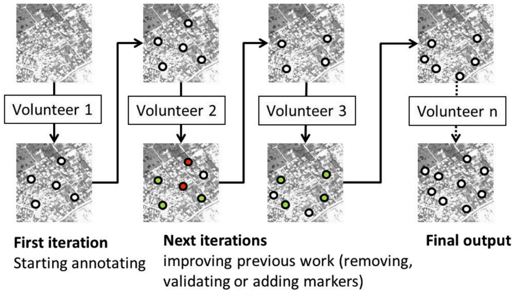
(Lee et al., 2019)

Background – Previous Research

- Maisonneuve & Chopard conducted a study comparing parallel and iterative crowdsourcing models[13]
  - Incorrect annotations were more likely with iterative model, but this model handled complex tasks better
  - Iterative model provided more complete results, as parallel model had many of the same “obvious” buildings
- Hybrid method proposed for most accurate results



(a) parallel model



(b) iterative model

(Maisonneuve & Chopard, 2012)

Background – Previous Research

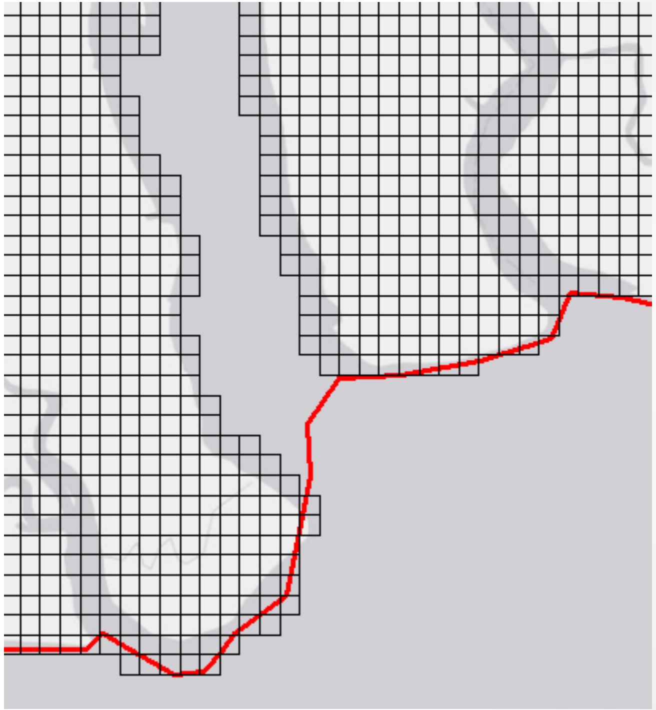
- Herfort and others determined accuracy and efficiency of combined approach versus independent (machine learning or crowdsourcing alone) to identify buildings
  - Crowdsourcing performed most accurately, however more likely to miss buildings
  - Machine learning performed almost as well, however resulted in many false positives
  - Existing datasets did not perform as well the new methods
  - Hybrid approach
    - 10-20% crowd/80-90% machine – increased overall performance
    - 70-90% crowd/10-30% machine – also increased performance
    - Anywhere in between – no performance gain
- The combined method shows that sending some of the more complicated areas to the crowd may result in more accurate dataset
  - "Humans rarely identify something as a building which is not a building" [10]

Goals & Objectives

- Determine accuracy of automated methods as compared to professional analyst with complex objects
- Improve the accuracy and efficiency of these image analysis methods for my company by testing and assessing additional hybrid approach
- Create effective training/sample dataset for current and future related projects

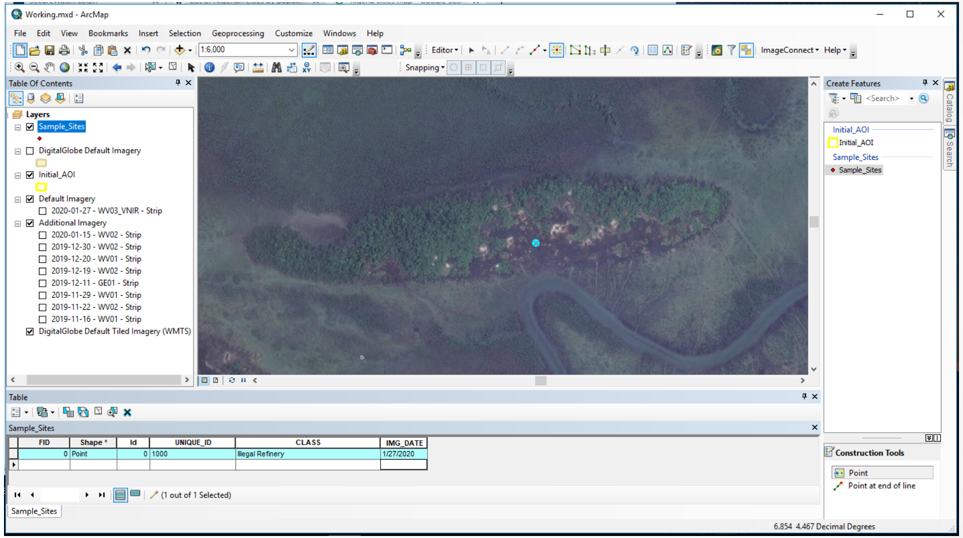
Methodology

- Process and create all image chips
  - High resolution (2m) imagery selection
    - Cloud free & natural color
    - Current & historical
  - Fishnet ~5000 chips at ¼ sq km size
    - Chips containing 100% water will be removed
- Additional setup for some methods
  - Example images for crowdsourcing
  - Training dataset for machine learning
- Conduct each method with all chips
  - Returns 4 point layers
- Analyze results
  - Accuracy assessment using binary confusion matrix



Methodology – Professional Analyst

- Background knowledge on subject
- Access to other minds and analysts
- Manual scour of study area to mark locations
- One analyst can take days/weeks to complete same as other methods

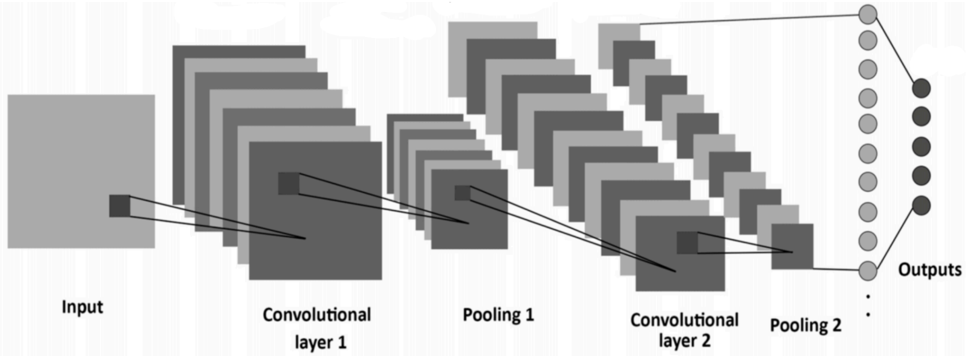


Methodology – Machine Learning

- Uses convolutional neural networks
- Needs base training samples from professional analyst
- Learns from the samples and tries to find similar objects
- Proprietary company algorithm
- Completes in a few hours

Convolutional Neural Networks

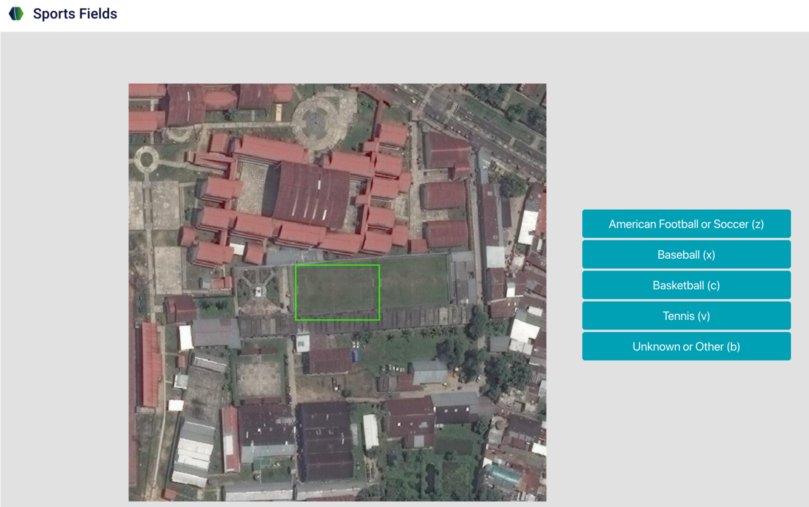
- Filtering
  - Values determined by how well each window matches a key part
- Pooling
  - Groups values and condenses layer by picking maximum value in window
- Normalization
  - Converts negative values to zero



(Stewart, 2019)

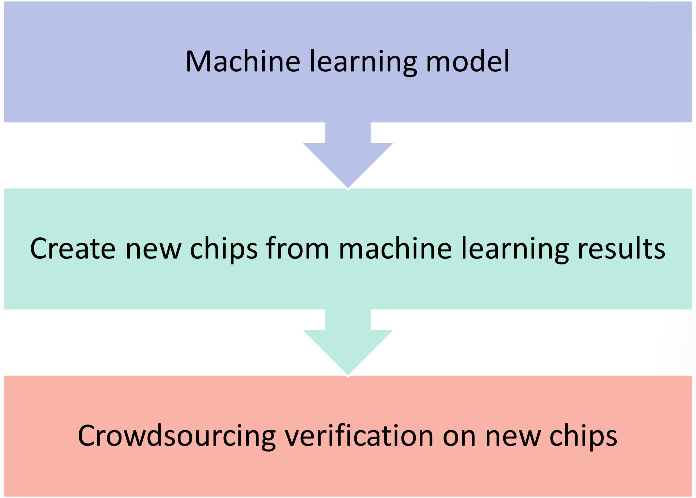
Methodology - Crowdsourcing

- Customizable
  - Discover features and draw
  - Validate by categorizing
- Provide instructions and examples
- Image chips are fed to crowd
  - Crowd is made up of individual civilians to find or verify any type of image or object
  - Each chip viewed by several individuals
- Completes in a few hours



Methodology – Hybrid

- Take results from machine learning method
- Make new chips (tiles) using these points
- Send new chips to be verified by the crowd



Accuracy Assessment

- Confusion matrices for each method[14]
  - Professional analyst will check each point for proximity match due to nature of object
  - Accuracy Metric

		Points determined by professional analyst	
		Detected	Not detected
Points from each analysis method	Detected	TP	FP
	Not detected	FN	N/A

TP Points that match

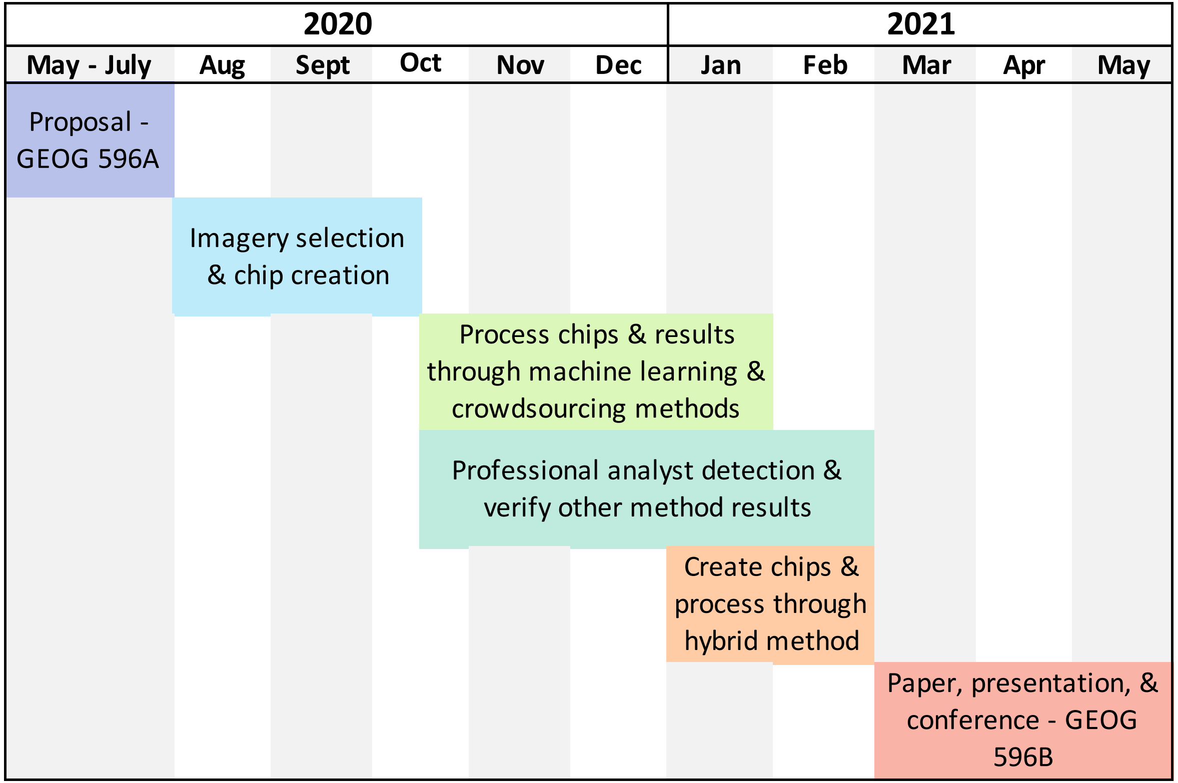
FN Points missed by automated method

FP Points missed by professional analyst

Anticipated Results

- Crowdsourcing will produce more accurate points than machine learning due to the complexity and variability of illegal refineries
- The hybrid approach will provide the most accurate results
  - My prediction is machine learning will weed out most of the regular vegetation, allowing the crowd to focus on the details of active illegal refineries versus other environmental damage that can look similar

Timeline



2020
2021
May - July
Aug
Sept
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Proposal - GEOG 596A
Imagery selection & chip creation
Process chips & results through machine learning & crowdsourcing methods
Professional analyst detection & verify other method results
Create chips & process through hybrid method
Paper, presentation, & conference - GEOG 596B

Conference & Takeaways

- Esri Petroleum GIS Conference[4]
  - No official dates set – May 2021
  - Houston, Texas
- Determine the most accurate approach to identify complex illegal refinery sites in hopes that future work will ultimately minimize environmental damage for local civilians and save oil companies money

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Closing

- Special thanks to Pat Kennelly for his advising and time
- Thank you all for listening

- Questions?