REIMAGINE WASTE
BIOPRODUCTS - BIOCHEMICALS - BIOFUELS
WARM Workshop, Nov. 15-16, 2023, Raleigh NC

Revolutionizing Waste Management: AI-Powered Real-time Characterization for Efficient Handling of Non-Recyclable Municipal Solid Waste

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Waste to Advanced Resource Matter
Session 3.2B Characterization/Separation
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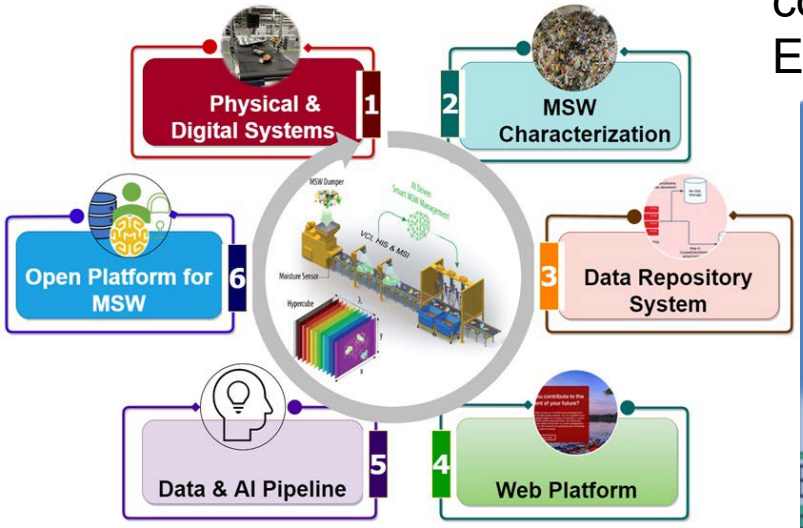
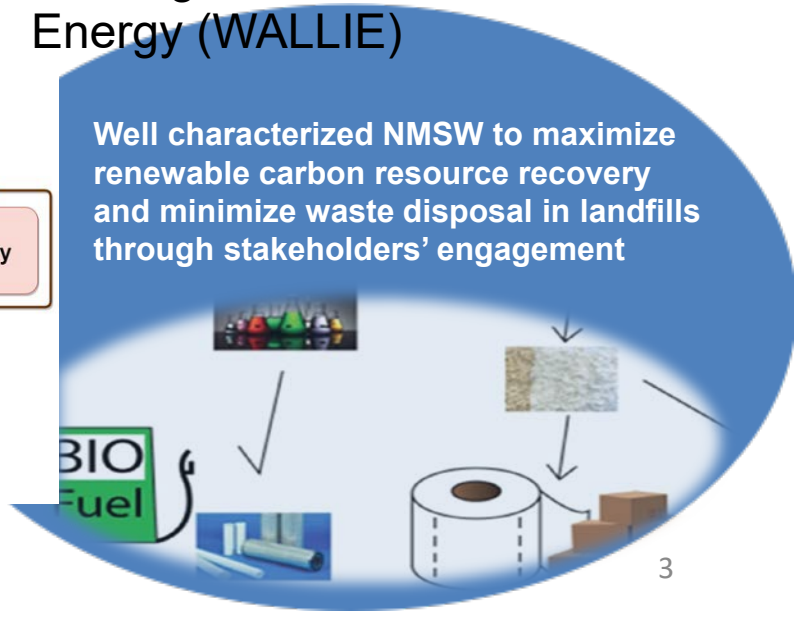
Characterization: AI-Enabled Hyperspectral Imaging Augmented with Multi-Sensory Information for Rapid/Real-time Analysis of Non-Recyclable Heterogeneous MSW for Conversion to Energy

Project Overview: The aim of this work is to develop and demonstrate a fully functional AI-enabled hyperspectral imaging (HSI) spectroscopy/object recognition-based technique for rapid/real time characterization of organic fractions (e.g., paper, plastic, food, and textiles) of non-recycled MSW (NMSW) in real time at multiple conveyer speeds.

AI-Enabled Waste to Advanced Low-cost Lignocellulose Innovation for Energy (WALLIE)





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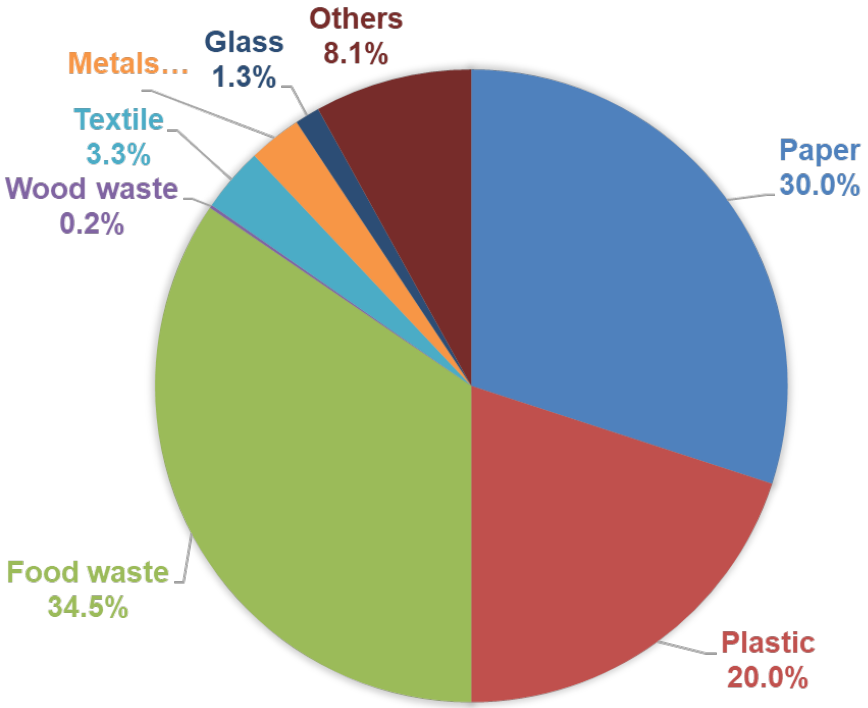
Characterization: Importance of Classification



Sorting as per ASTM D5231 standards

1) First, remove any hazardous
2) Categories waste in major fractions
    - Paper
    - Plastic
    - Food Waste
    - Textile
    - Metals
    - Glass
    - Yard Waste
    - Wood waste
    - Others

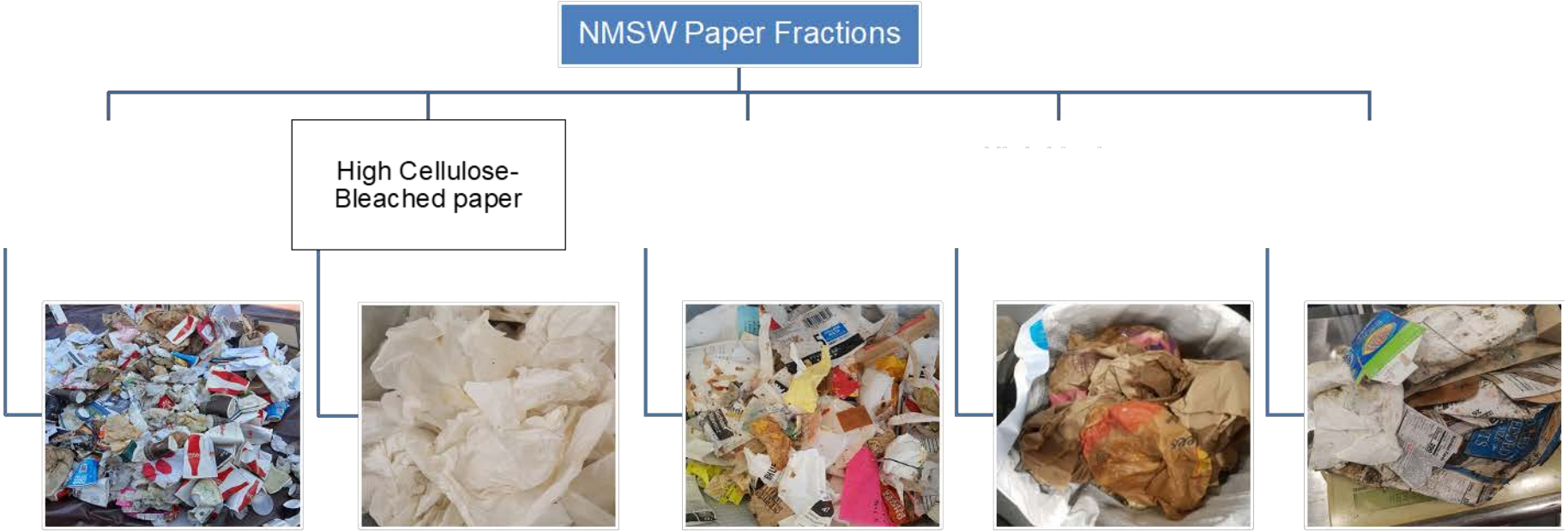
Others include potential hazardous materials, grease containing materials, razor, enclosed containers, diapers, car parts and others which are not included above

Characterization: Importance of Classification

Major Category	Subcategory
Paper	OCC, Office paper, Napkin, Secondary box, tetrapack, package, disposables
Plastic	Plastic (1-7), Chipsbag, Hard plastic
Food waste	Starch based, Protein based, Fruits and vegetables, Egg shell and bones
Textiles & Leather	Synthetic, Cotton, Mixed, Natural
Metals	Ferrous, Non-ferrous
Glass	Clear, Colored, Ceramic
Other organics	Wood waste, yard waste
Others	Pcs smaller than 12mm, Hazardous waste, Electronics, Mixed category and others

Characterization: Unique Classification Classes for Paper Fraction

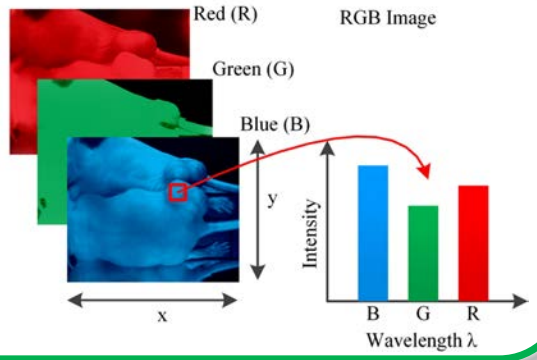
- **NMSW Characterization – Paper Fractions**
  - **Paper is the highest percentage of MSW on oven dry basis.**
  - **Development of innovative process of reclassification and characterization of various subclasses of papers**

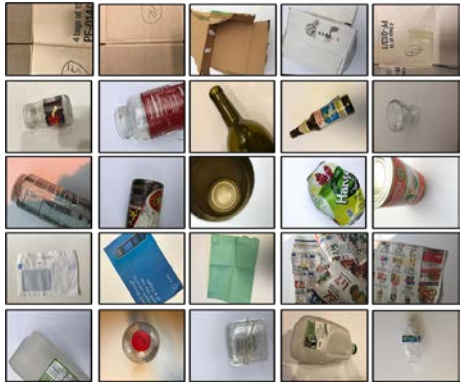


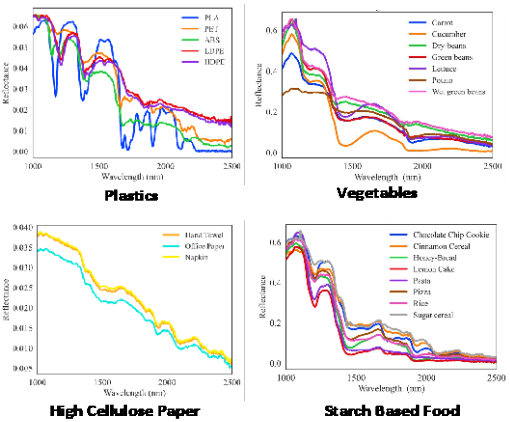
MSW Optical Characterization Techniques

Traditional Imaging

- Captures three bands of color (red, green, and blue).

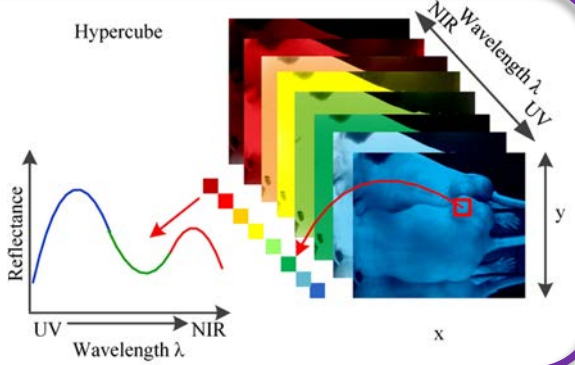






Hyperspectral Imaging

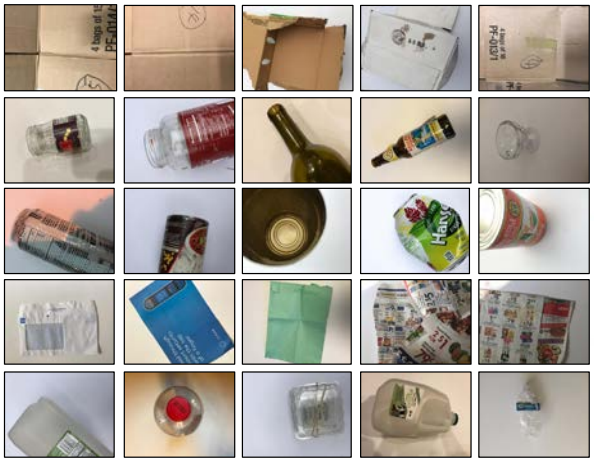
- Involves capturing and processing hundreds of bands, often from the ultraviolet to the infrared regions.



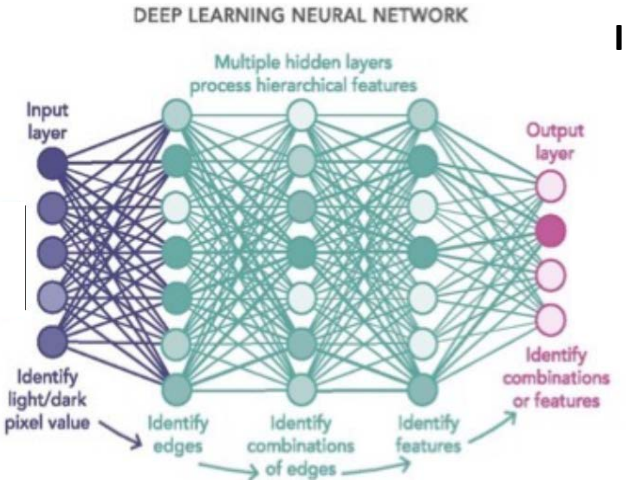
Ozdemir, A., & Polat, K. (2020). Deep learning applications for hyperspectral imaging: a systematic review. *Journal of the Institute of Electronics and Computer*, *2*(1), 39-56

Characterization: Visual Imaging for classification

- Pre-existing datasets of MSW material obtained from Kagel ((https://www.kaggle.com/datasets/techsash/waste-classification-data)
- Original Set
- 2,390 total images were obtained
  - 403 images of cardboard,
  - 501 images of glass,
  - 410 images of metal,
  - 594 images of paper
  - 482 images of plastic.



- Machine Learning model
  - Convolutional Neural Network (CNN)



Imaged Augmented Set

Sample Type	x2	x5	x10
Cardboard	806	2015	4030
Glass	1002	2505	5010
Metal	820	2050	4100
Paper	1188	2970	5940
Plastic	964	2410	4820

Initial Image Classification

	Accuracy (%)
Cardboard	84%
Paper	41%
Glass	78%
Metal	85%
Plastic	45%

Characterization: Visual Imaging for high accuracy AI classification

	Publicly Available	NCSU/NREL Project
Type of images	Random Images	Real MSW Samples
Number of Classes	Max. 44 sub-categories in Huwei dataset	54 subclasses
Metadata for characterization	Not specified	Physical, thermal, chemical metadata collected along with the images
Lighting conditions for imaging	Not specified	Tracking the luminosity
Number of Images	Max. 10,000 in Huwei dataset	Over 500,000 images and counting

Key features of our dataset

- Maximum subcategories of images
- More controlled visual imaging
- Including the characterization data
- Real waste sample destined for landfill
- Capturing spatio-temporal heterogeneity
- Capturing chemical signature

Characterization: Hyperspectral Imaging

HSI - Resolutions

- **Spectral resolution**
  Spectral resolution refers to the width of the bands. **Higher spectral resolution allows for more detailed spectral information.**
- **Radiometric resolution**
  Radiometric resolution refers to the sensitivity to different levels of light intensity, **allowing detection of subtle variations in reflectance.**
- **Spatial resolution**
  Spatial resolution is the level of detail in the spatial dimension. **It indicates how small objects or features can be distinguished.**

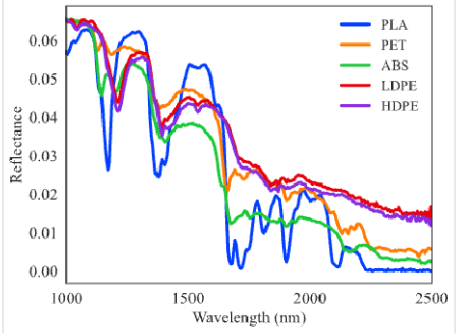
Spectral Fingerprint

The spectral fingerprint is the unique spectral signature or pattern associated with a particular material.

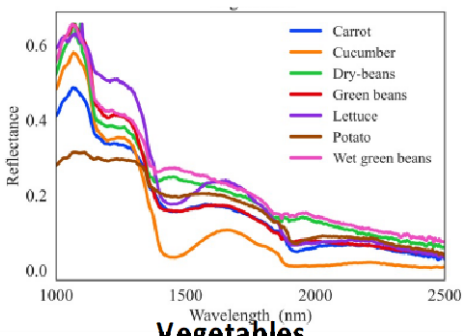
- **Average spectral**
  The average spectral signature is a representation of the typical reflectance or radiance values of a material across different wavelengths.
- **Endmembers**
  Endmembers are pure spectral signatures that represent the most extreme or distinctive spectra for specific materials in a scene.
- **Linear spectral unmixing**

Characterization: Hyperspectral Imaging

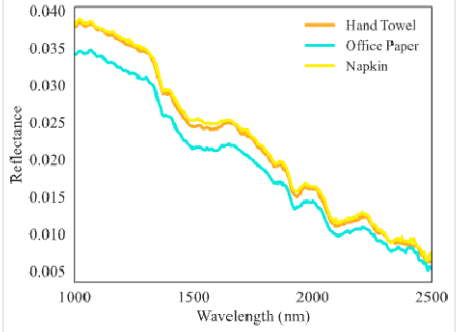
Material Identification



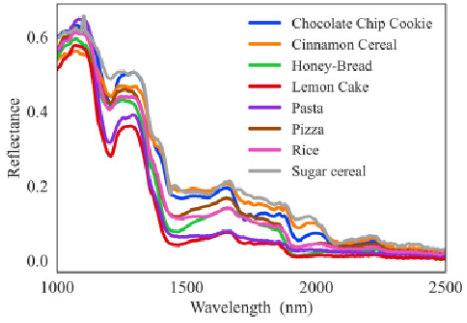
Plastics



Vegetables

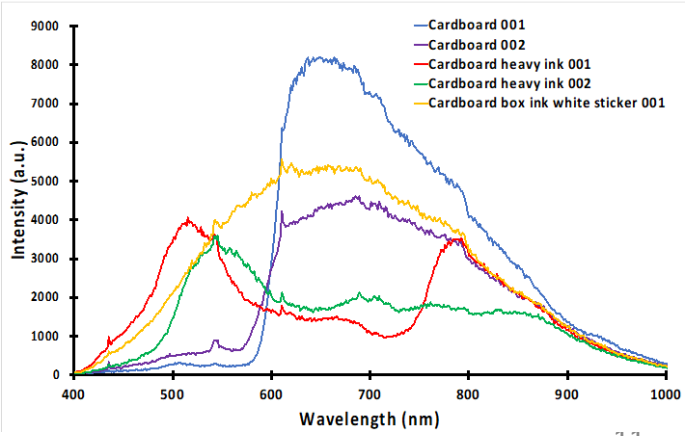


High Cellulose Paper

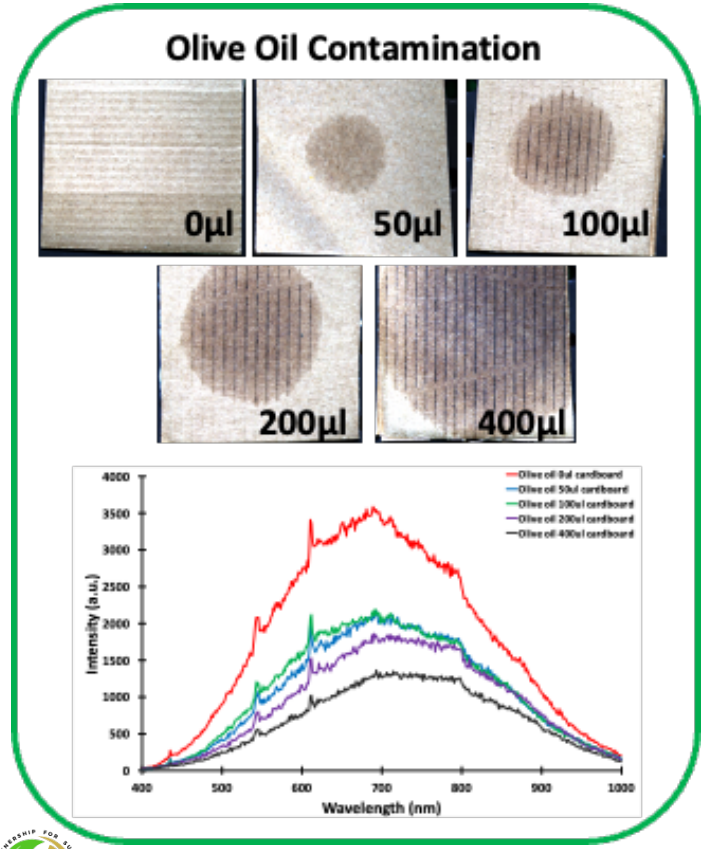


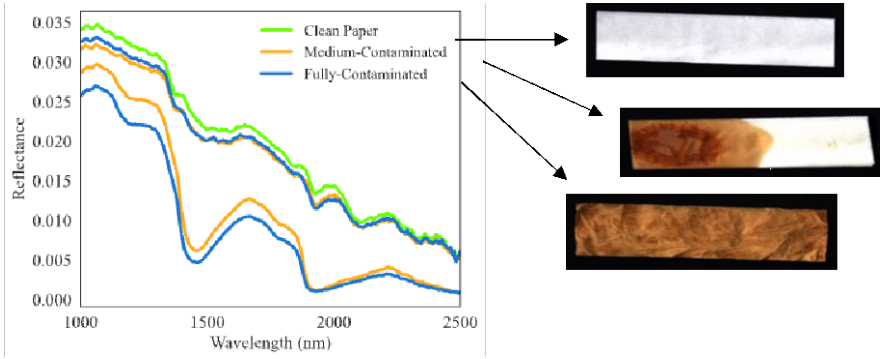
Starch Based Food

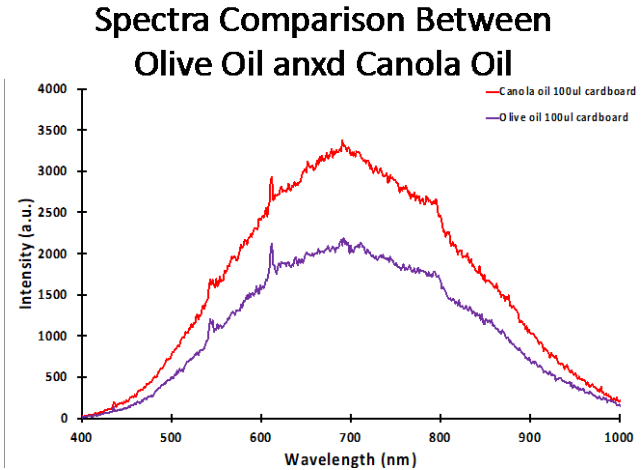
Material Characterization



Characterization: Hyperspectral Imaging for Detecting Contaminants

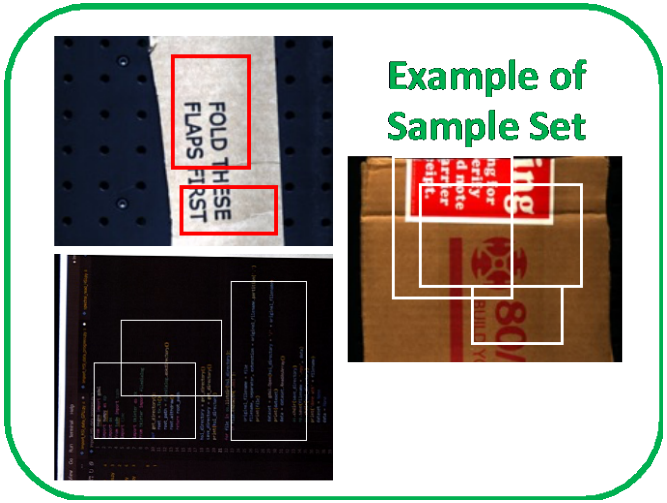






Characterization: Initial machine learning with Hyperspectral Imaging

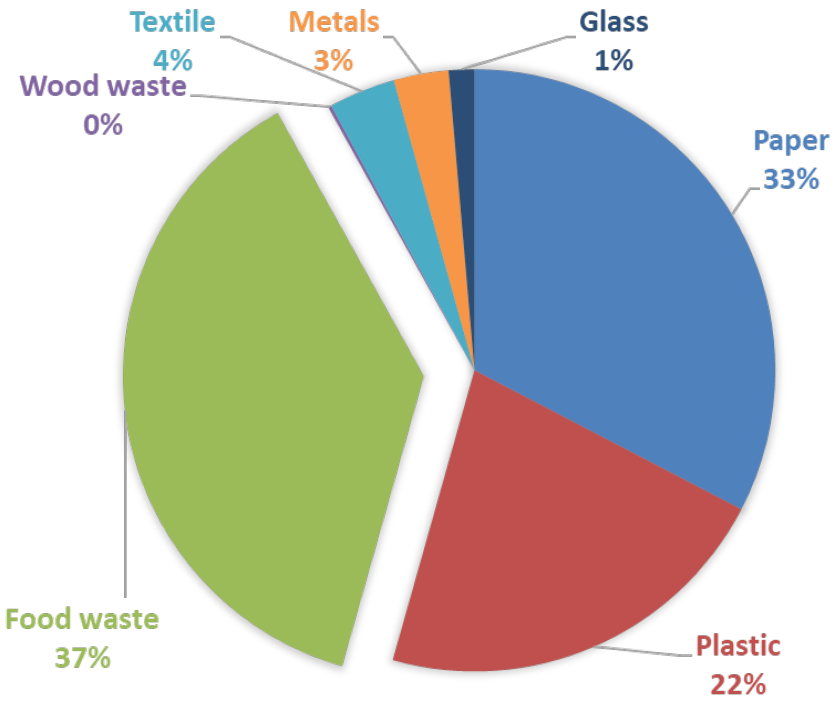
- Original Set
  - 60 total images were obtained
  - 30 HSI images of cardboard,
  - 30 HSI images of paper
- Expanded training Set
  - 119 HSI images of cardboard
  - 119 HSI images of paper



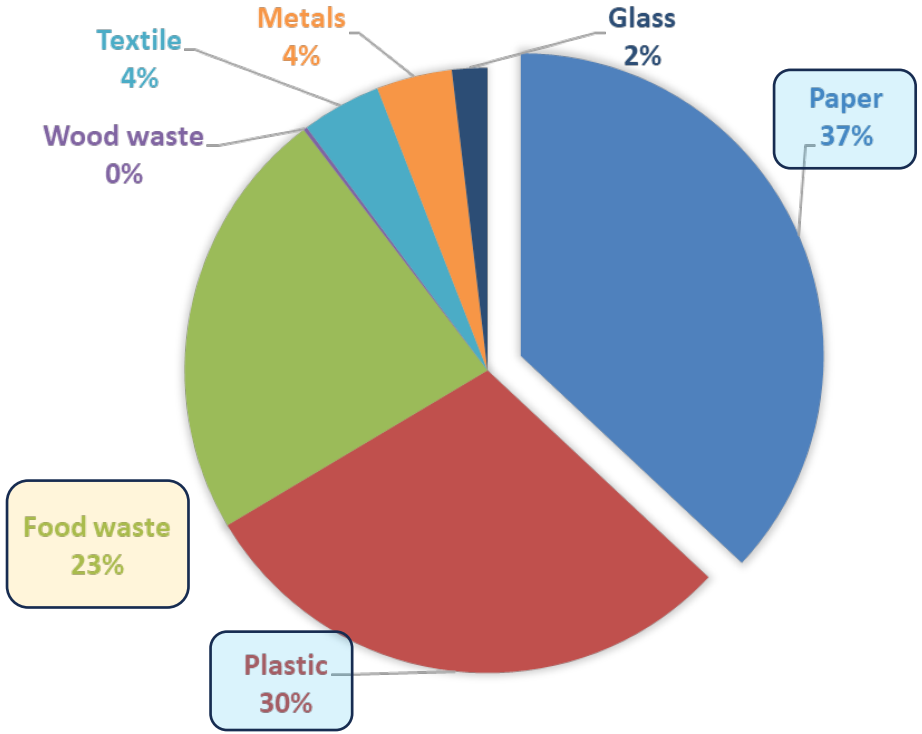
Initial Machine Learning model Results

- Convolutional Neural Network (CNN): **54% accuracy** in classifying paper against carboard
- XGBoost: **76% accuracy** in classifying paper against cardboard

Characterization: Physical



Wet basis (excluding others)



Oven dry basis (excluding others)

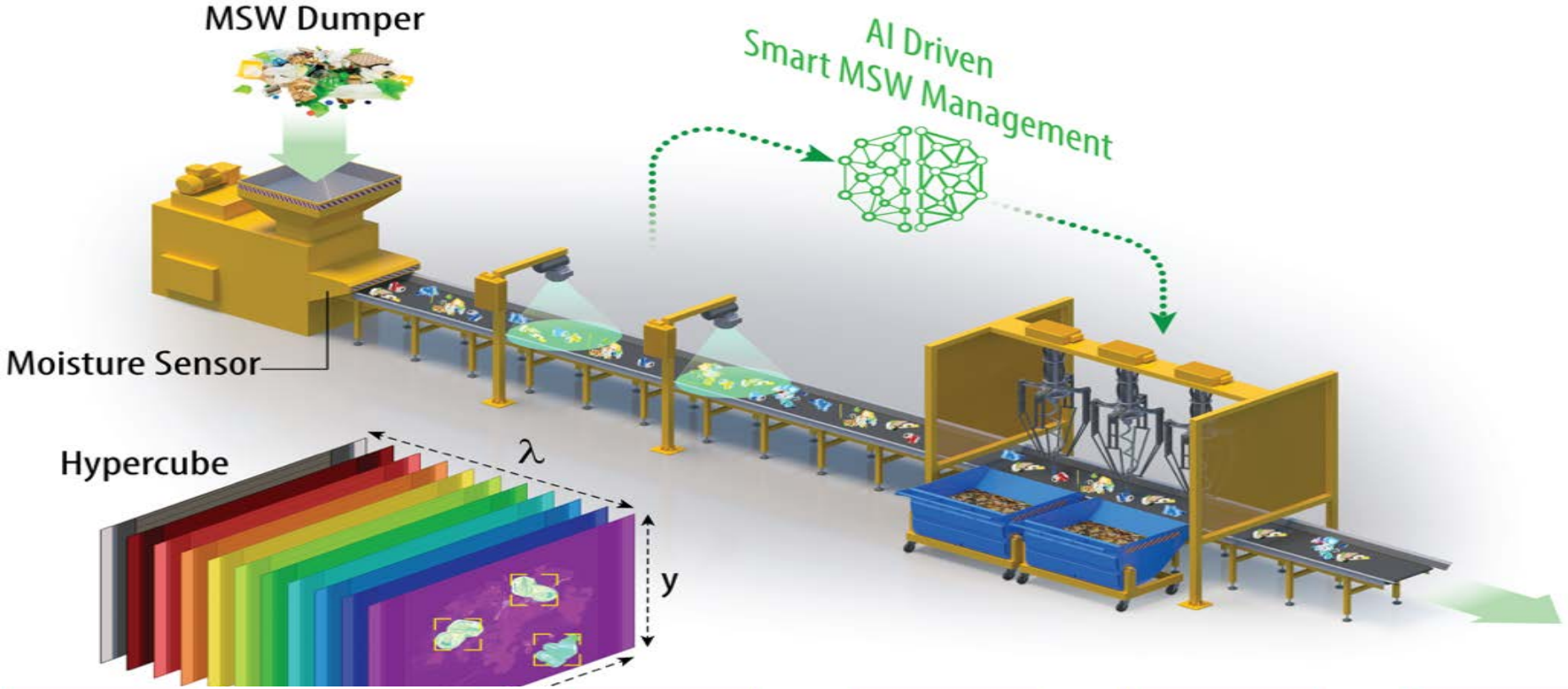
Characterization: Composition, Carbone/Nitrogen and Heating values

Feedstock	Glucan	Xylan	Arabinan	Total Carbohydrate	Acid Insoluble
Mixed Paper Fractions from NMSW	50.4	16.4	1.2	68.1	10.6
Corn Stover	37.7	21.1	3.3	62.1	15.1
Hardwood Poplar	43.3	14.8	1.1	59.2	25.5
Switch grass	29.0	18.6	3.3	50.9	15.3
Loblolly Pine	38.1	6.7	1.8	46.6	33

Feedstock	C%	H%	N%	S%	O%/other (diff)
Mixed Paper Fraction NMSW	41.7	6.2	0.3	0.1	51.8
Hardwood Poplar	42.6	6.5	0.2	0	50.8

Feedstock	HHV, MJ/kg	LHV, MJ/kg
Mixed Paper Fraction NMSW	15.77	14.21
Hardwood Poplar	16.32	14.70

Characterization: Data and AI Pipeline Development



Goal
Non-recycled MSW characterization

Connect and Access Data

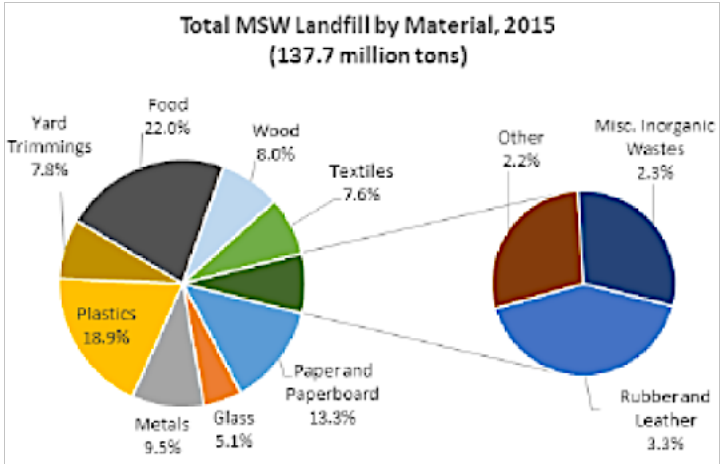
Data Preparation

Build and Train ML/DL model

Model Deployment

Monitor Analyze and Manage

SAF Production Potential from NMSW



NMSW Fraction	CAAFI, FT*, MPGY**	Furfural***, MPGY
Paper	499	653
Food	323	328
Wood	234	256
Yard Trimming	137	250
Plastics	1,527	1,527
Textile, rubber, leather	733	733
Total	3,462	3,743

*Fischer Tropsch
**Million gallons per year
*** Conversion of sugars to SAF via furfural upgrading; assumes 60 gal of SAF range hydrocarbons per dry ton of NMSW

Source:
- https://www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/national-overview-facts-and-figures-materials
- CAAFI; ; Klein et al. 2021 - https://doi.org/10.2172/1819430

Acknowledgment: Team Leads

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Ashutosh Mittal, NREL
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Q&A

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