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Hyperspectral Imaging Analysis for Mechanical and Chemical Properties of Concrete and Steel Surfaces

Genda Chen, Ph.D., P.E.
Professor and INSPIRE UTC Director, Missouri S&T
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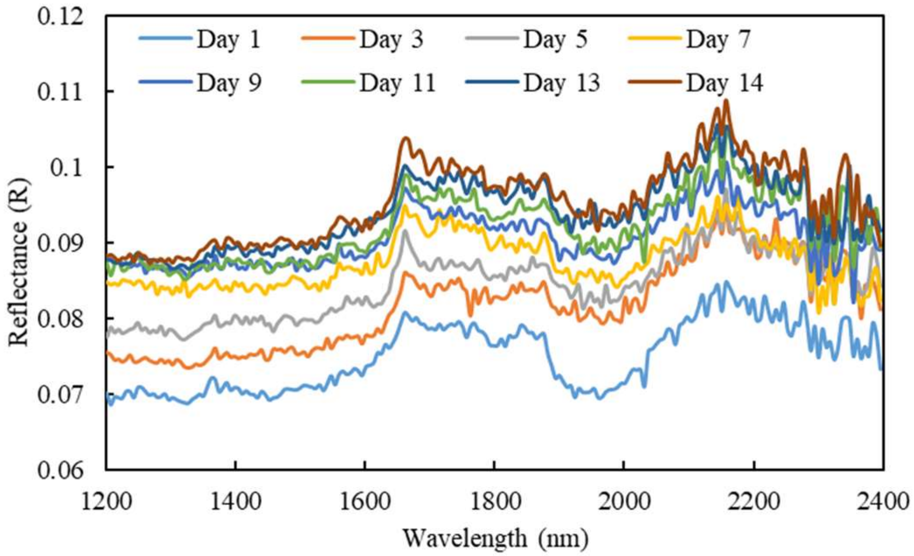
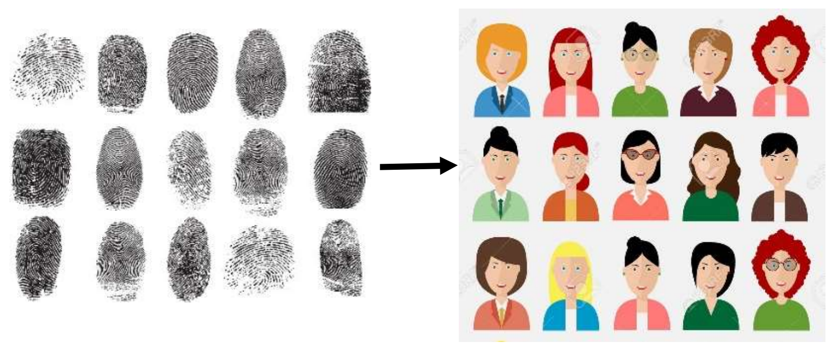
Outline

- Introduction
- Objectives
- Experiments
- Material Classification by Machine Learning
- Results and discussion
- Conclusions
- Acknowledgement

Introduction

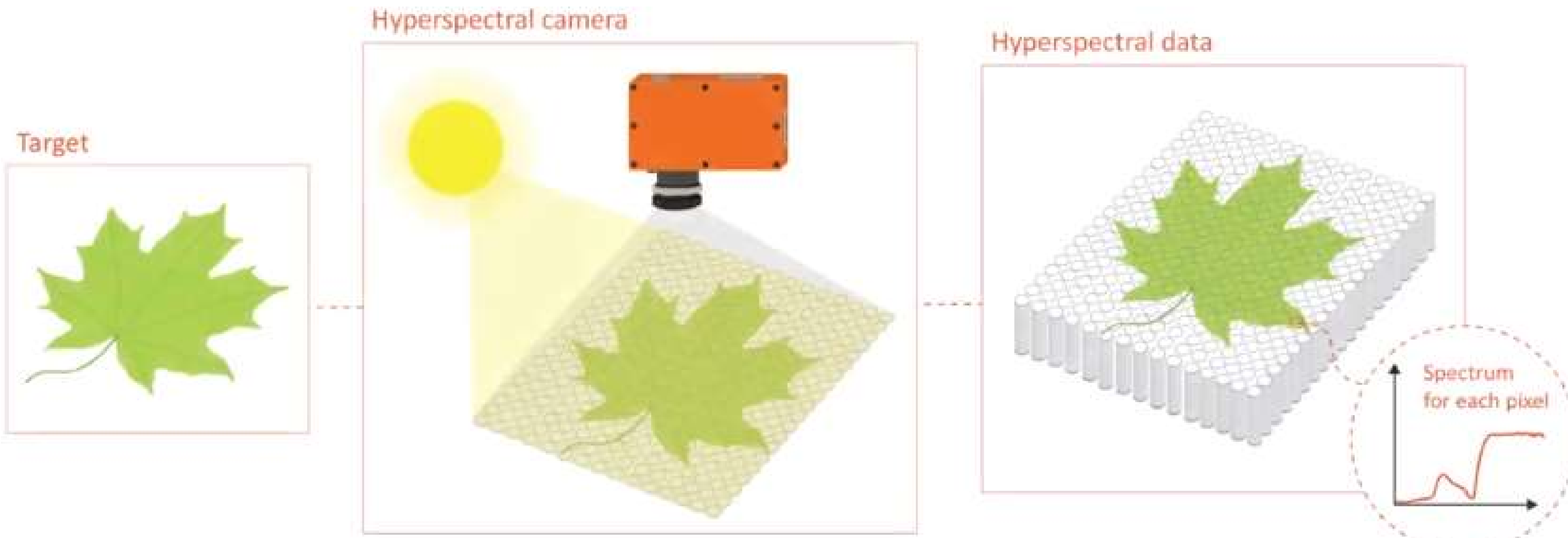
- **Spectroscopy** represents an interaction between light and targeted materials in order to examine behavior of the light and recognize spectral signatures of the materials from their electromagnetic spectrum.
- **Spectrum** describes the intensity of light in different wavelengths. It helps to understand how much of light is emitted, reflected, or transmitted from a target. The typical way of representing the spectrum is on a graph of reflectance vs. wavelength.





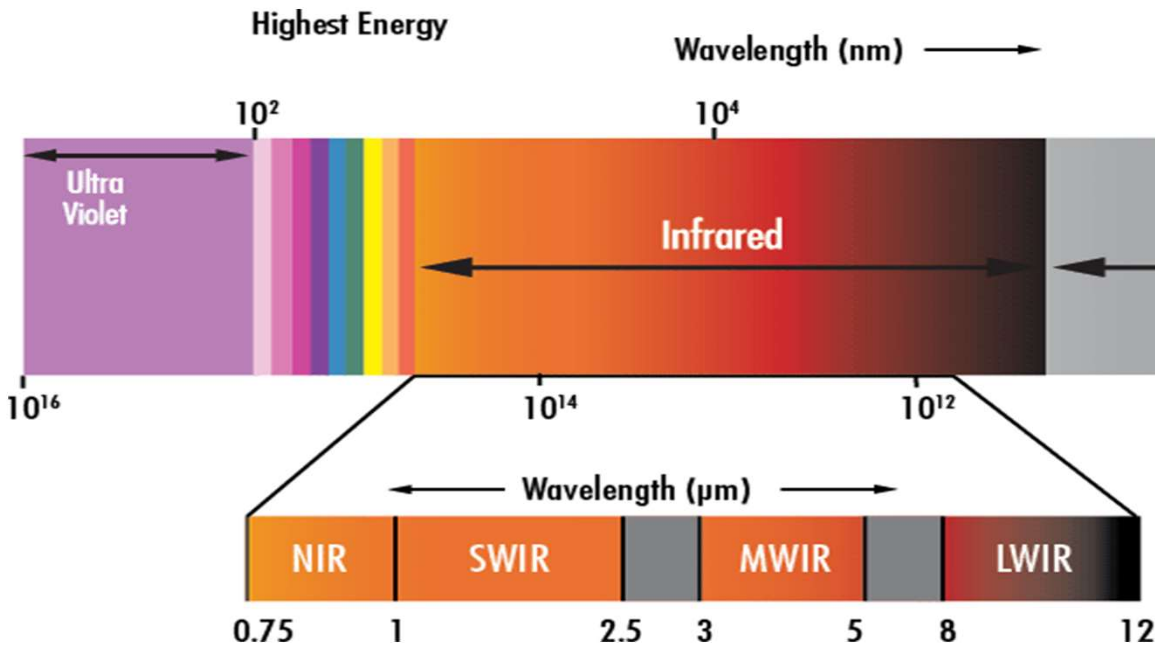
Introduction

- **Hyperspectral Imaging**
  - A combination of imaging and spectroscopy
    - ✓ *Each pixel has a light spectrum that can help identify objects/materials or detect processes associated with them.*
    - ✓ *It is a collection of thousands of images in various wavelengths.*
  - Characterization of vegetation, mineral, and food products
    - ✓ *Reflectance spectra can be analyzed to identify features.*
    - ✓ *For example, infected/healthy leaves can be distinguished.*



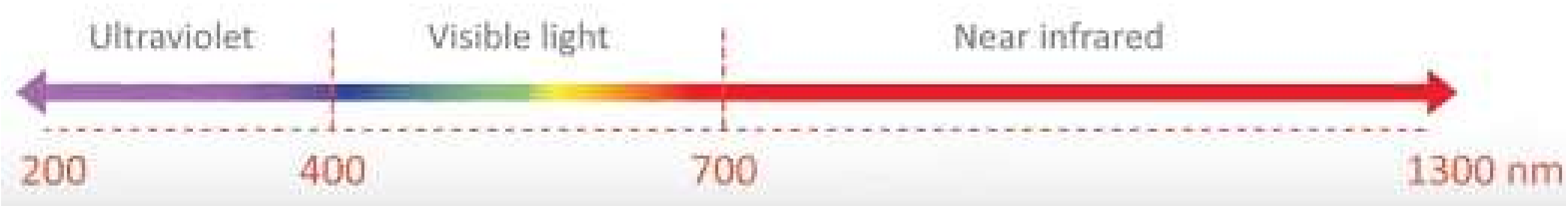
Introduction

- **Key Factors in Hyperspectral Imaging**
  - Proper illumination with the bandwidth of a light source at least matching that of the camera
  - Reflectance references (dark and white references)
  - Distance and spatial resolution
  - Wavelength range



Introduction

- **Headwall Co-Aligned Dual-Sensor Hyperspectral Camera (400 – 2500 nm)**
  - **VNIR (400 – 1000 nm) and SWIR (900 – 2500 nm)**



Introduction

- **Technical Specifications**

Camera	VNIR	SWIR
Spectral range	400-1000nm	900-2500nm
Image resolution at 4-6 ft. away	1-2 pixel	1-3 pixel
Spectral pixels	270	267
Spatial pixels		640
Max frame rate	350 Hz	200 Hz
Typical applications	Airborne and ground remote sensing that require coverage between 400-2500nm	
Size	Approx. 10.7" x 8.2" x 6.5" (272mm x 208mm x 165mm)	
Weight	6.25 lb (2.83 kg)	

Objectives

- To develop an open-source catalogue of concrete and steel surfaces and their spectral/spatial features (discoloration, characteristic wavelength, roughness, texture, shape, etc.),
- To extract spatial/spectral features of hyperspectral images,
- To develop/train a multi-class classification or regression classifier through machine learnings (supervised and/or semi-supervised),
- To validate the classifier as a decision-making tool for the assessment of concrete crack and degradation processes, in-situ concrete properties, and corrosion process in steel bridges.

Experiments

- **Mix of Mortar Specimens by Weight (kg/m^3)**

Types of mortar samples	C1	C2	C3
Water	288	270	245
Ordinary Portland cement	480	540	615
Missouri river sand	1482	1482	1482

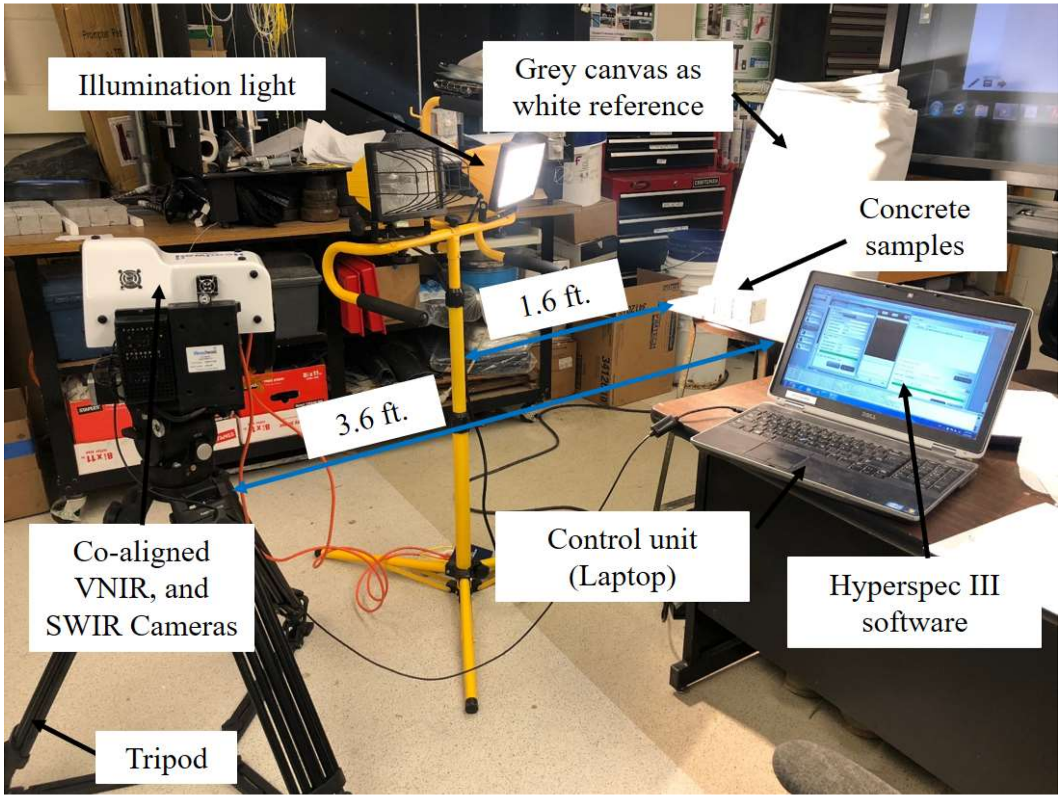
Experiments

- **Steel Specimens**

Hot rolled A 36 steel	Dimension	Solution	Corrosion method	HSI scanning time	Outcome spectrum with corrosion rate
Sample_1	2.5” long × 2.5” wide × 0.5” thick	18 g NaCl+ 500ml H2O	Half Immersed in solution	Scanned after 71 day (1704hrs)	high reflectance with low corrosion rate
Sample_2	2.5” long × 2.5” wide × 0.5” thick	36 g NaCl+ 500ml H2O	Half Immersed in solution	Scanned after 71 day (1704hrs)	low reflectance with high corrosion rate
Sample_1’	3.0” long × 3.0” wide × 0.5” thick	18 g NaCl+ 500ml H2O	Applied five drops each 5ml of solution	Scanned after 71 day (1704hrs)	high reflectance with low corrosion rate
Sample_2’	3.0” long × 3.0” wide × 0.5” thick	36 g NaCl+ 500ml H2O	Applied five drops each 5ml of solution	Scanned after 71 day (1704hrs)	low reflectance with high corrosion rate

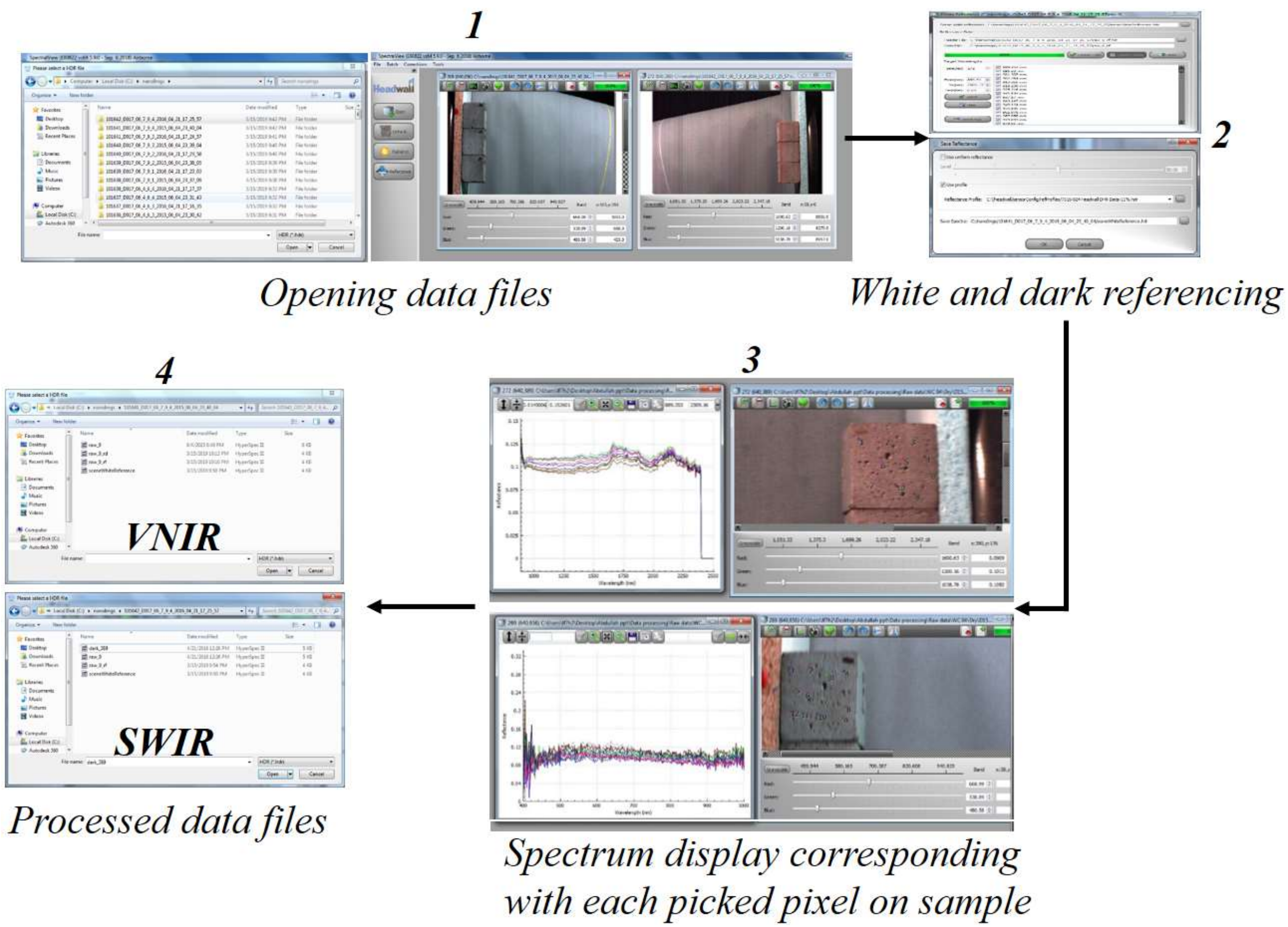
Experiments

- **Test Setup**
  - ➢ Distance: 3.6 ft
  - ➢ Reference: white
  - ➢ Light source: LED
  - ➢ Software: Hyperspec III
  - ➢ Frame period and exposure time: adjusted to have 60% of saturated light intensity on a grey canvas



Experiments

- **Data Acquisition**
  - **Software: SpectralView**



Experiments

- **Data Processing**
  - **For pre-processing, dark reference is deducted from an image to eliminate the background noise and increase the signal to noise ratio.**
  - **With white reference, the light reflectance is calculated by**

$$R=I/I_s$$

I_s represents the reflected light intensity of a standard grey canvas (with 50% reflection), and I represents the reflected intensity of the sample.

periments

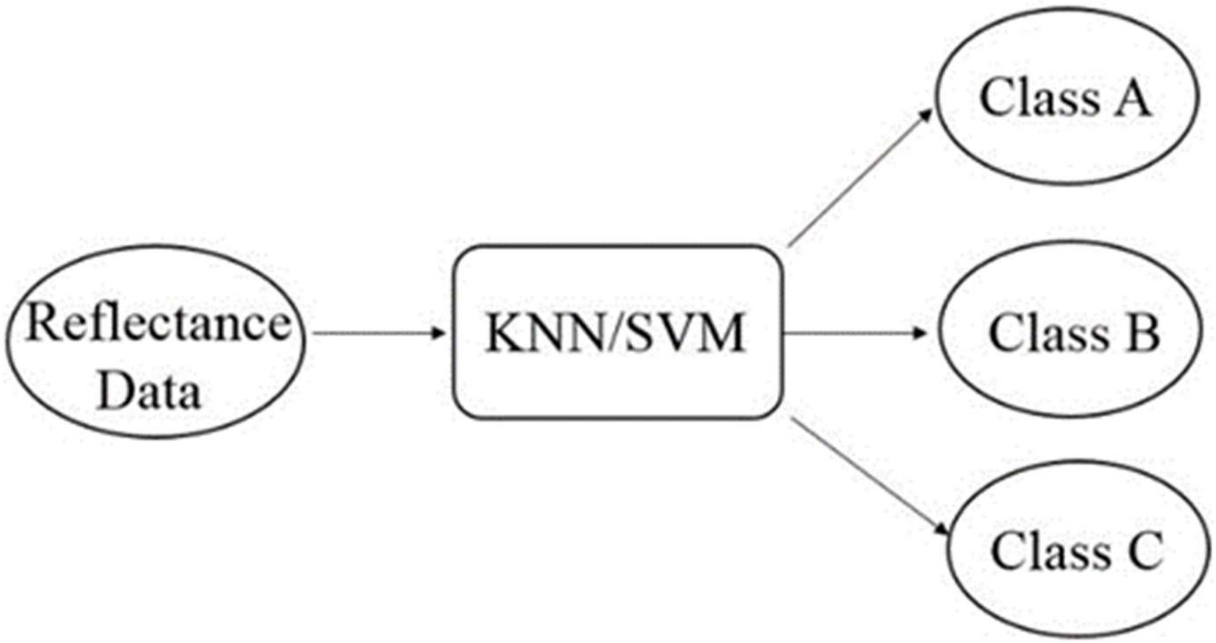
perspectral Image of a Mortar Specimen

- (a) raw
- (b) after subtraction of dark reference
- (c) after dark and white reference deduction

(a) (b) (c)

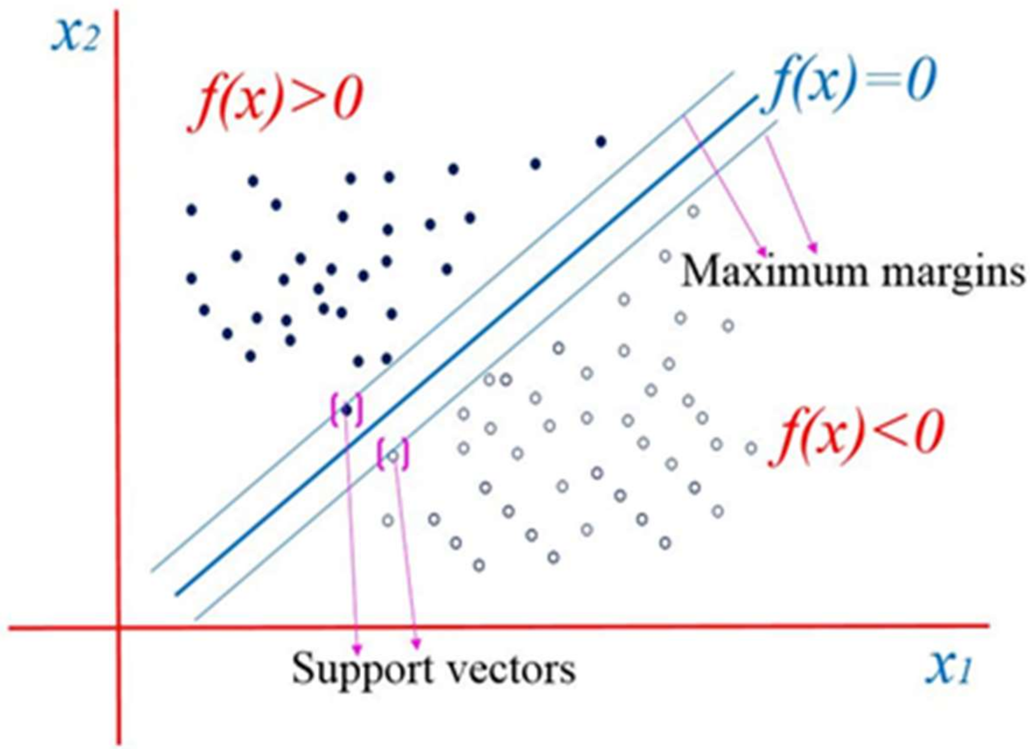
Material Classification

- **Machine Learning**
  - K Nearest Neighbors (KNN)
  - Support Vector Machine (SVM)
  - Class A, B, C for a w/c ratio of 0.6 (C1), 0.5 (C2), 0.4 (C3)



Material Classification

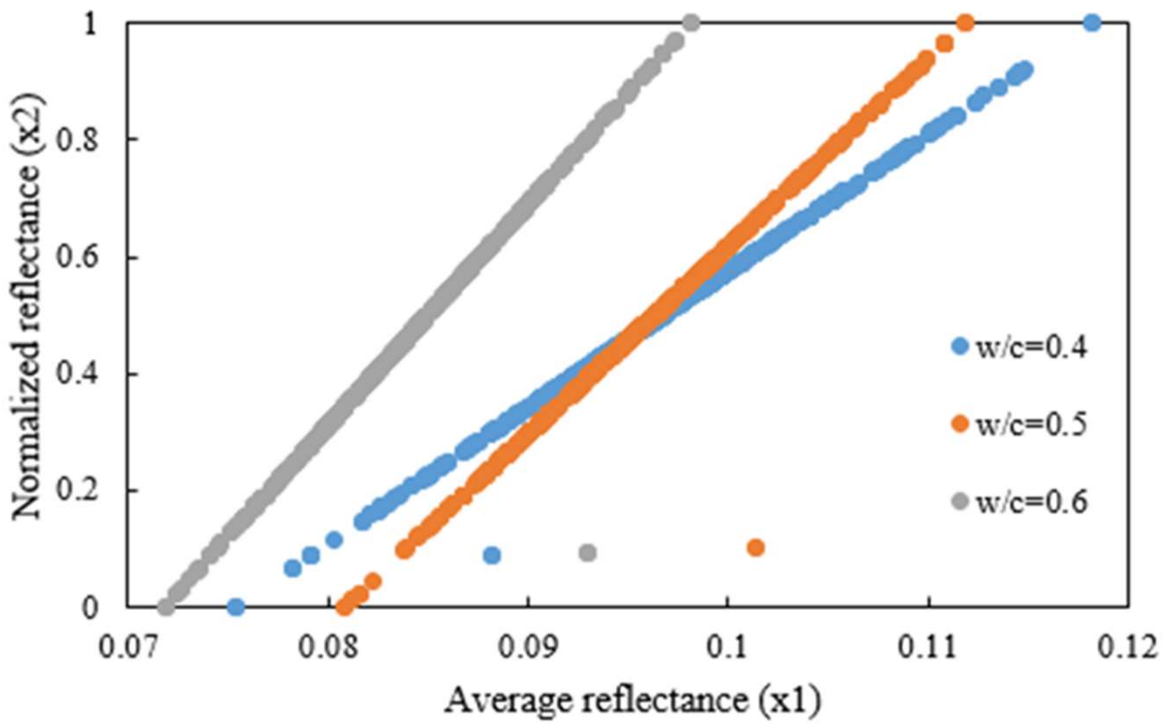
- **Support Vector Machine (SVM)**
  - **A linear classifier with maximum margins that divides the data into two sets**



Material Classification

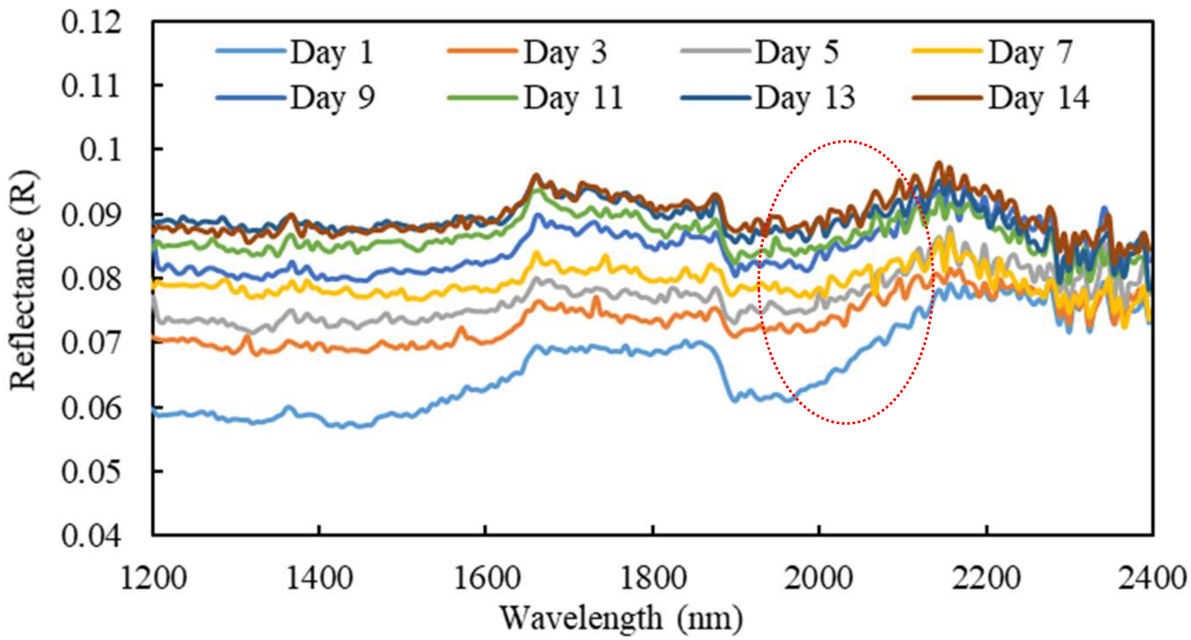
- **Normalization of Reflectance**
  - **Min. and Max. represent the minimum reflectance and the maximum reflectance of the whole data set during each test day, respectively**

$$x2 = \frac{\mathrm{dR}\ (1920 - 1980)\ - \mathrm{Min.}}{\mathrm{Max.} - \mathrm{Min.}} \times 100\%$$



Results and Discussion

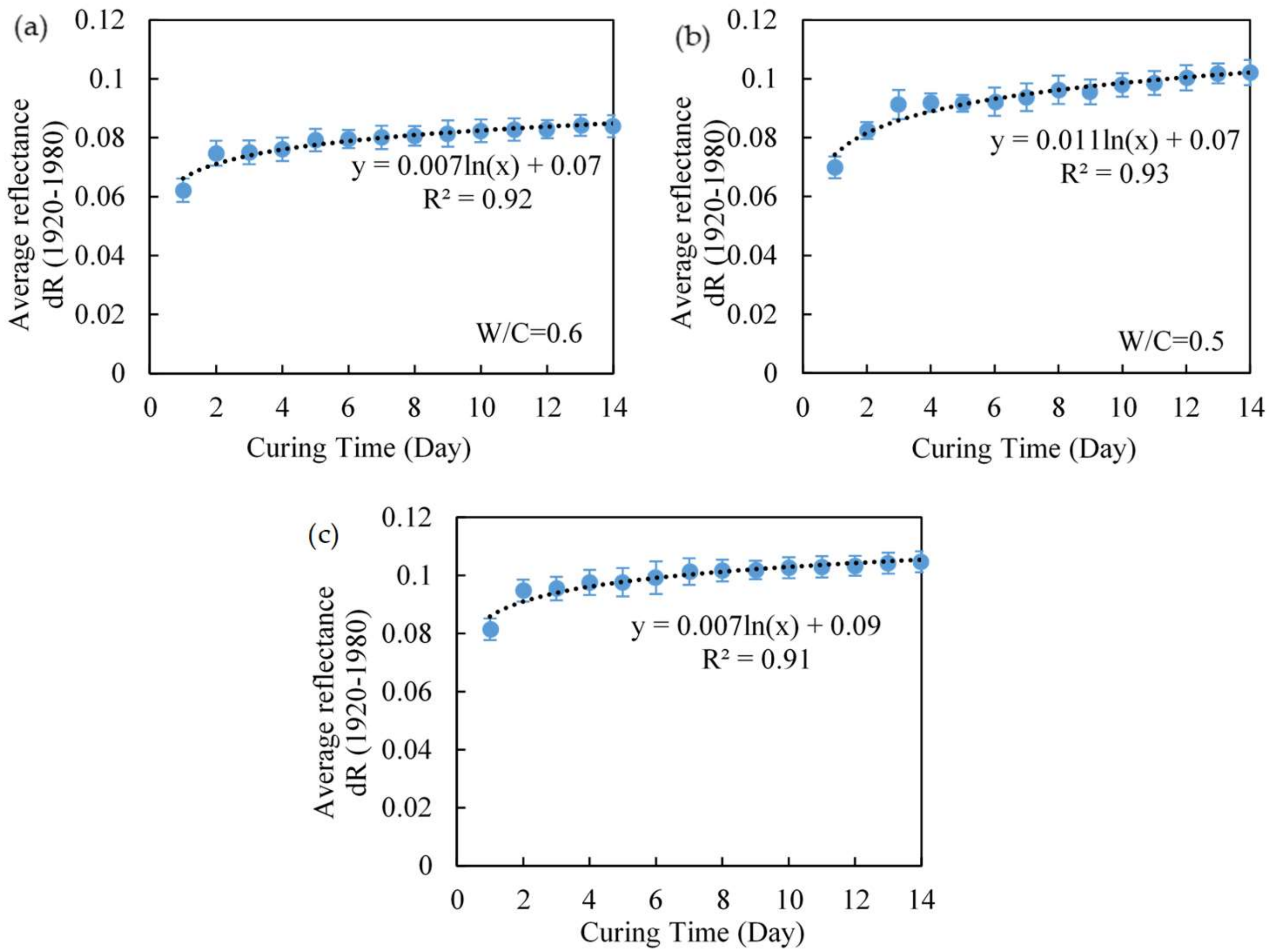
- **Reflectance from a Mortar Specimen within the First 14 Days**
  - **Reflectance increases over time due to changes in moisture, color, and density.**
  - **The combination of OH and H_2O corresponds to 1920-1980 nm.**



w/c=0.6

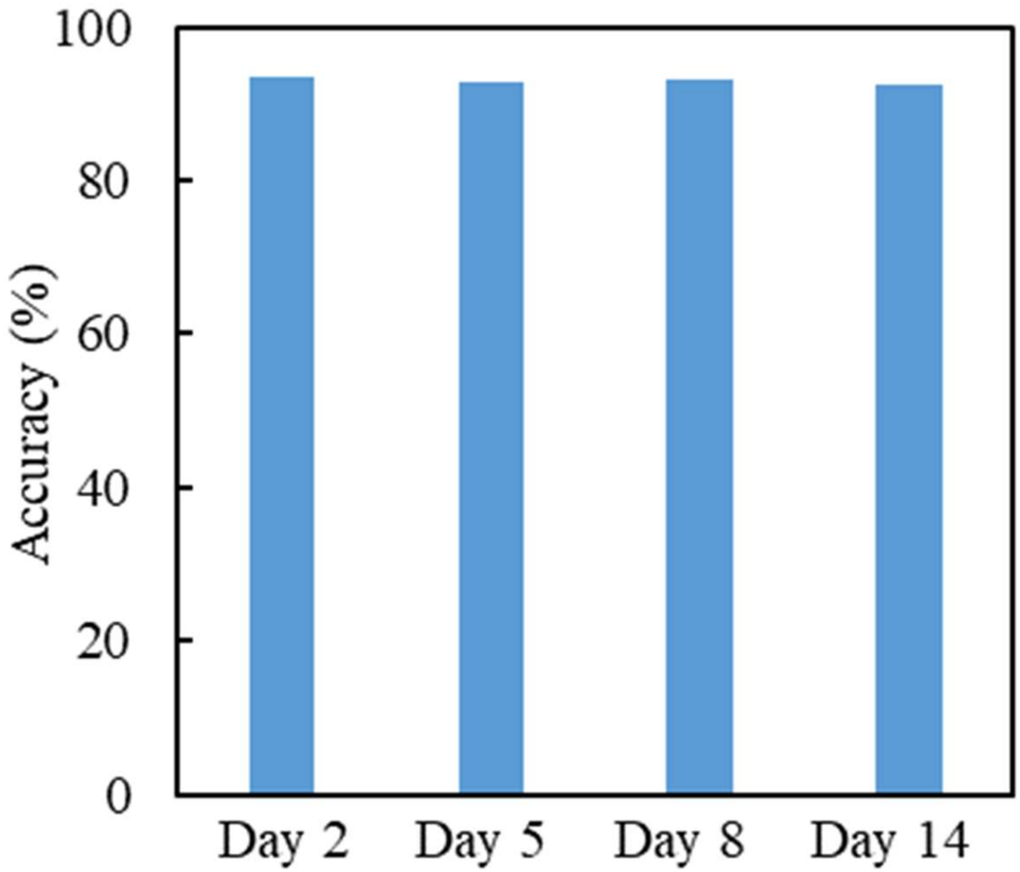
Results and Discussion

- **Average Reflectance between 1920 and 1980 nm within the First 14 Days**



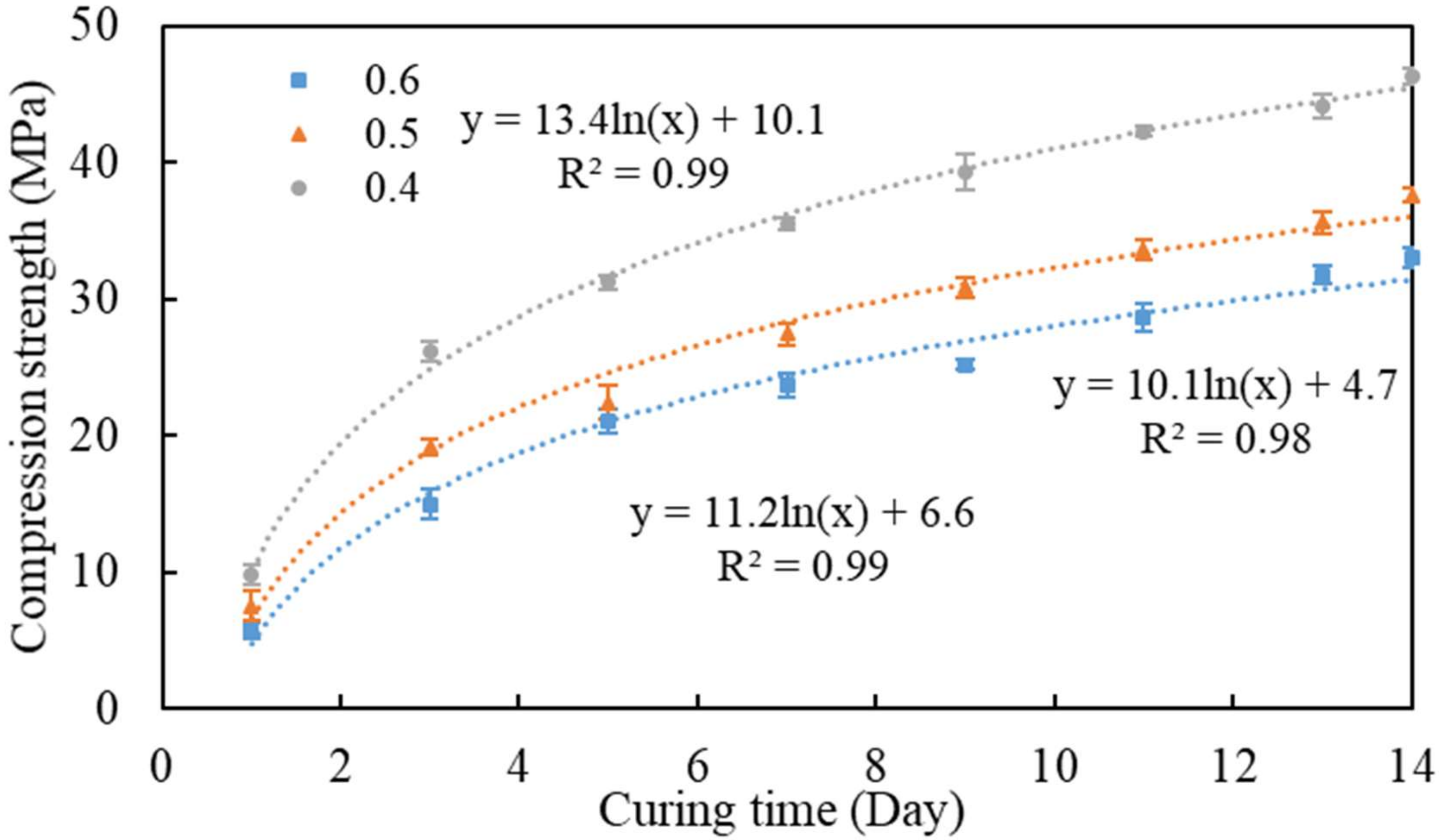
Results and Discussion

- **Classification Accuracy after 2, 5, 8, and 14 Days of Testing by Support Vector Machine**
  - **$C=10^3$ and $\sigma=10$**



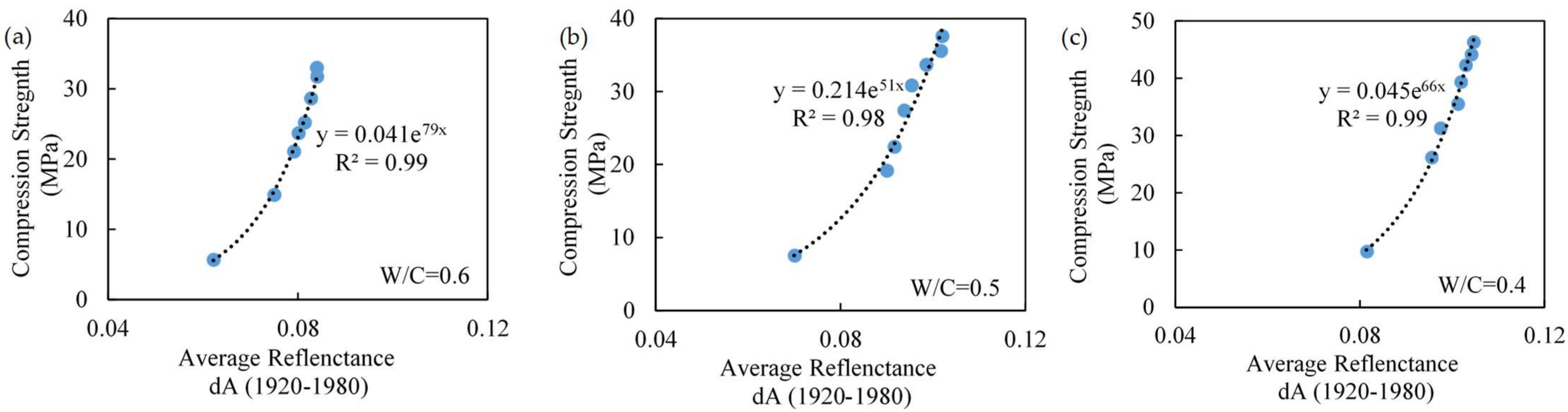
Results and Discussion

- **Compressive Strength of Three Mortar Specimens in the First 14 Days**



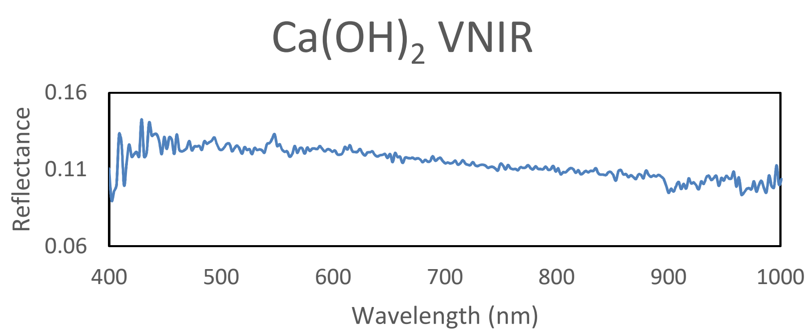
Results and Discussion

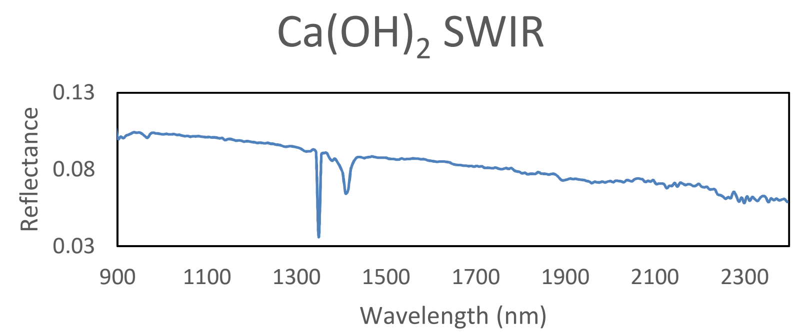
- **Mean Reflectance vs. Compressive Strength**
  - **The compressive strength of mortars increases exponentially with the average reflectance (1920-1980) over 14 days, which can be used to monitor the hardening process of mortar.**

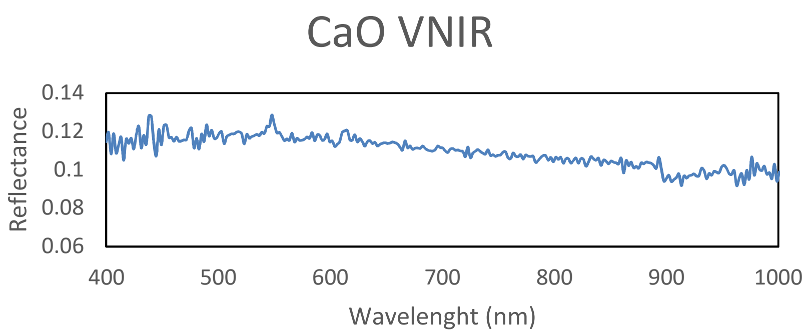


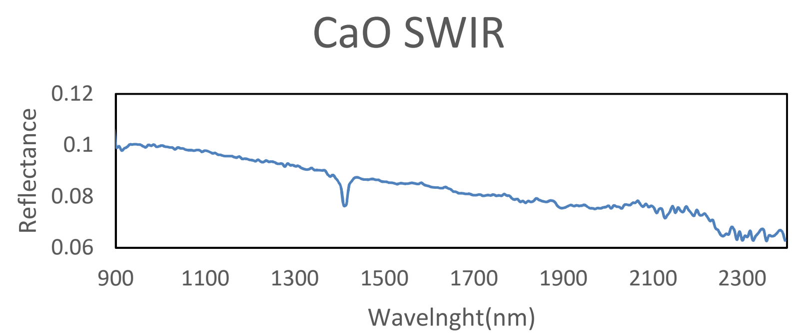
Results and Discussion

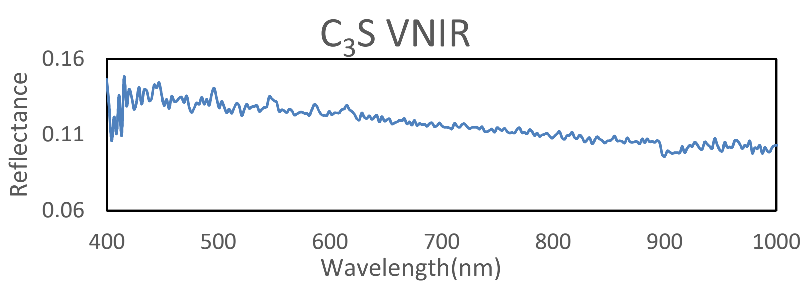
- **Spectra Library of Cement/Concrete Ingredients**

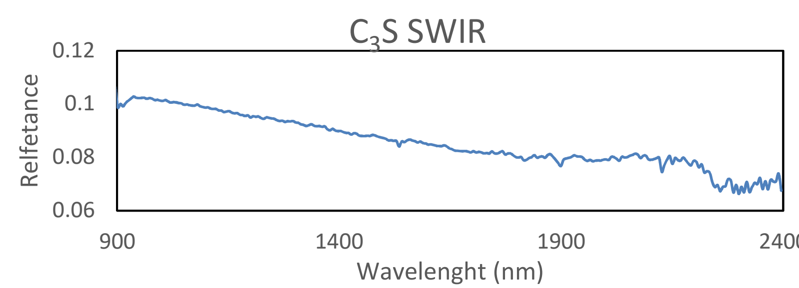






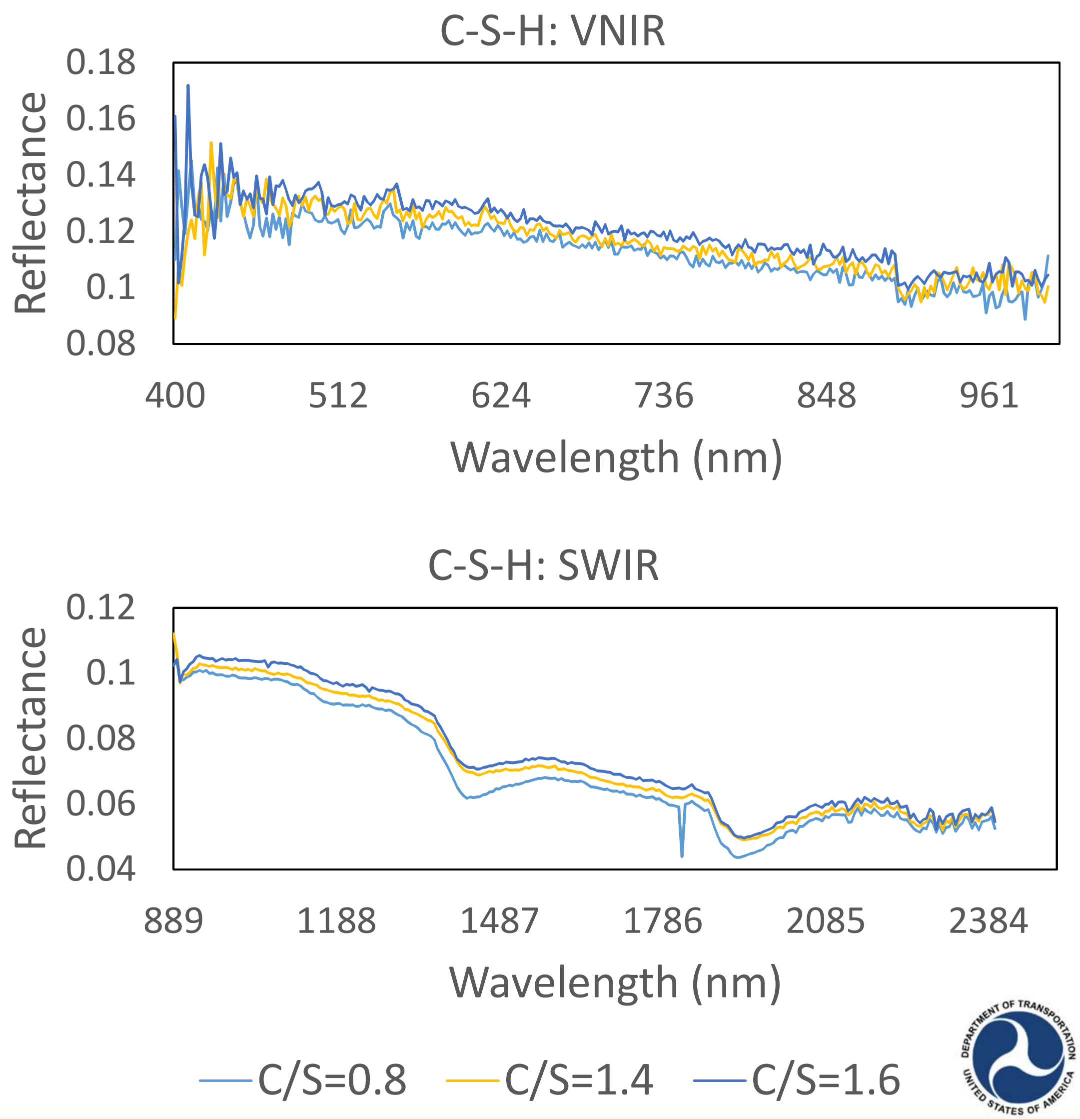






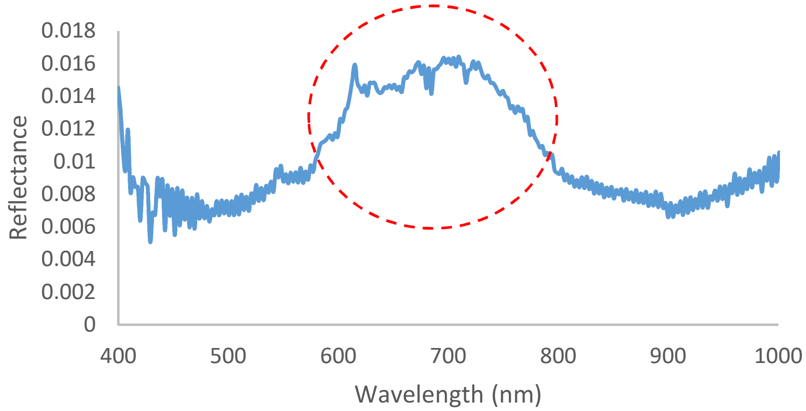
Results and Discussion

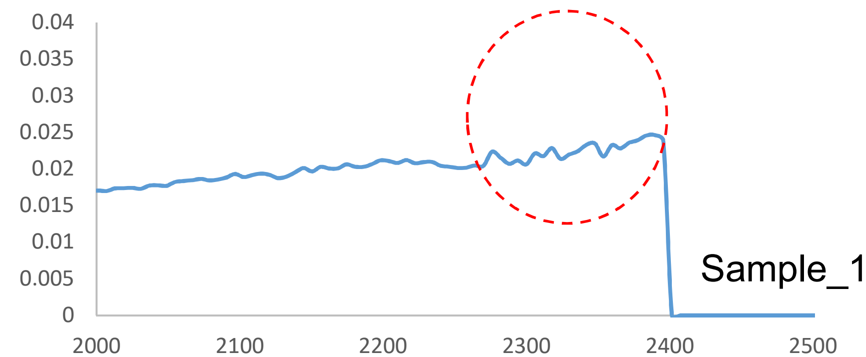
- **Spectra Library of Cement/Concrete Ingredients**



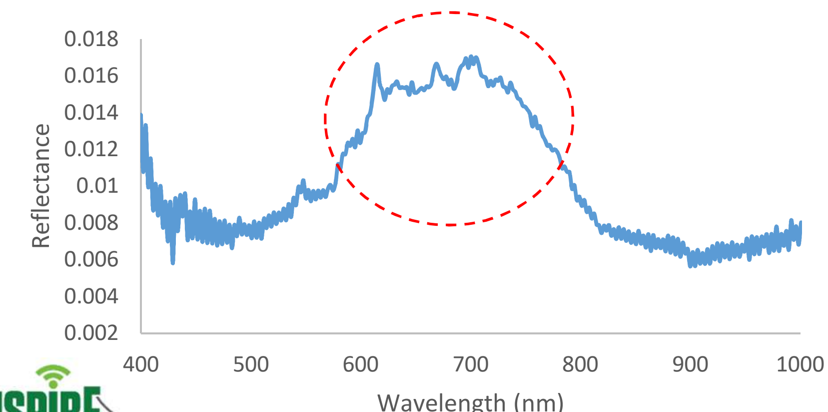
Results and Discussion

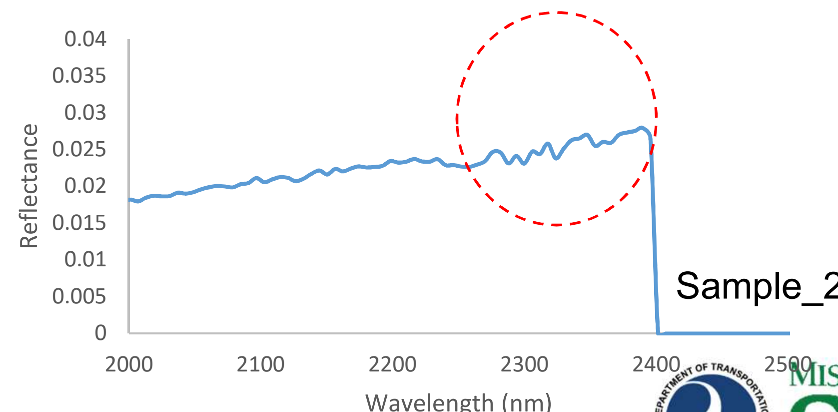
- **Average reflectance of corroded steel after 48 hours of immersion in 18g NaCl solution**





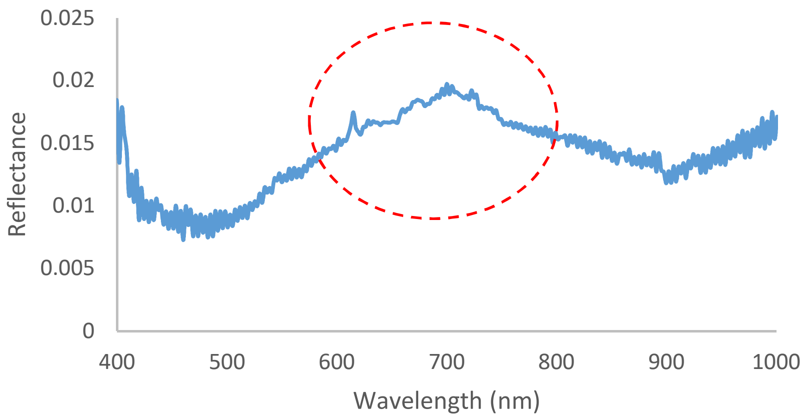
- **Average reflectance of corroded steel after 48 hours of immersion in 36g NaCl solution**

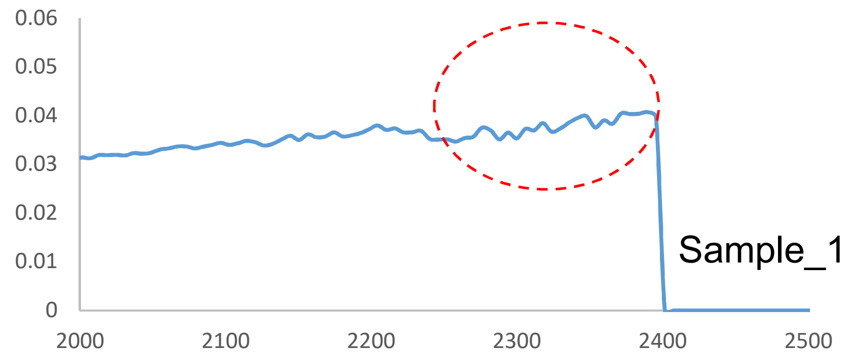




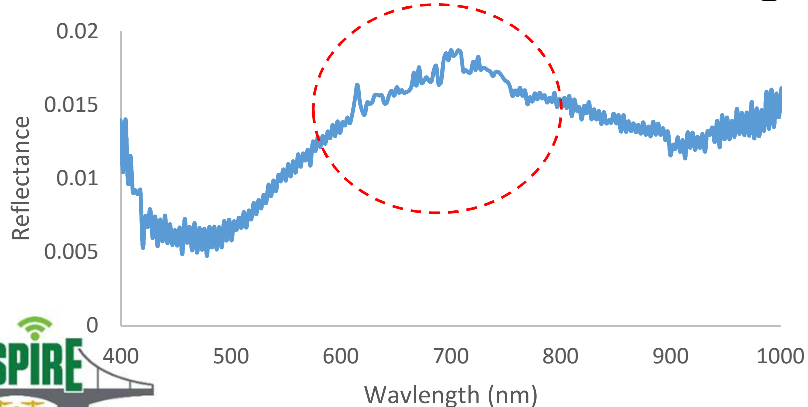
Results and Discussion

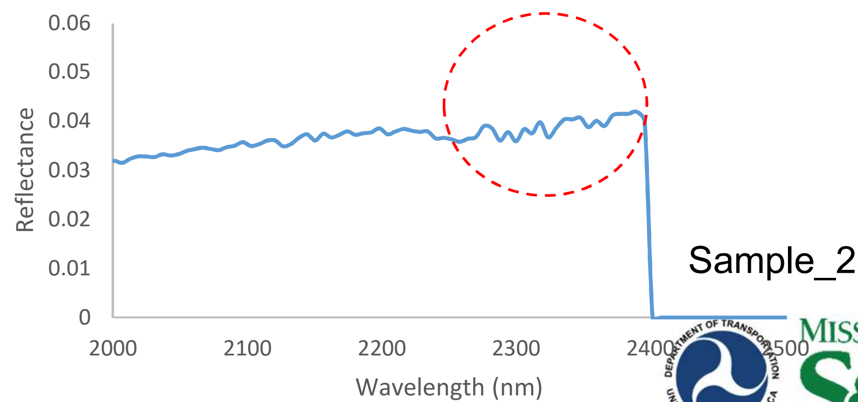
- **Average reflectance of corroded steel after 336 hours of immersion in 18g NaCl solution**





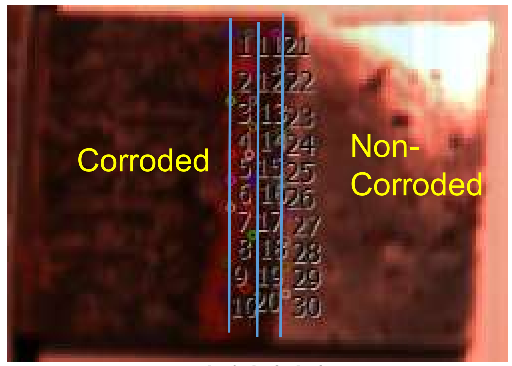
- **Average reflectance of corroded steel after 336 hours of immersion 36g NaCl solution**





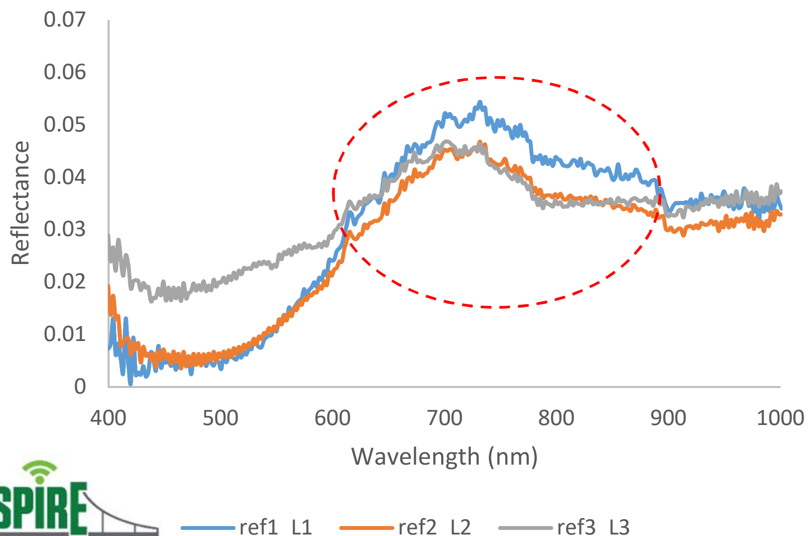
Results and Discussion

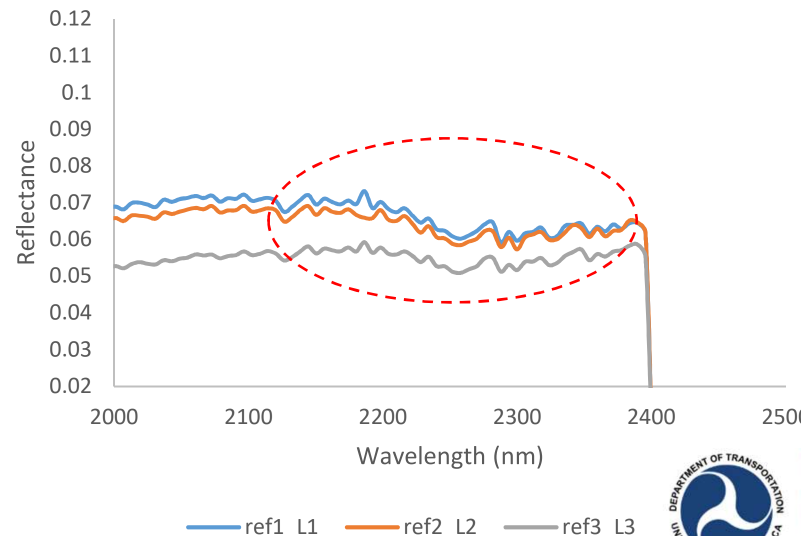
- **Average reflectance of the transitional zone between the corroded and non-corroded steel after 71 days (1704 hours) of immersion in 18g NaCl solution**



L1 L2 L3

Sample_1





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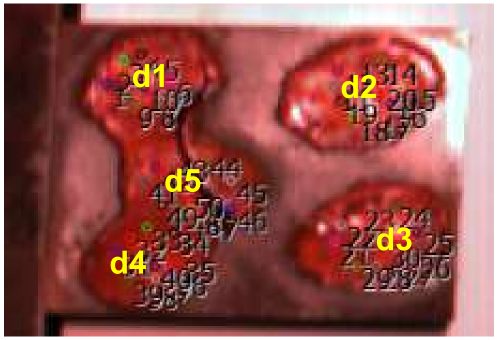
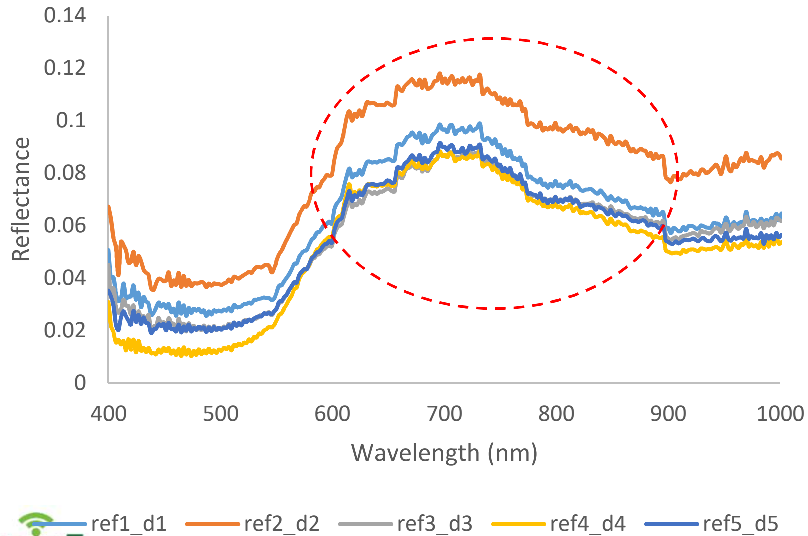
Results and Discussion

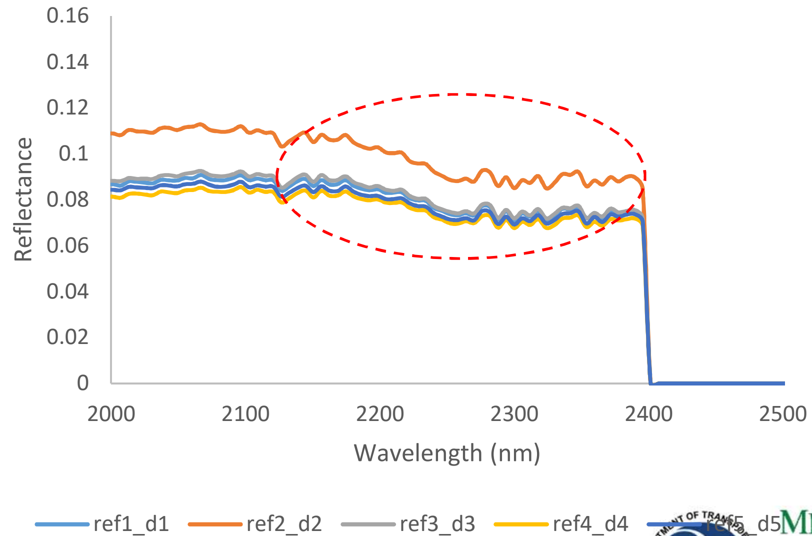
- **Average reflectance of pitting corrosion locations on a steel sample surface after 71 days (1704hr) of applied drops of 36g of NaCl solution**

Drops (d) locations



Sample_2'





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Conclusions

- The average reflectance in 1920-1980 nm wavelength increases logarithmically with time because water molecules on each sample surface are gradually reacted during the hydration process. As the water content of mortar is reduced, less light is absorbed and more light is reflected. The average reflectance can be accurately predicted from the curing time with their correlation coefficient of over 0.9.
- The SVM classification model with $C=10^3$ and $\sigma=10$ are the best fit to the test data with a prediction accuracy of approximately 90%.
- The compressive strength of mortar can be exponentially related to the average reflectance in 1920-1980 nm wavelength with a correlation coefficient of over 0.95. With this strong exponential relation, hyperspectral imaging can be used as a rapid and nondestructive evaluation tool to predict the compressive strength of mortar.

Conclusions

- **Accomplishments**
  - “Hyperspectral imaging features for mortar classification and compressive strength assessment”. Construction and Building Materials. https://www.sciencedirect.com/science/article/pii/S0950061820309405.
  - There are potentially interesting features related to steel corrosion products that can be evaluated using the hyperspectral imaging technique.
- **Planned Activities**
  - Correlate the feature reflectance of hyperspectral images with the steel mass loss due to corrosion
  - Correlate the hyperspectral images with corresponding NextEngine 3D laser scanner’s images of corroded steel samples

Acknowledgement

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