Identifying Safe Intersection Design Through Unsupervised Feature Extraction From Satellite Imagery : Australia

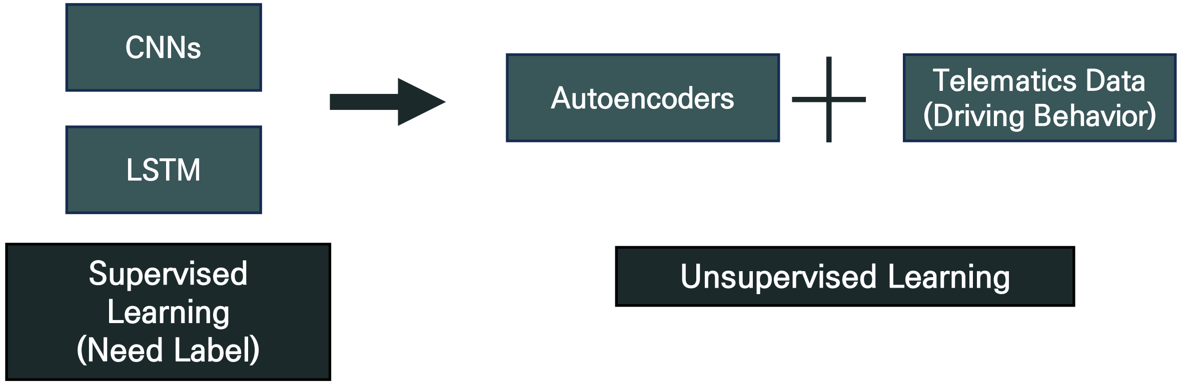
Wijnands et al. (2020), *Computer-Aided Civil and Infrastructure Engineering, 36(3), 346-361*

Geospatial Machine Learning in Remote Sensing (MUSA 650) Yujin Song

01. Background

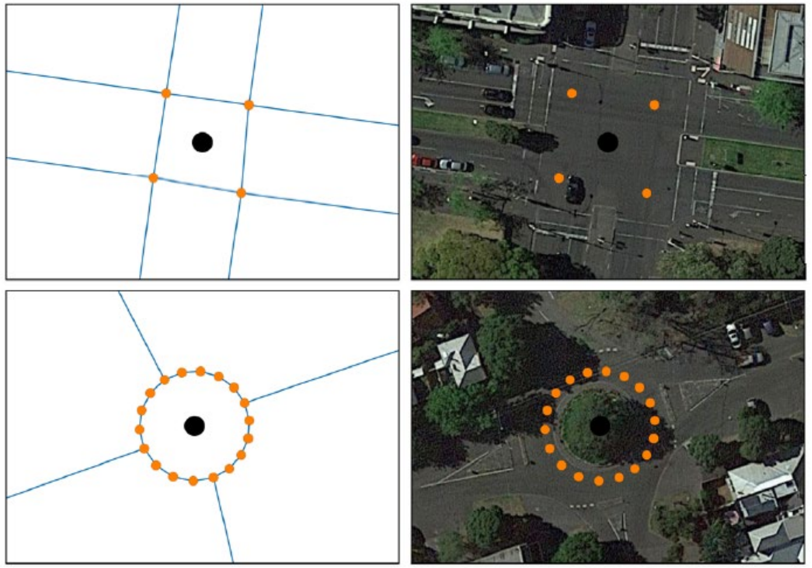
Context

- **Intersection as Crash Hotspots**
  - Multiple Modes Converge
- **Limitations of Traditional Approaches**
  - Reliance on local physical surveys & police-reported crash data
- **Emergence of Big Data & Remote Sensing**
  - Various resources (OSM, Google Maps) + Advances in AI



Data Collection

1. **OpenStreetMap (OSM)**
   - Extracted 900,000 intersection nodes (e,g., junction: roundabout)
2. **Google Maps Static API**
   - Downloaded 256 × 256 pixels color satellite images for each intersection



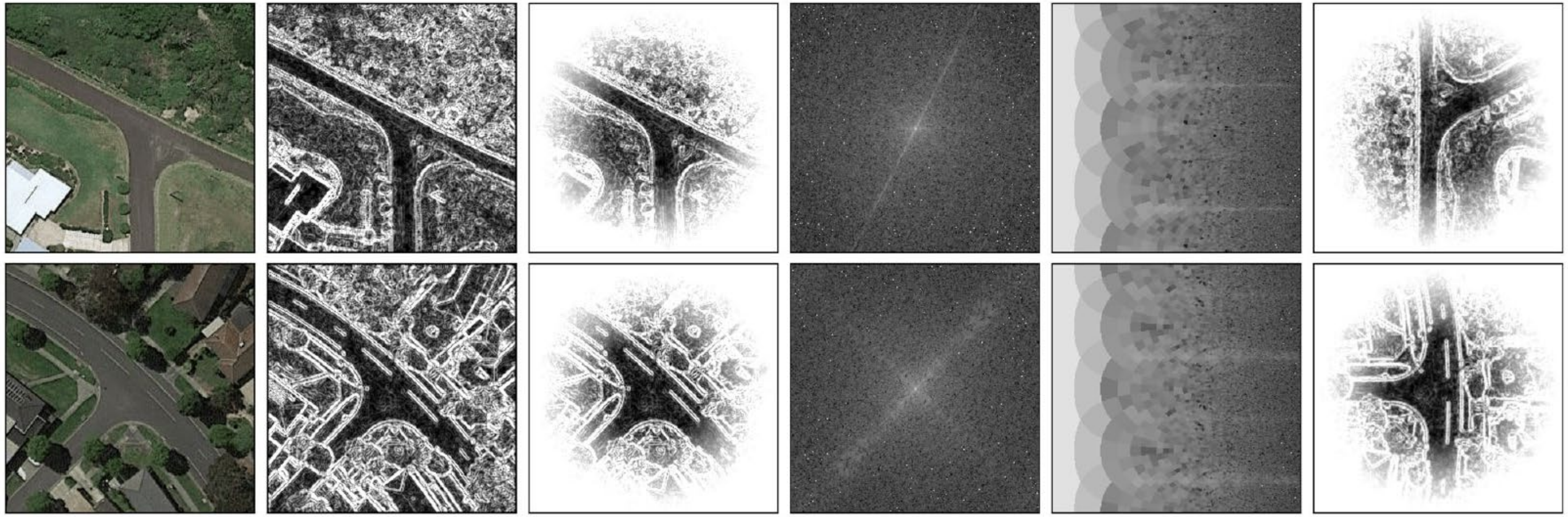
Intersection identification using OSM

Comparison With Satellite imagery

02. Data Preprocessing

Data Preprocessing

1. **Gaussian Blur (3 x 3 Kernel)**
   - Smooth minor noise
2. **Grayscale Conversion**
   - Remove color to emphasize lane and road outline
3. **Scharr Operator**
   - Sharp edge detection and Minimize vegetation and building texture
4. **Fading Scheme**
   - Maintain clarity in the intersection center
5. **Fourier Transform Rotation**
   - Ensure consistent orientation



(a) Original Google Street View Image

(b) After Scharr operator

(c) After Fading Scheme

(d) Fourier Transform

(e) Determining rotation angle

(f) Final Rotated Image

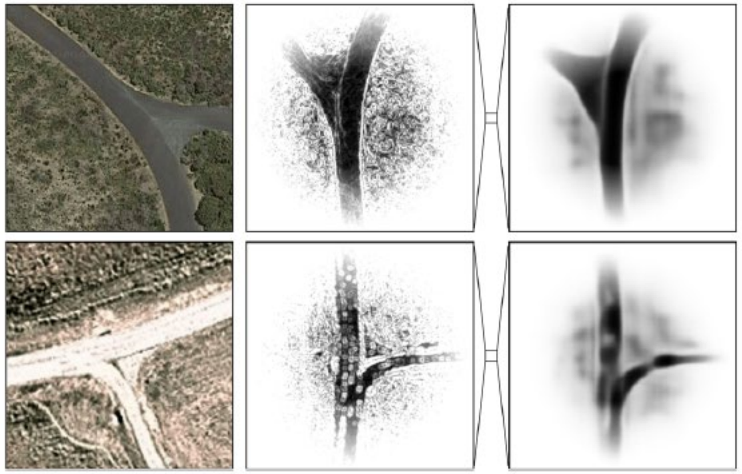
03. Deep Autoencoder for Feature Extraction

CNN-Based Autoencoder

- Original images: 256*256=65,356 pixels → extremely high dimensional
- Reduce 65k-pixel image to 2048-dimensional latent feature vector
- **ReLU Activation Function –** Adds nonlinearity to each convolution layer
- **Loss function**
  - L2 Norm on Weights ($\alpha \Sigma_k \|W_k\|_2$): Primarily helps prevent overfitting by penalizing large weights,
  - L1 Norm on Latent ($\beta \|z\|_1$): Promotes dimension reduction

$$\mathcal{L} = \sum_{i=1}^{256} \sum_{j=1}^{256} X_{ij} + \alpha \sum_{k} \|W_k\|_2 + \beta \|z\|_1$$

L2 Norm L1 Norm



Original Preprocessed AE regenerated

Layer	Operation	Dimensions
0	Input image	256 × 256 × 1
1	Conv2D, 3x3 kernel, stride 2	128 × 128 × 64
	Conv2D, 3x3 kernel, stride 2	64 × 64 × 96
3	Conv2D, 3x3 kernel, stride 2	32 × 32 × 128
4	Conv2D, 3x3 kernel, stride 2	16 × 16 × 192
5	Conv2D, 3x3 kernel, stride 2	8 × 8 × 256
6	Conv2D, 3x3 kernel, stride 2	4 × 4 × 384
7	Conv2D, 4x4 kernel, flatten	2,048
8	Conv2D_T, 4x4 kernel	4 × 4 × 512
9	Conv2D_T, 4x4 kernel, stride 2	8 × 8 × 512
10	Conv2D_T, 4x4 kernel, stride 2	16 × 16 × 512
	Conv2D_T, 4x4 kernel, stride 2	32 × 32 × 384
12	Conv2D_T, 4x4 kernel, stride 2	64 × 64 × 384
13	Conv2D_T, 4x4 kernel, stride 2	128 × 128 × 256
14	Conv2D_T, 4x4 kernel, stride 2	256 × 256 × 256
15	Conv2D_T, 4x4 kernel, stride 1	256 × 256 × 1

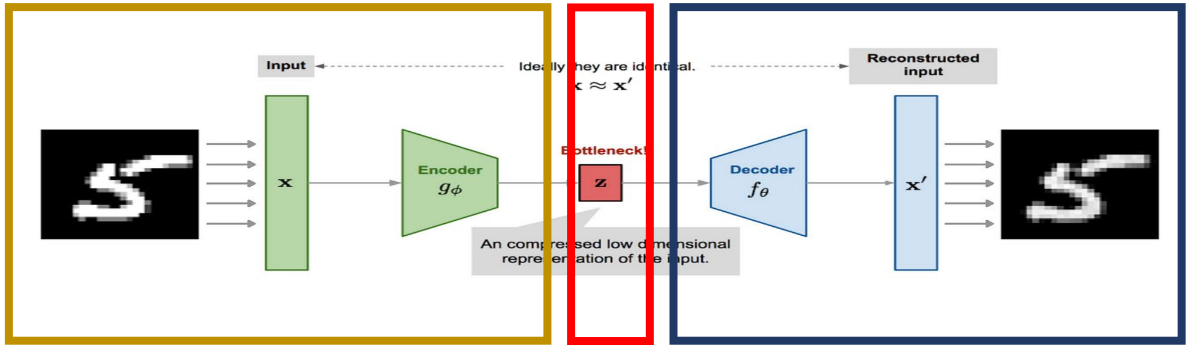
Encoder

Reducing

Bottleneck Layer

Decoder

Rebuilding



Encoder (Reducing Spatial Dimensions)

Bottleneck

Decoder (Rebuilding Original Dimensions)

Image Source: https://medium.com/@bhipanshudhupar/loss-functions-in-simple-autoencoders-mse-vs-l1-loss-4e838ae425b9

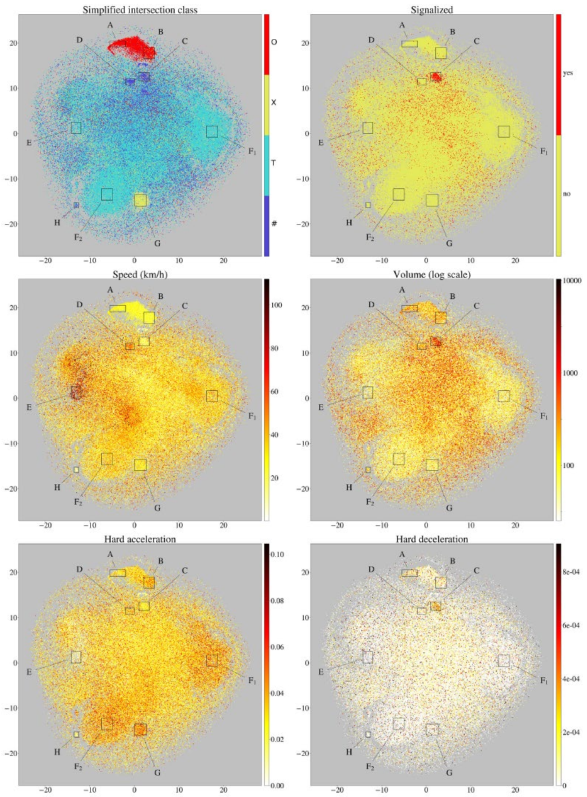
04. t-SNE & Telematics Integration

t-SNE

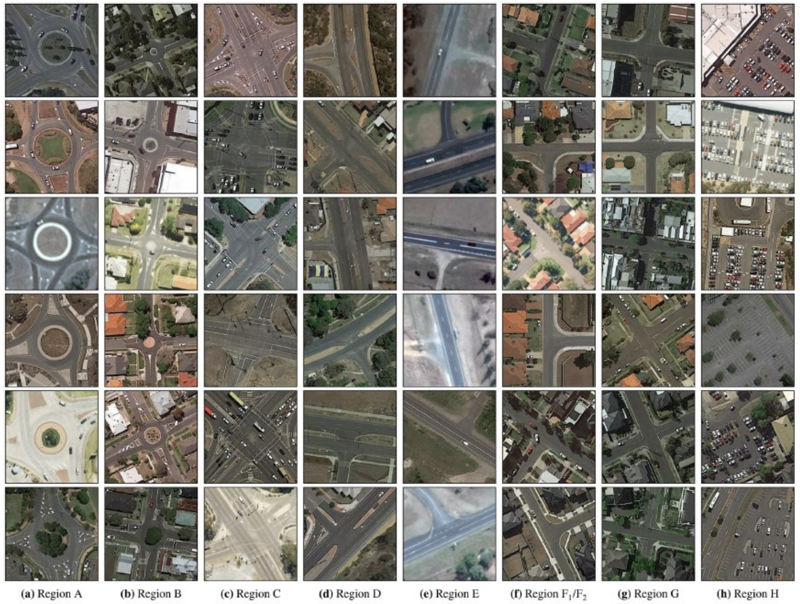
- 2,048-dimensional input space to a 2D

Telematics Integration

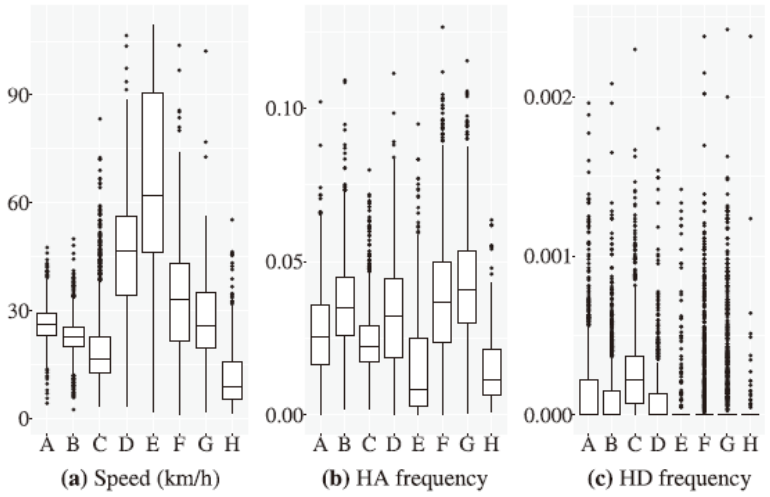
- Coordinate Matching: Linked each record to the nearest intersection from the autoencoder-based dataset



Overlaying Data on the 2D Map



Manual Selection of Eight Regions (A-H)



Boxplot Analysis

05. Overall Takeaways & Insights

Large-Scale Feasibility

- Combining satellite imagery (Google Maps) with open data (OSM) and advanced AI (autoencoders) enables national or even global analysis.

Unsupervised Approach

- Autoencoders don't require labeled images, making them ideal for vast intersection datasets.
- The latent space (2,048-d) effectively captures essential geometry while discarding irrelevant details.

Link to Real-World Behavior

- Merging telematics (speed, abrupt stops) shows how design influences driver actions, revealing potential safety issues.

Practical Outcomes

- Identifies clusters of risky designs (e.g., multi-lane four-ways) vs. safer designs (roundabouts).
- Data-driven basis for prioritizing intersection redesign and targeted interventions.

Open Q&A

- Remote sensing and deep learning are **game changers in transportation planning.**
- Applications beyond intersection safety:
  - Predicting crash risk from road geometry and telematics.
  - Real-time monitoring of infrastructure changes via satellite imagery.
  - Optimizing traffic flow using AI in smart cities.

How can urban planners integrate these AI-driven insights into infrastructure upgrades and traffic management to enhance road safety in evolving transportation systems?