Bridging the Gap with Machine Learning Techniques: Structural Damage Detection Framework in Bridges

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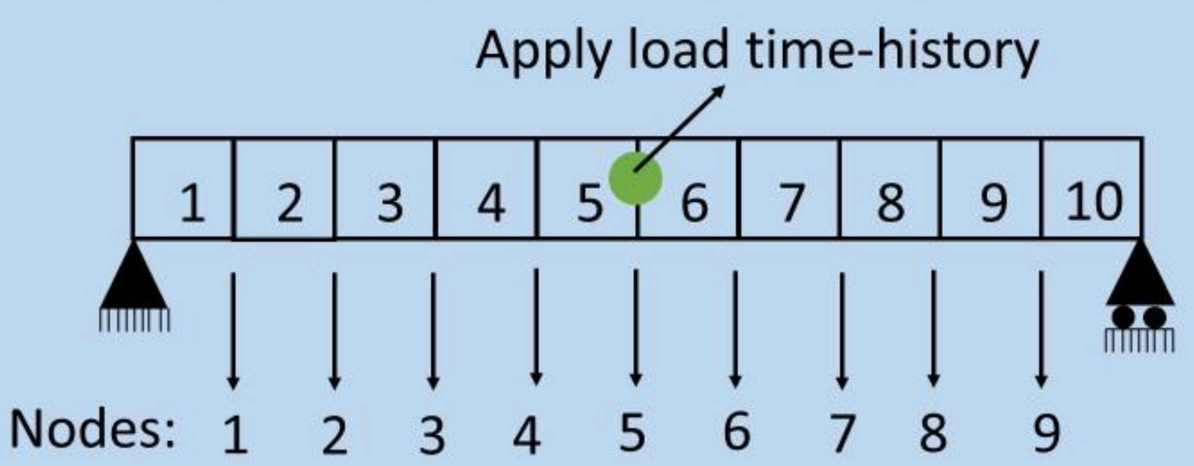
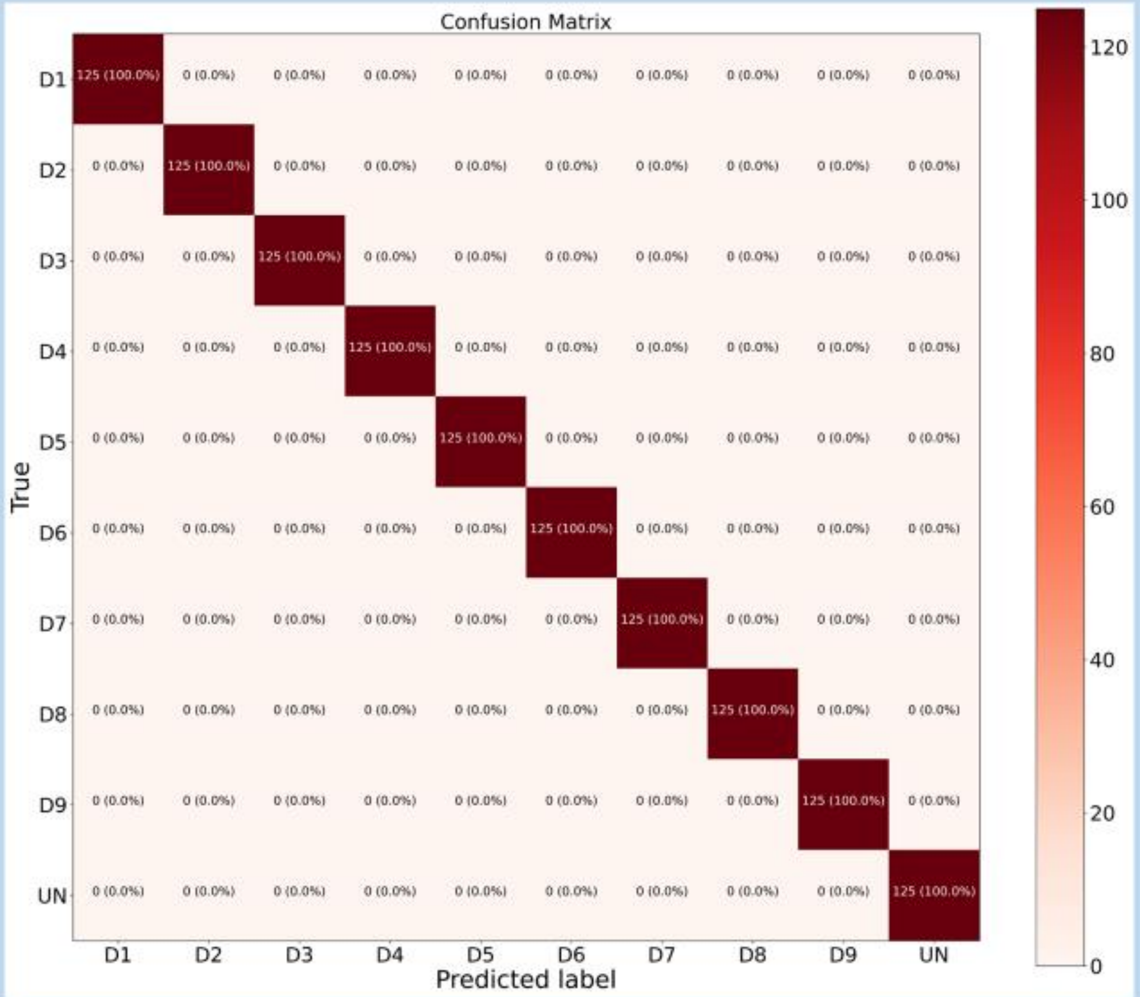
Supervised Technique: Deep Learning-based Two-step damage detection using Convolutional Neural Network

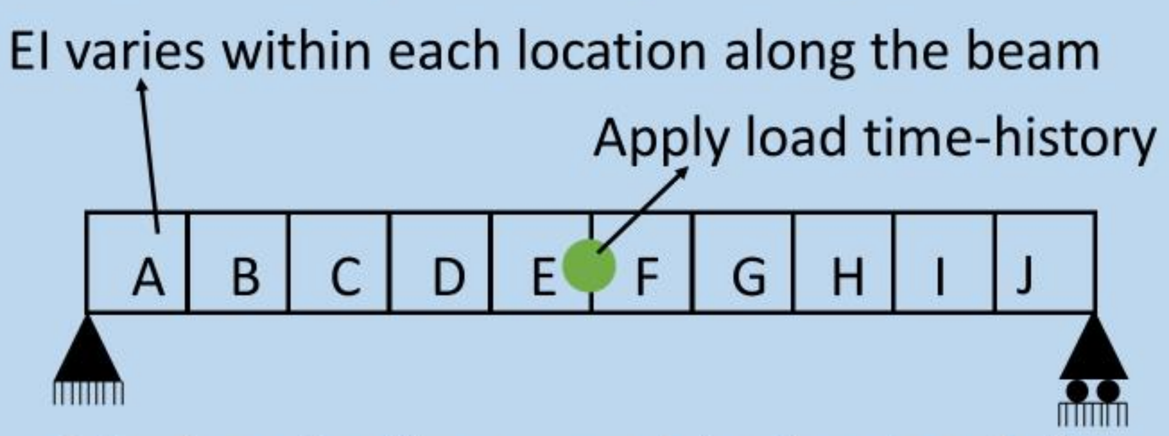
Step-1 Identification of damage severity



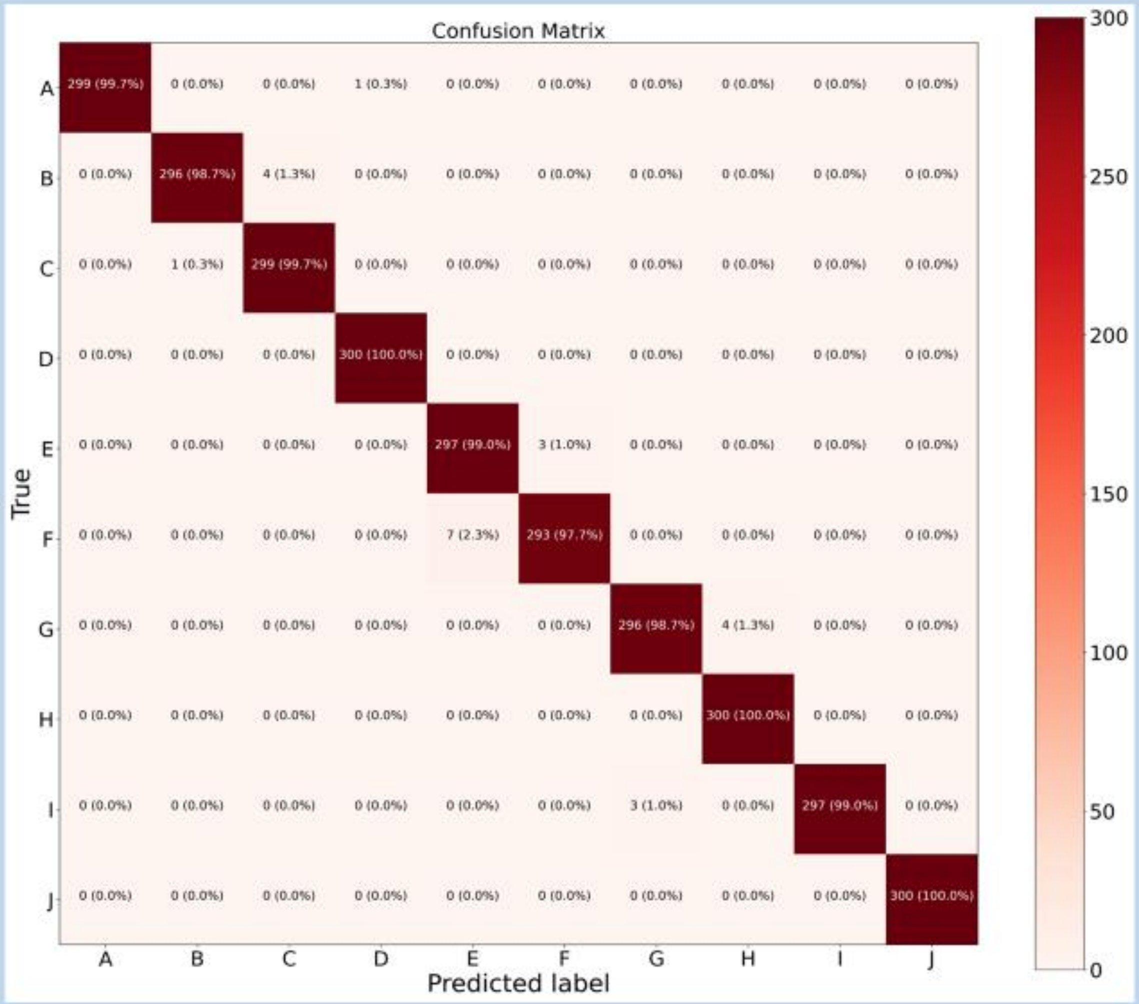
- Damage is represented by EI reduction (10%, 20%, …, 90%) at Member-5
- D1 is the heavily damaged case whereas the UN is the healthy case.
- Obtain the acceleration response at the nodes and convert them into gray-scale images
- %100 testing accuracy



Step-2 Identification of damage location

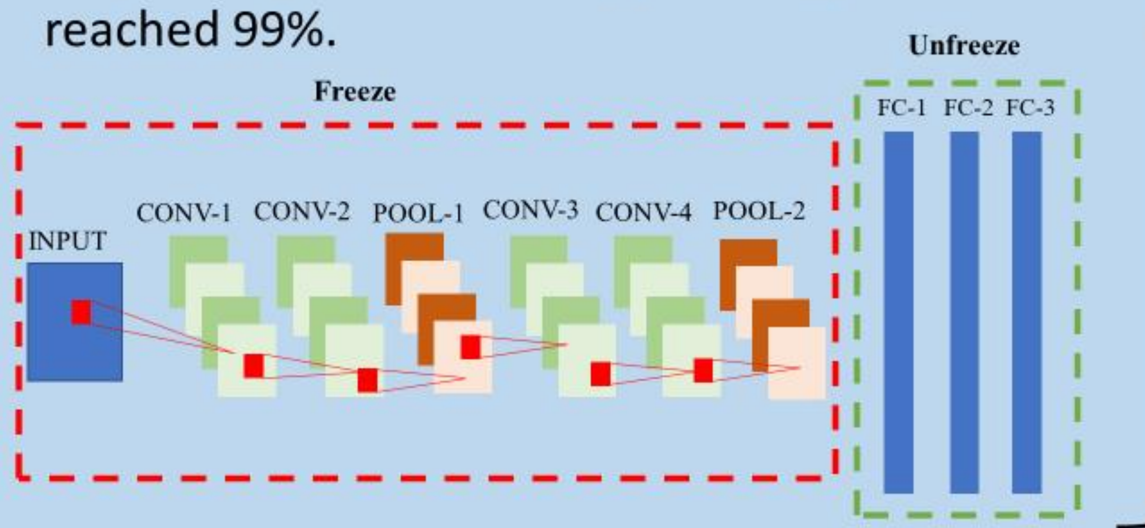


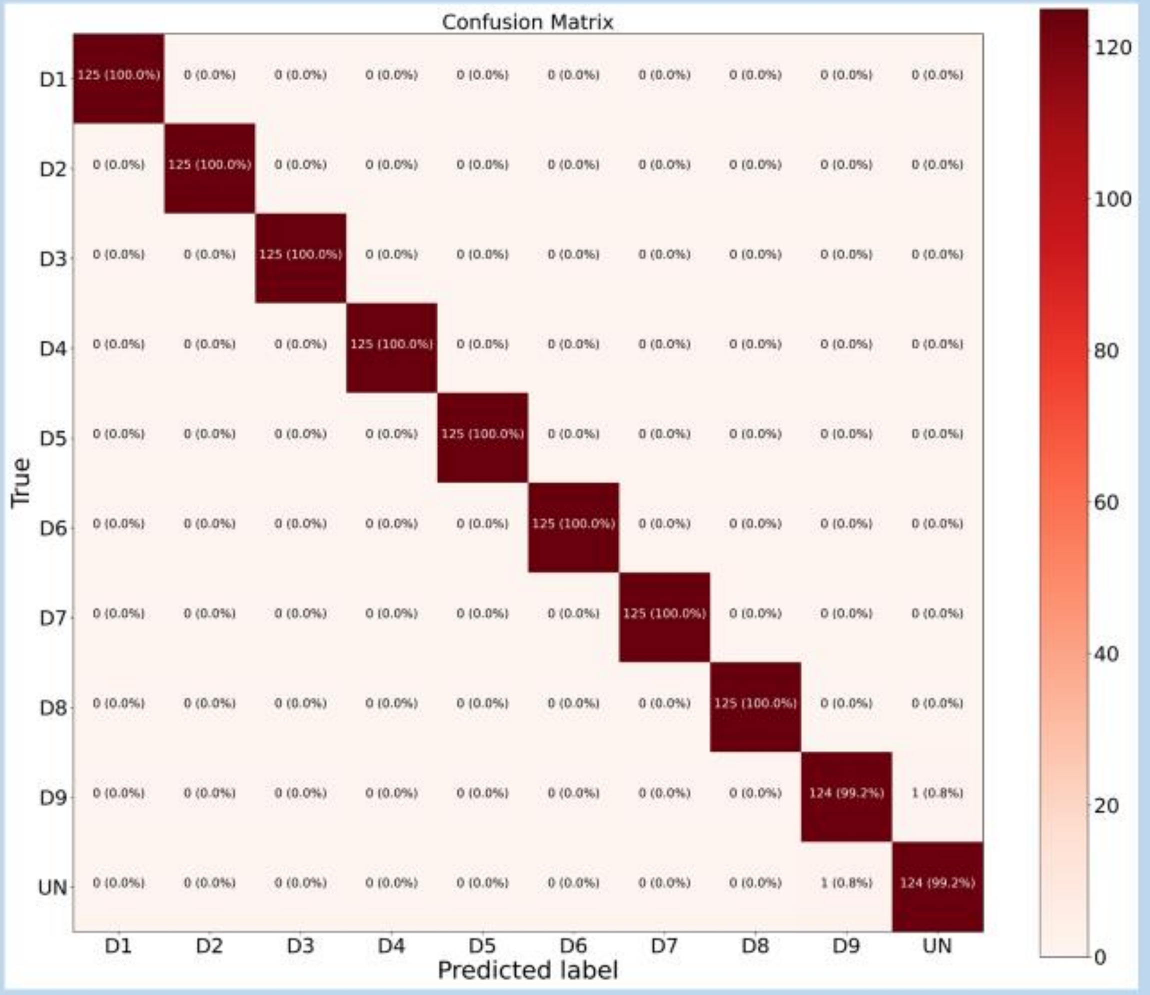
- Collect acceleration sensor data at each node for each corresponding load time history and EI value.
- Convert the data into gray-scale images for the CNN implementation.
- %99 testing accuracy



Transfer Learning: Re-weighting

- The aim is to transfer the knowledge between the structures.
- The length of the beam in Step-1 is changed 5% and a new dataset is generated.
- Before TL, the network accuracy was 50%, after TL (freezing and unfreezing process), the accuracy reached 99%.



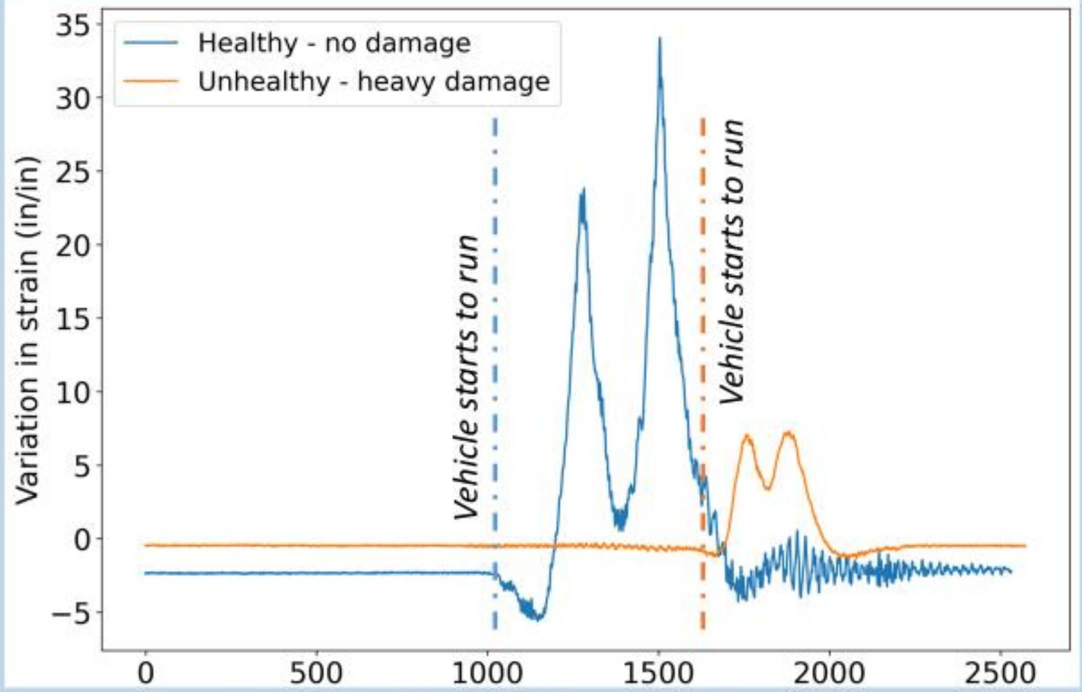


Unsupervised Technique: Novelty Index Calculation for a field test of truss bridge

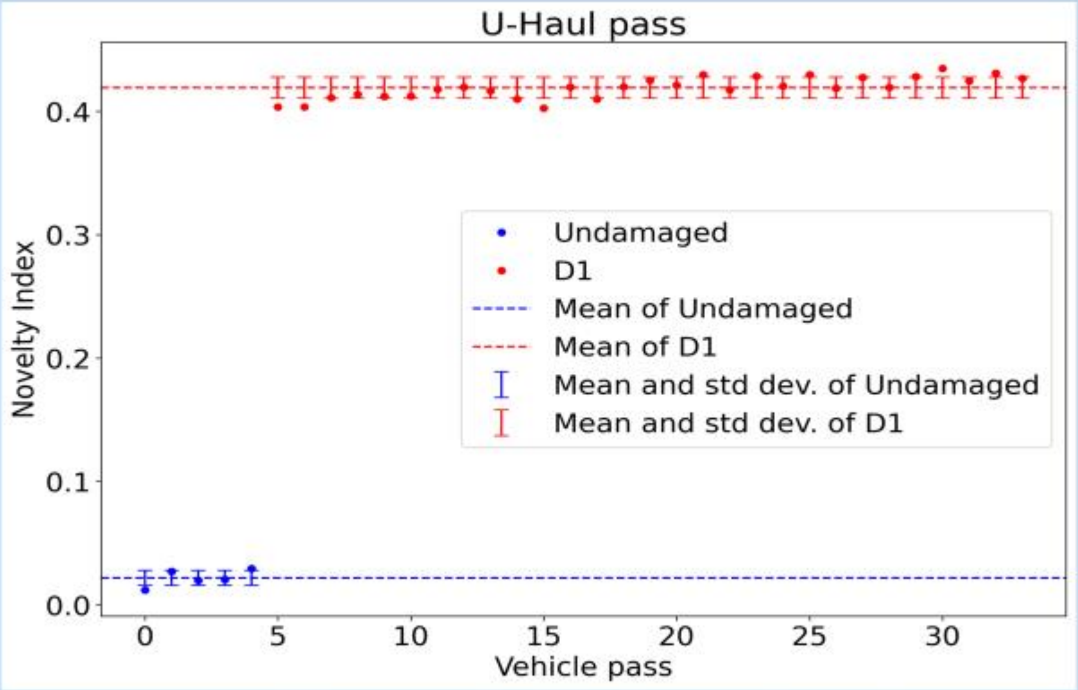
Tested truss bridge

Two-axle 26-ft U-Haul truck

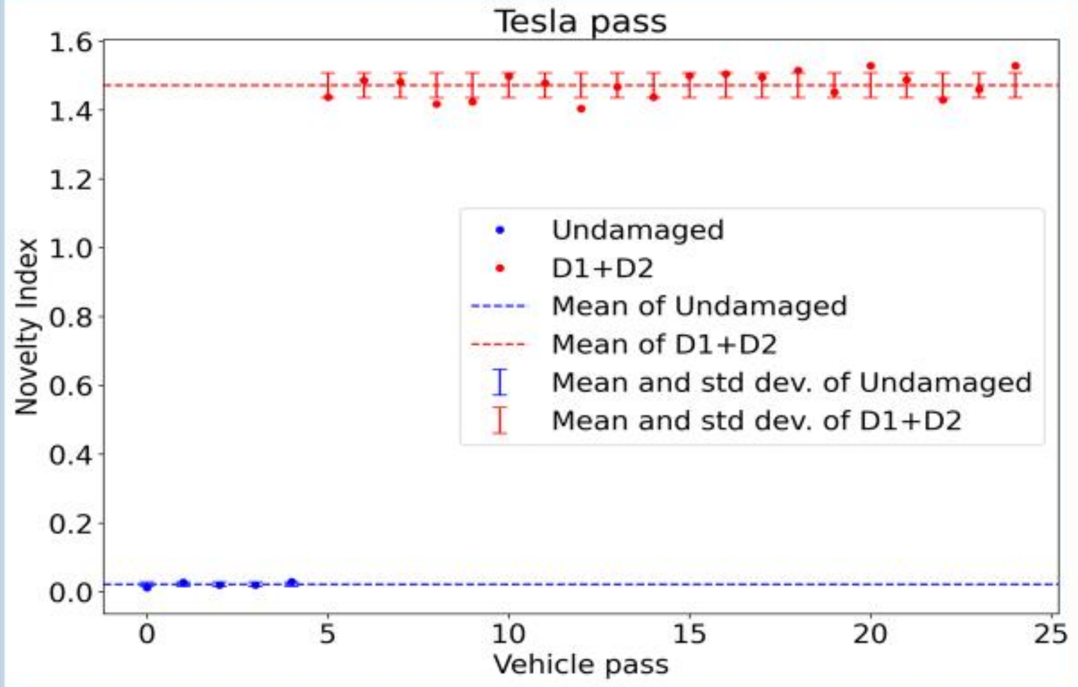
Tesla



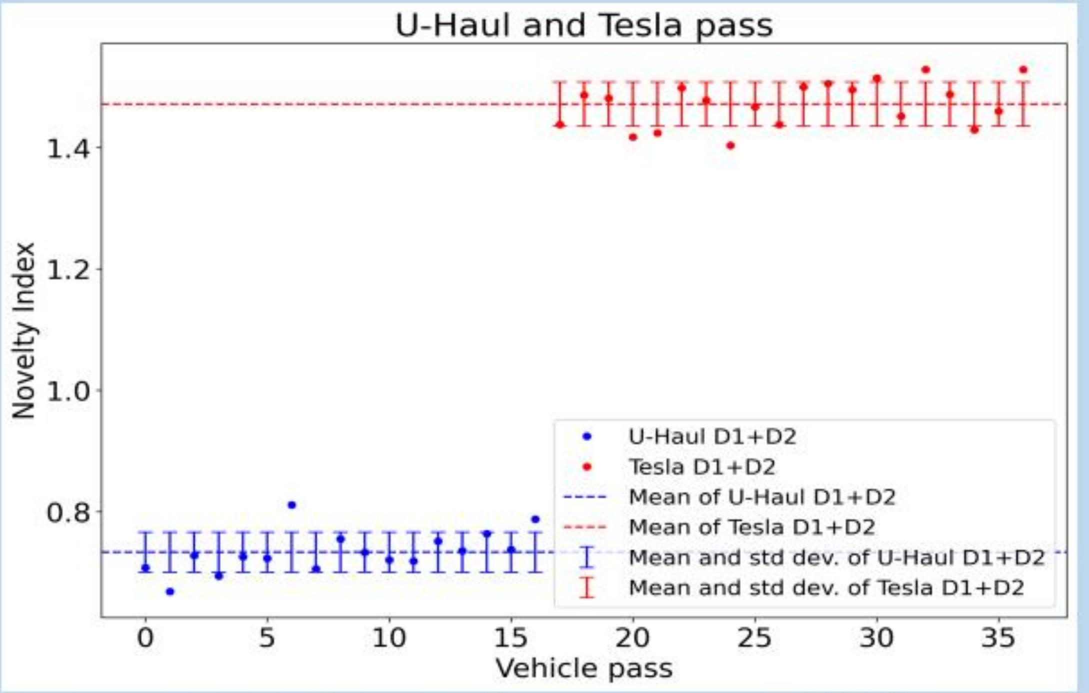
Collected strain data vs. time steps



Healthy vs. unhealthy (U-Haul Truck)



Healthy vs. unhealthy (D1+D2, Tesla)



U-Haul vs. Tesla for heavy damage (D1+D2) case

CONCLUSIONS:

- *The proposed frameworks and methodologies can successfully detect the damage and classify them.*
- *It offers a robust and computationally inexpensive way for structural damage identification. In this way, actions can be taken in a fast way to ensure transportation serviceability and functionality.*
- *Unprocessed sensor data can be used.*
- *A slight damage levels that are not visible to the naked eye can be identified.*

Future works:

- *TL is planned to be applied over a variety of structures (FEM) and through an experimental scheme of beams presented.*
- *Create a generalized network that can make a classification and identification of the damage for variable structures.*

Funding Statement:

This research is partially supported by NSF Award Number:1762034, Spokes: MEDIUM: MIDWEST: Smart big data pipeline for Aging Rural bridge Transportation Infrastructure (SMARTI) as well as US Army Crops of Engineers, Engineering Research and Development Center grants W912HZ21C0060 – Multilevel Analytics and Data Sharing for Operations Planning (MADS-OPP) and W912HZ23C0005 – SMART Analytics for Critical

Structural Health Monitoring and Damage Detection-Prediction of Truss Bridges Using Artificial Neural Networks and Transfer Learning

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Overview

Bridge condition assessment is usually done by either visual inspection or installation of a large number of sensors. **However, this might be unsafe and extremely costly.**

Objectives

- ❑ Develop an automated hybrid experimental-numerical (POD-ANN) framework to detect and locate damage.
- ❑ Transfer gained knowledge to another domain to generalize well for similar bridges

Field Testing

Bridge Information:

90-foot simply supported; five-span truss bridge located in Lancaster County in the State of Nebraska. The superstructure of the bridge consists of multiple steel girders and stringers supporting a cast-in-place concrete deck.

Instrumentation:

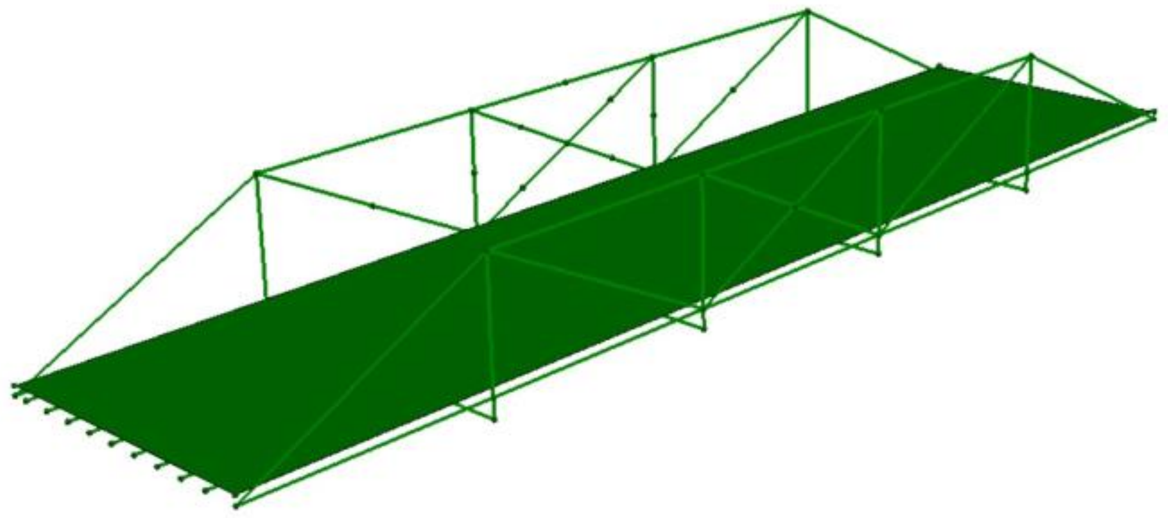
- 18 strain transducers were installed at the stringers
- 20 were installed on the truss.
- 3 accelerometers were installed on the flooring system to measure the acceleration.
- 3 LVDTs were installed at the mid-span of the three internal panels.

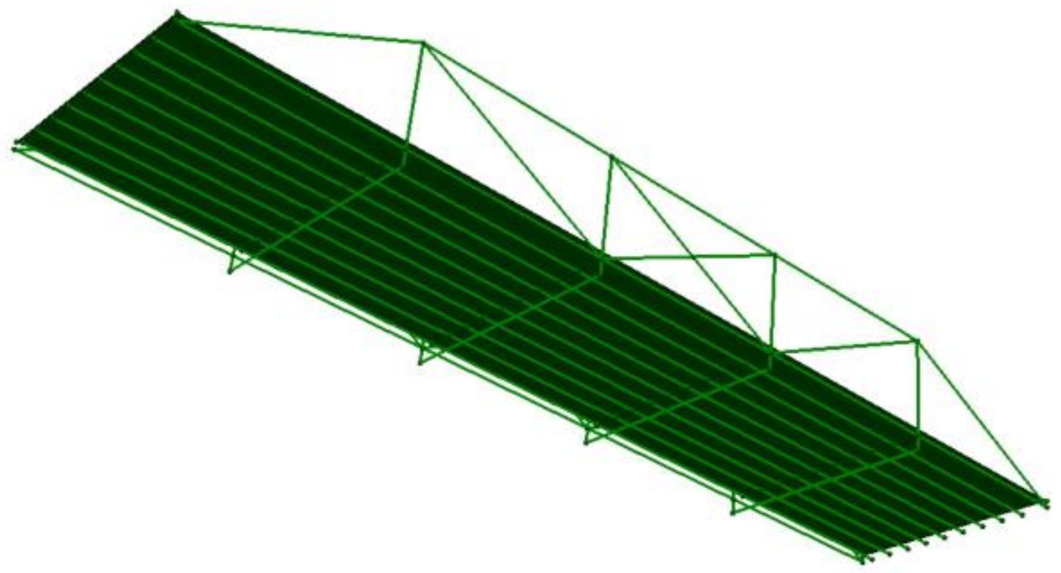
Tests:

- The tests were performed by an empty 26-foot UHAUL that weighs 12,640 lbs. and a Tesla car.
- Performed tests:
  - ➢ Healthy state
  - ➢ Damage case (1): lower flange was cut up to half of the web of the beam at the middle span
  - ➢ Damage case (2): lower flange was cut up to half of the web of the beam at the second span
- Runs were performed at 5 mph, 10 mph, static tests, and crawling tests.

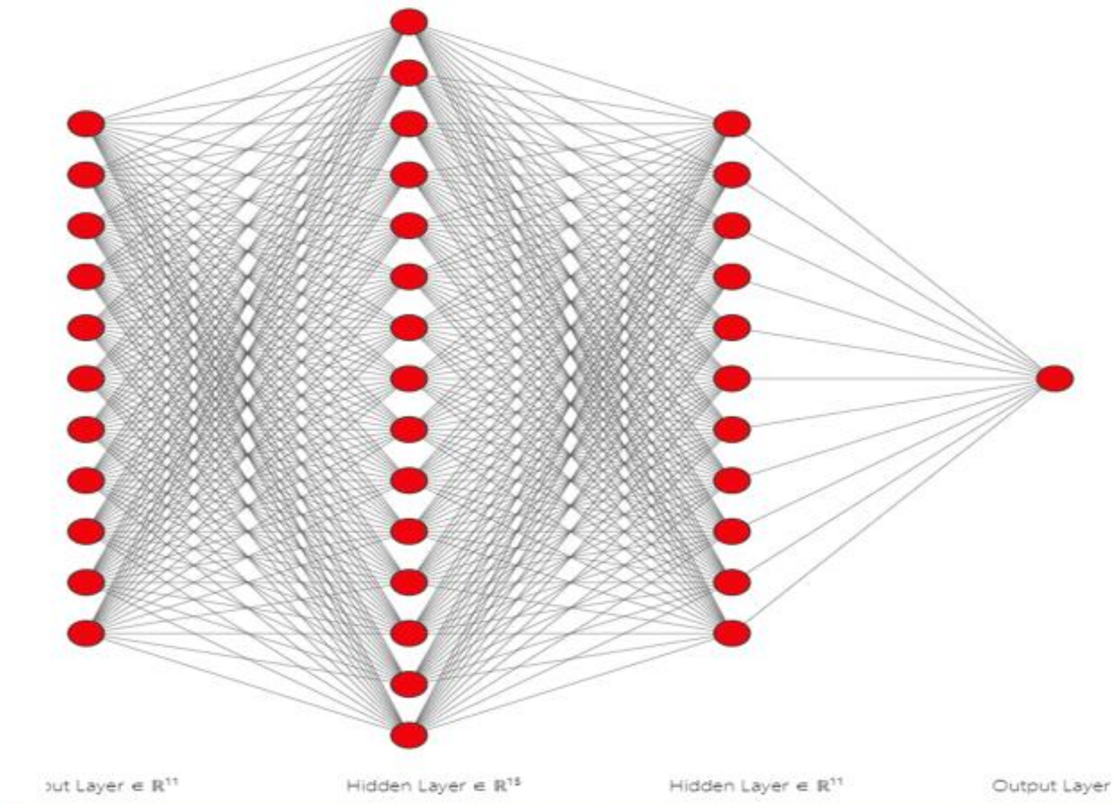
POD-ANN Damage Identification

- Modelling the bridge using OpenSees.



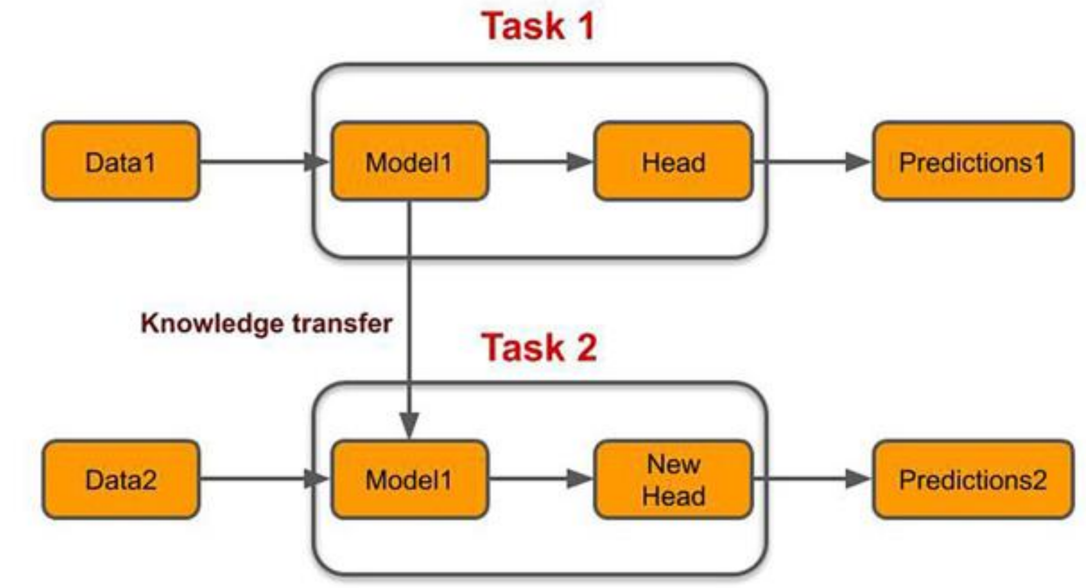


- Generating strain data for healthy and damage scenarios (matching the field).
- Performing the POD and obtaining POMs for the numerical data.
- Training an ANN to detect the POMs – Supervised Learning.
- Performing the POD on the field data and obtaining the POMs.



Domain Adaptation and Transfer Learning

- Another truss bridge will be chosen (target domain).
- POD-ANN analysis will be conducted from the knowledge transferred from the source domain.
- Predicted POMs will be obtained.



Validation of Transfer Learning Results

- Test the target domain and obtain field (real) results.
- Comparisons between TL results and field results.

University of Nebraska – Lincoln **University of Nebraska at Omaha** **University of New Hampshire** **Kinnami Software Corporation**

Securing Machine Learning at the Edge for Autonomous Structural Health Monitoring (SHM)

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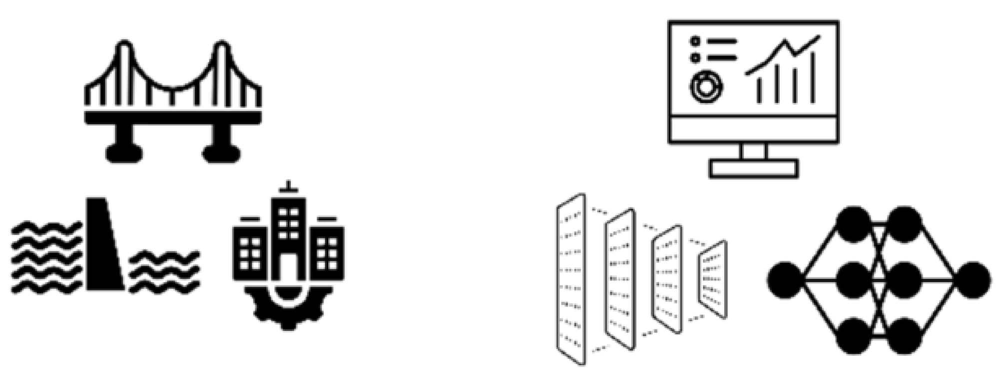
Project Aims

- Investigating security implications of machine learning deployed at the edge
- Identification of vulnerabilities in autonomous structural health monitoring solutions



Research Questions

RQ1: What are the security threats faced by machine learning deployed at the edge for SHM?

RQ2: How can these threats undermine autonomous operations of SHM solutions?

Methodology

1: Identify usecases for **ML-based approaches** for SHM.

2: Conduct a **security analysis** of studied approaches.

3: **Propose** a framework to study the effects of security threats on autonomous SHM operations.

4: **Evaluate** the proposed framework using real world solutions.

Data Collection for SHM

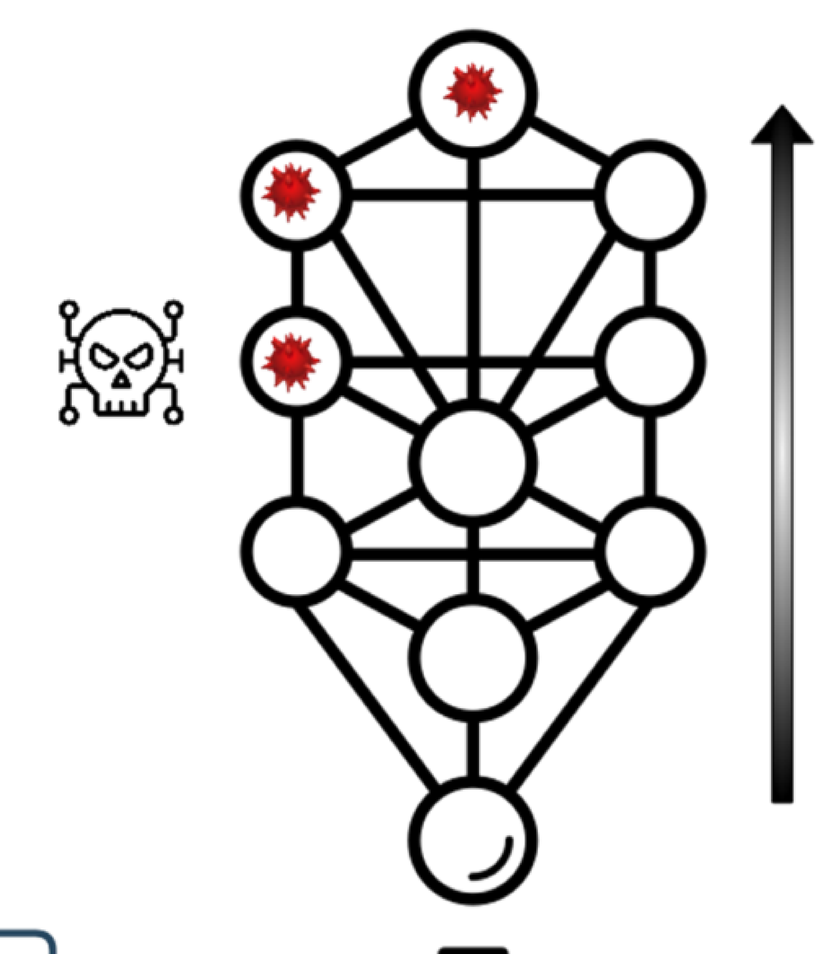
1: Contact-based Approach

2: Vision-based Approach

Machine Learning for SHM

Machine Learning for SHM

- Convolutional Neural Network (CNN)
  - Fully CNN
  - Deep CNN
  - 1-Dimensional CNN
  - Multi-scale CNN
  - Faster Region-based CNN
- Support Vector Machine
- Naive Bayes Data Fusion



Attacks

- Data Poisoning
- Evasion
- Model Extraction
- Inference

Current Status and Next Steps

Current Status:
The current machine learning algorithms used for structural health monitoring lack security analysis and are prone to different adversarial attacks. We investigated different attacks [1, 2].

Next Steps:
We are developing testbed for assessing the machine learning models for structural health monitoring. It will hugely facilitate the research community in framing the solutions.

Acknowledgment

This research is partially supported by US Army Crops of Engineers, Engineering Research and Development Center grants W912HZ21C0060 – Multilevel Analytics and Data Sharing for Operations Planning (MADS-OPP) and W912HZ23C0005 – SMART Analytics for Critical Infrastructure inside a Resilient Data Fabric (SMART-RDF).

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1 Azimi, Mohsen, et al. "Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review." Sensors, vol. 20, no. 10, May 2020, p. 2778. DOI.org (Crossref), https://doi.org/10.3390/s20102778

2 Champneys, Max David, et al. "On the Vulnerability of Data-Driven Structural Health Monitoring Models to Adversarial Attack." Structural Health Monitoring, vol. 20, no. 4, July 2021, pp. 1476–93. DOI.org (Crossref), https://doi.org/10.1177/1475921720920233.

University of Nebraska Omaha

Deep Reinforcement Learning based Approaches for Bridge Structural Health Monitoring

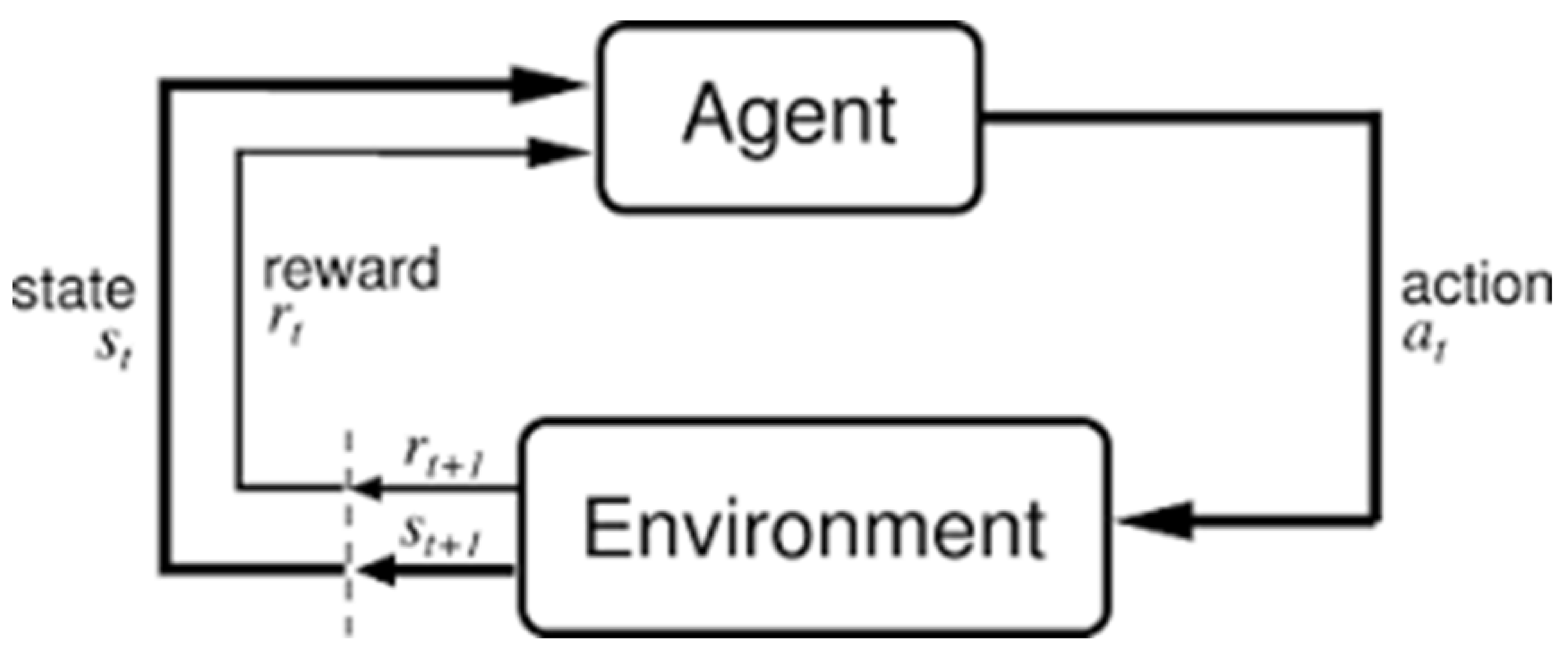
University of Nebraska at Omaha

CONTRIBUTORS:

- Divija Swetha Gadiraju
- Deepak Khazanchi

Introduction

- DRL has various applications in IoT, healthcare and autonomous transportation.
- DRL Agent learns through agent environment interaction



Why DRL?

- Traditional DL Methods suffer from the curse of dimensionality
- Bridges have high number of factors affecting their condition.
- DRL can handle high dimensional state space

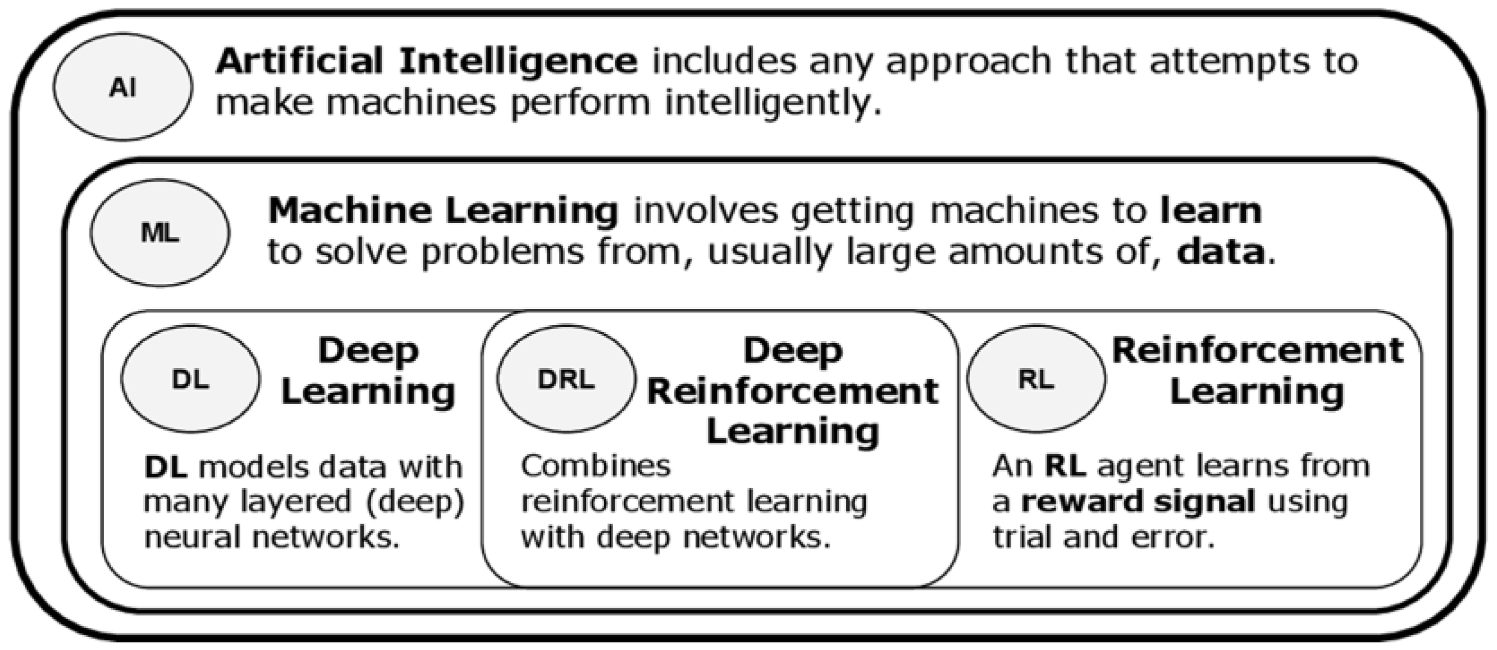


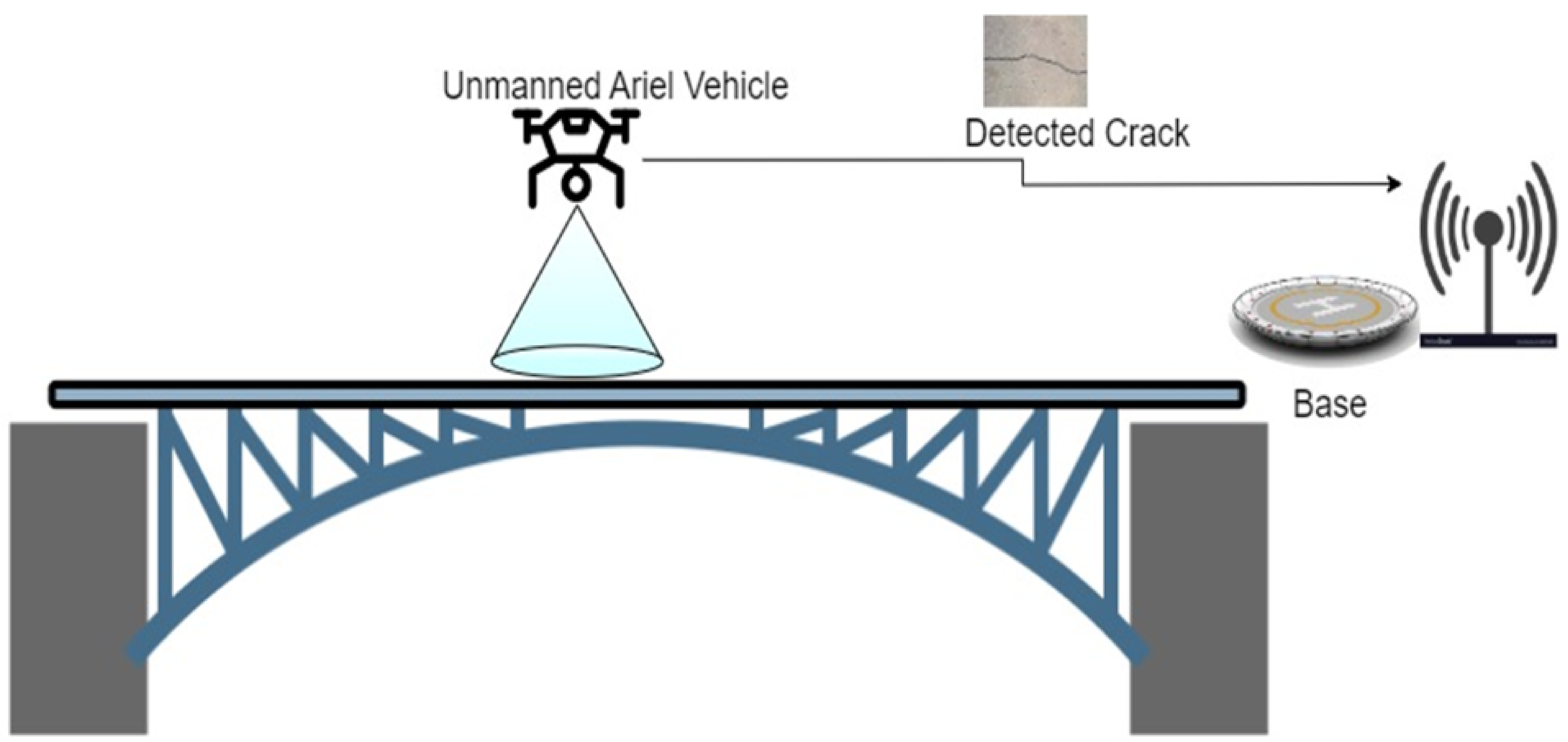
Image Source: Whittlestone, Jess et al. "The Societal Implications of Deep Reinforcement Learning." *J. Artif. Intell. Res.* 70 (2021): 1003-1030.

Offline DRL Approach

- DRL can be applied to the NBI dataset to maintain the bridge health
- The repair schedules can be chosen based on the past historical data of condition ratings and transition probabilities
- The problem is formulated as a Markov Decision Process and is solved with DRL algorithm

UAV based Crack detection

- Maintenance Schedules take too long and recordings are prone to errors
- Frequent surveying helps detection of new cracks and check the condition of old ones



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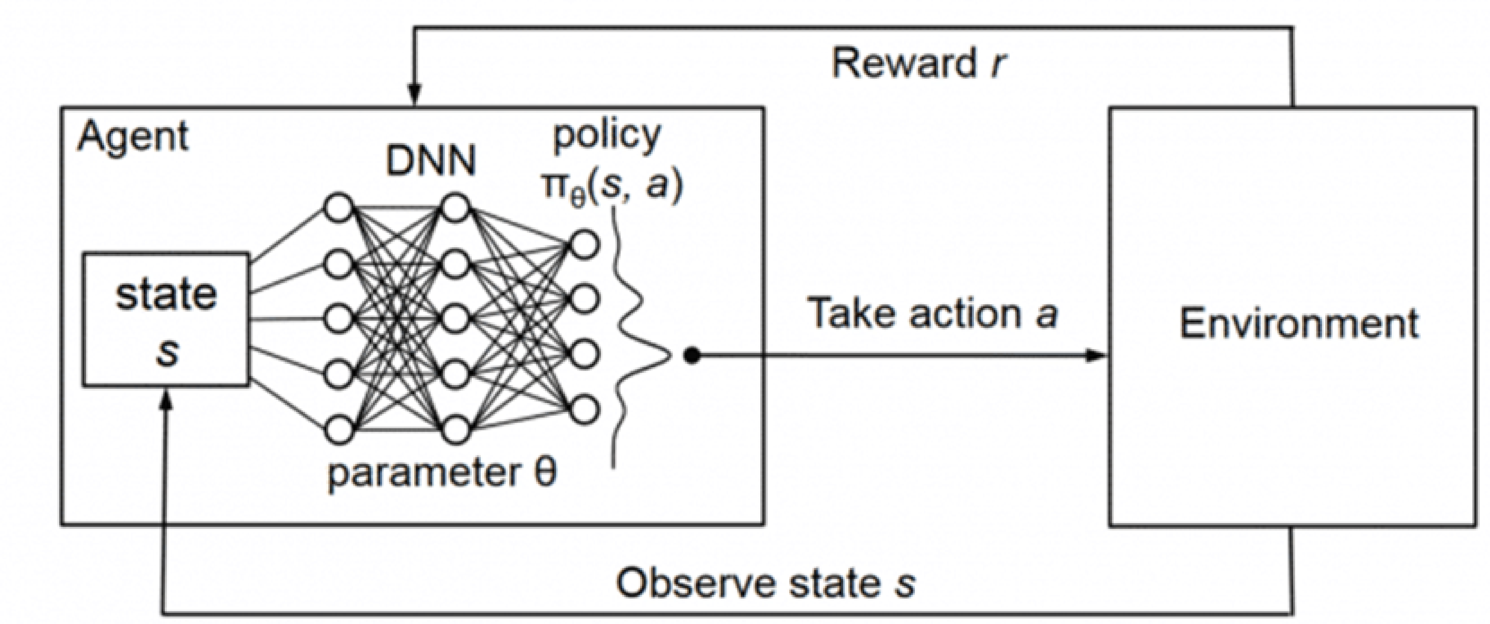
Methodology

- DQN has achieved human-level control in many of Atari games
- Q-learning learns the action-value function Q(s, a): how good to take an action at a particular state.
- Deep Neural Network is used as a function approximator



Conclusion

- DRL based approaches can be used in various aspects of structural health monitoring for bridges
- Two such use cases of the ongoing work are presented.

Important References

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2. Yi, Lingzhi, Xianjun Deng, Laurence T. Yang, Hengshan Wu, Minghua Wang, and Yi Situ. "Reinforcement-learning-enabled partial confident information coverage for IoT-based bridge structural health monitoring." IEEE Internet of Things Journal 8, no. 5 (2020): 3108-3119.

UNIVERSITY OF Nebraska Omaha

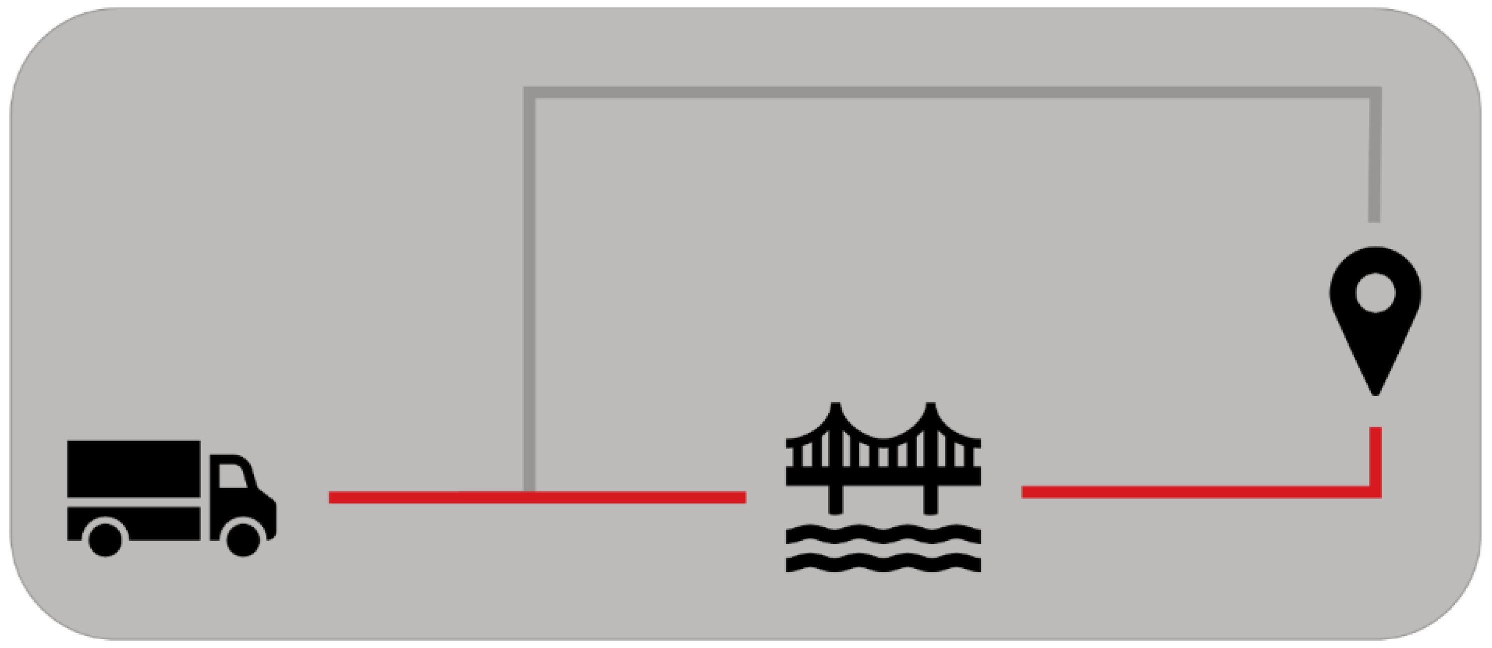
Developing Architecture for a Routing System using Bridge Data and Adversary Avoidance

William Heller, Brian Ricks, Yonas Kassa, Rahul Kamar Nethakani, Brandon Lacy
University of Nebraska at Omaha

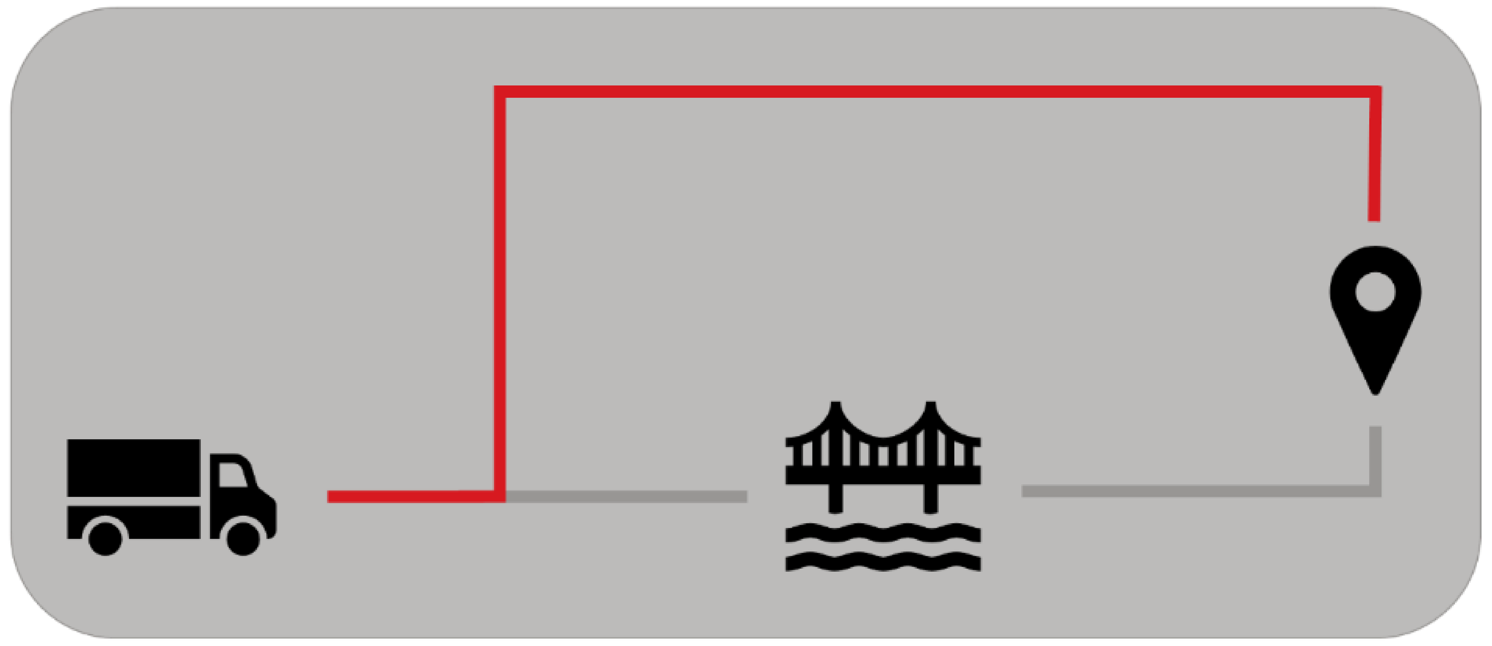
Goal

Traditional Routing

Traditional routing ignores bridge integrity



Bridge-observant Routing



Our routing will avoid unsafe and damaged bridges

Architecture + Big Data

End-User Applications

- Any Valhalla-based use case
- Live simulations
- Web-based routing application

Valhalla

- Open-source routing system
- Use our custom NBI data
- Editable components
  - Sif – Dynamic costing algorithm for bridge safety
  - Thor – Custom routing algorithm for adversary avoidance

Merged Dataset (NBI + OSM)

- Merge data using a custom program
- Resulting data format is in OSM (XML)
- Can be used in any bridge-oriented routing solutions

National Bridge Inventory (NBI)

- Government-managed data
- Publicly available
- Bridges are inspected once every two years
- Data is highly accurate and detailed
- Bridge health, location, max load, recommended load…

Open Street Map (OSM)

- Open-source GIS data
- Worldwide data
- Inconsistent in rural areas
- Widely supported
- Roads, buildings, lakes, bridges

This study was financially supported by the NSF-BD-Spokes Program (Award #1636805) and the NSF-Spokes Program (Award #1762034). Their support is gratefully acknowledged

Preserving and Enhancing Data Integrity for Edge Sensors

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College of Information Science & Technology, University of Nebraska at Omaha.

Problem Statement

Structural Health Monitoring (SHM) solutions produce large amounts of data using edge sensors.

If a malicious actor modifies or deletes this data, any decisions made based on this data could result in catastrophic incidents or accidents.

It is therefore critical to investigate **how to preserve the integrity of data produced by sensors on the edge** of SHM solutions.

Research Questions

- According to the literature, what are the threats to data integrity for edge sensors used in SHM solutions?
- If the integrity of data from edge sensors is compromised, what is the impact on specific SHM solutions?
- How can the integrity of data from edge sensors be preserved and enhanced to support SHM solutions?

Research Method

- Survey threats to data integrity for edge sensors and enumerate consequences for SHM
- Identify and catalog vulnerabilities within SHM solutions
- Propose a framework to address the data integrity requirements in edge sensors
- Perform analysis of data integrity controls in a lab environment

Current Data Integrity Solutions for Edge Solutions

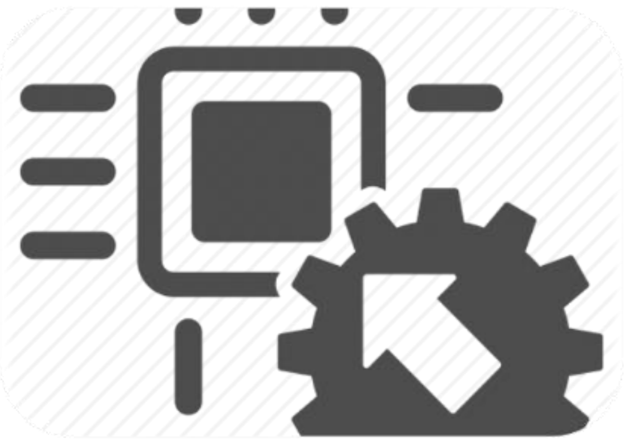
Data encryption
- Encryption utilization

Integrity protection
- Utilize digital signature

Secure communication
- Employ secure lightweight protocol

Robust authentication and access control
- OAuth 2.0
- X.509 certificate

Real time anomaly detection
- ML and statistical analysis analysis



Secure firmware and software updates
- Secure boot and FOTA with digital signature

Physical security Measures
- Hardware Security Modules (HMS)

Data backup and disaster recovery
- Redundant Array of Independent Disks (RAID)

Compliance with privacy regulations
- Differential Privacy and Secure Multi Party Computations

Awareness and training
- Training the users

Security auditing and testing
- security and code review

Current Status and Next Steps

Current Status: Cybersecurity aspect of SHM has mainly been overlooked. We are assessing existing edge sensor platform's security and vulnerabilities [1,2] to develop secure ecosystem for data integrity of edge sensors.

Future Works: Developing testbeds to test proposed methods for data integrity of edge sensors.

Acknowledgements

This research is partially supported by US Army Crops of Engineers, Engineering Research and Development Center grants W912HZ21C0060 – Multilevel Analytics and Data Sharing for Operations Planning (MADS-OPP) and W912HZ23C0005 – SMART Analytics for Critical Infrastructure inside a Resilient Data Fabric (SMART-RDF).

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[2] Deep, Samundra, et al. "A Survey of Security and Privacy Issues in the Internet of Things from the Layered Context." Transactions on Emerging Telecommunications Technologies, vol. 33, no. 6, 2020, https://doi.org/10.1002/ett.3935.

University of Nebraska Omaha

How to Select Simple-Yet-Accurate Model for Bridge Maintenance?

Akshay Kale, Yonas Kassa, Brian Ricks, and Robin Gandhi

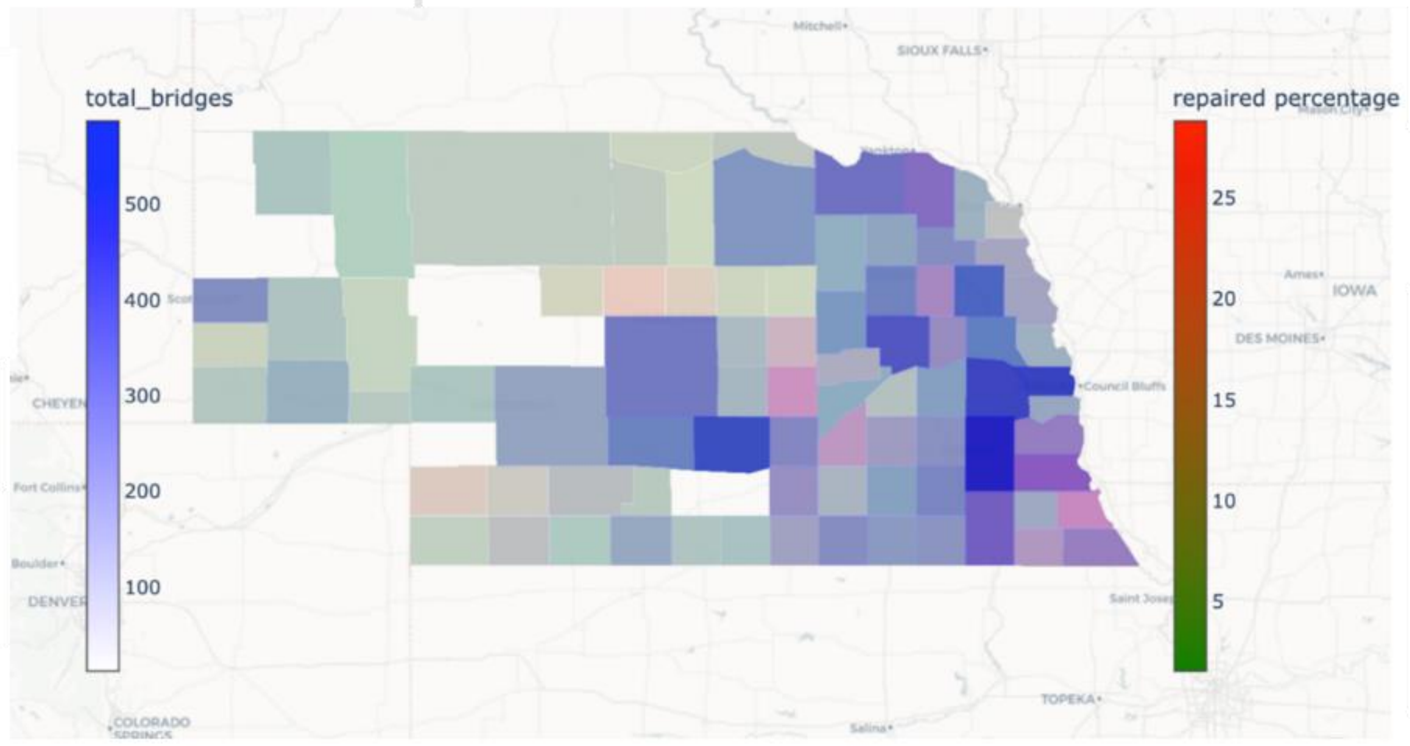
Background

15,376 Bridges

NBI and LTBPP

28 Bridge Features

8 ML Algorithms

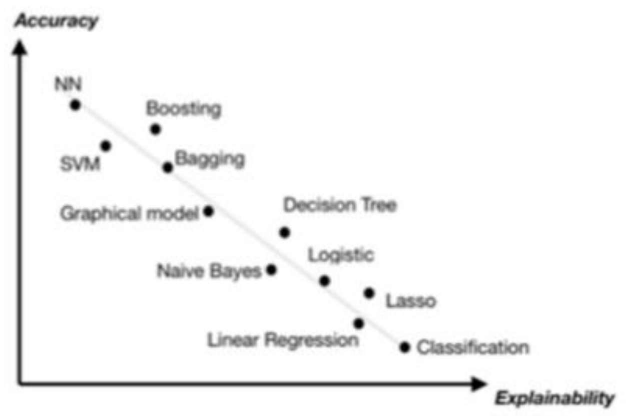


Summary of Bridge Deck Repair by County

Image Credit: Akhil Kodali

Challenge

Challenge 1:
Explainability is inversely proportional to accuracy



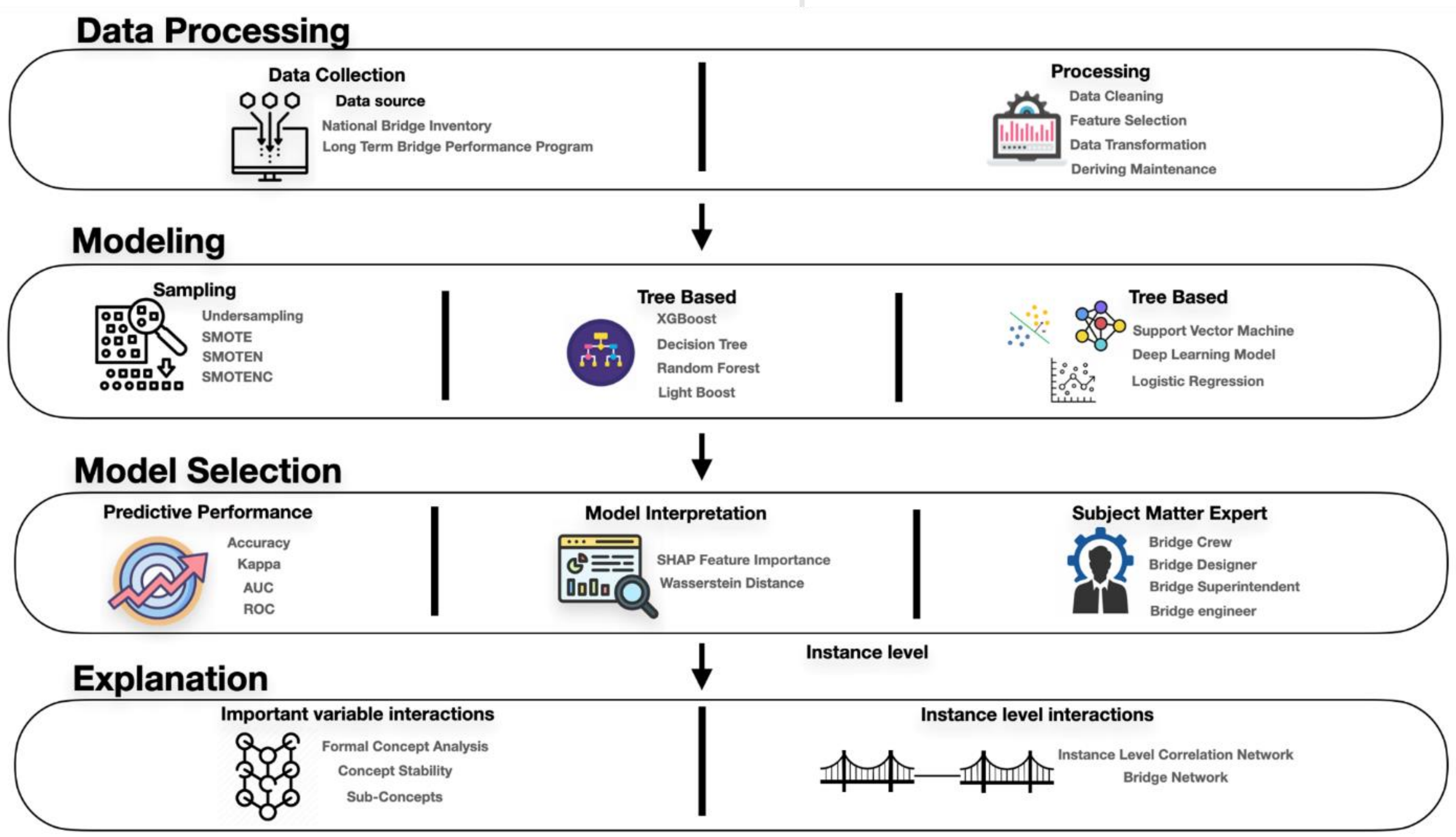
Challenge 2:
Every model tells a different story about bridge health

Table 12. Comparison of influential factors identified throughout literature

Method	Physical	Region	Structural and material	Environmental	Service
Case-based reasoning (Morcous et al. 2002)	✓*	—	✓	—	—
Cox hazards model with LASSO a and stepwise regression (Wettach-Glosser et al. 2020)	✓*	—	✓*	✓*	✓*
Linear regression and Monte Carlo simulation (Hasan and Elwakil 2020)	—	✓*	✓*	✓*	✓*
Bayesian survival analysis (Fleischhacker et al. 2020)	✓*	—	✓*	✓*	✓*
Artificial neural network and k-nearest neighbor (Assaad and El-adaway 2020)	✓*	—	✓	—	✓
Logistic regression and classification tree (Chang et al. 2019)	✓*	—	—	—	—
Ordered probit model (Saeed et al. 2017)	✓*	✓	✓	✓	✓
Multiple regression and GIS (Kim and Yoon 2010)	✓*	—	✓*	✓*	✓*
Baseline difference score	✓*	✓*	✓*	✓*	✓*

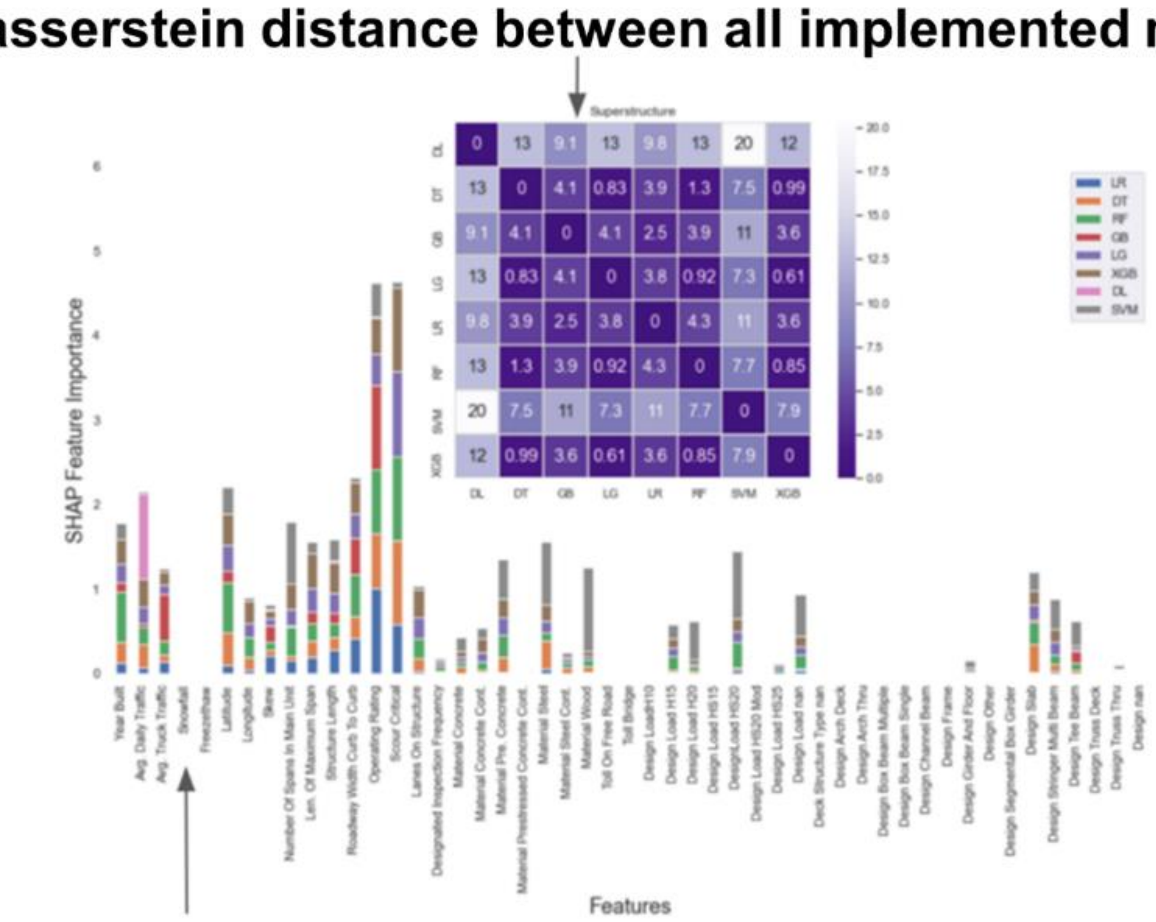
Note: A check mark indicates factor category tested; an asterisk indicates the factor category found to be influential. The text with the bold font is the proposed method in this manuscript.

Methodology

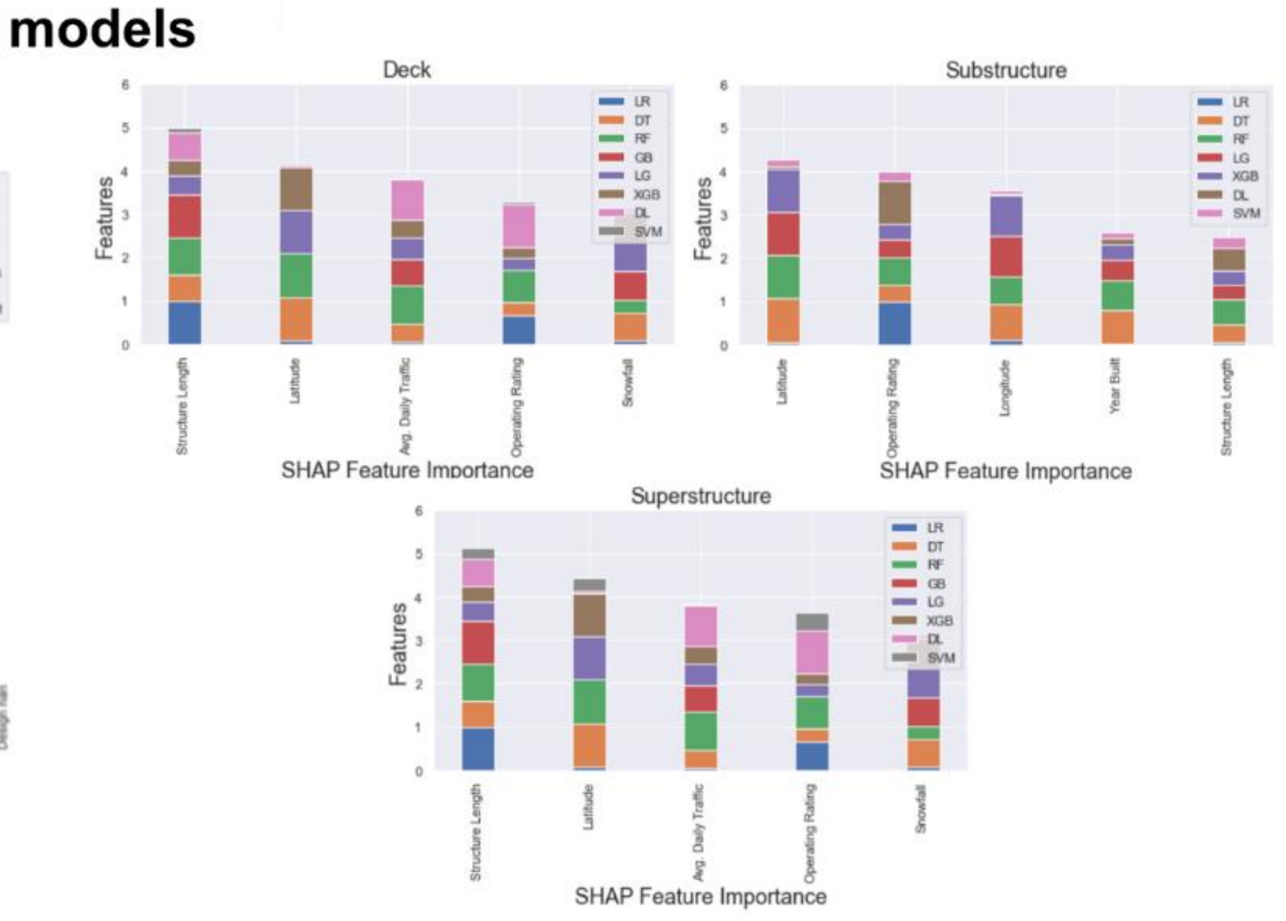


Results

The Similarity between model explanation using Wasserstein distance between all implemented models



Distribution of SHAP Feature importance of all implemented models



Top five influential factors across all bridge components

NSF Award Number: 1762034 (Sep 2018 – Aug 2023) SMARTI

Efficient Convoy Routing and Bridge Load Optimization User Interface

Brandon Lacy, Will Heller, Yonas Kassa, Brian Ricks, and Robin Gandhi

Overview

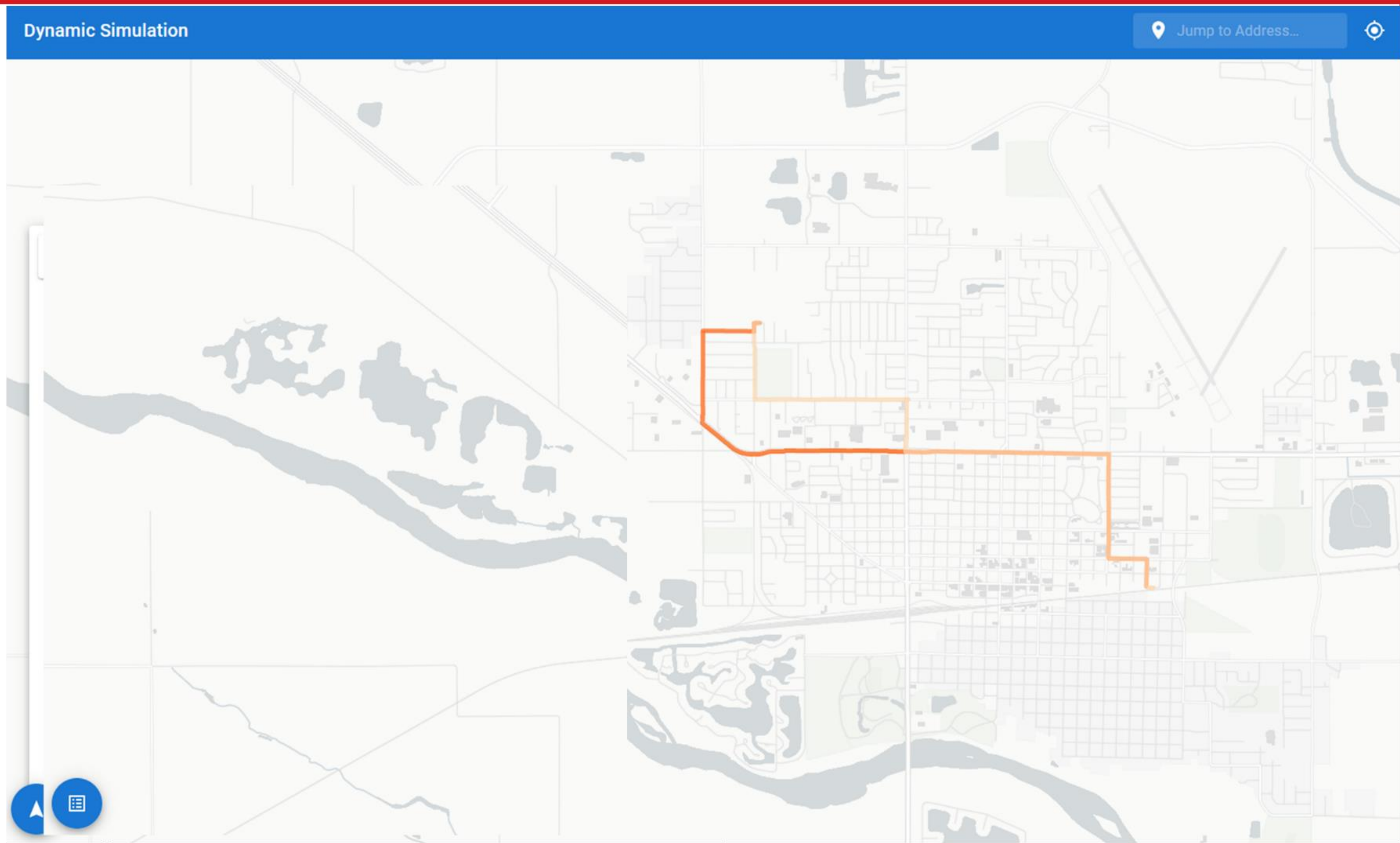
Displays merged OpenStreetMap (OSM) and National Bridge Inventory (NBI) data

Plans routes around bridge structural data

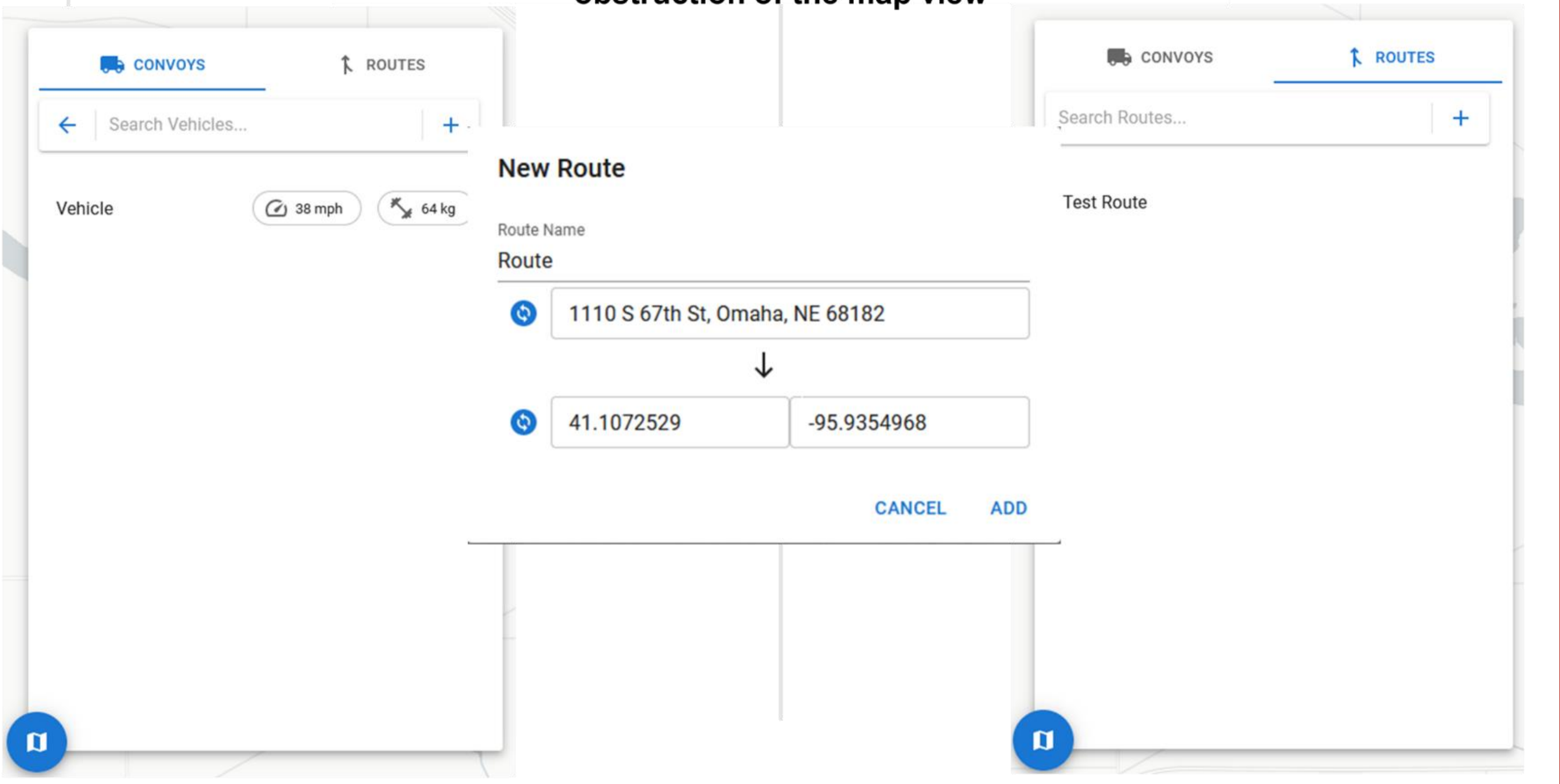
Save Routes and Convoys for later use

UI written in React and Material UI
API written in C#

Easy conversion between addresses and coordinates with Nominatim



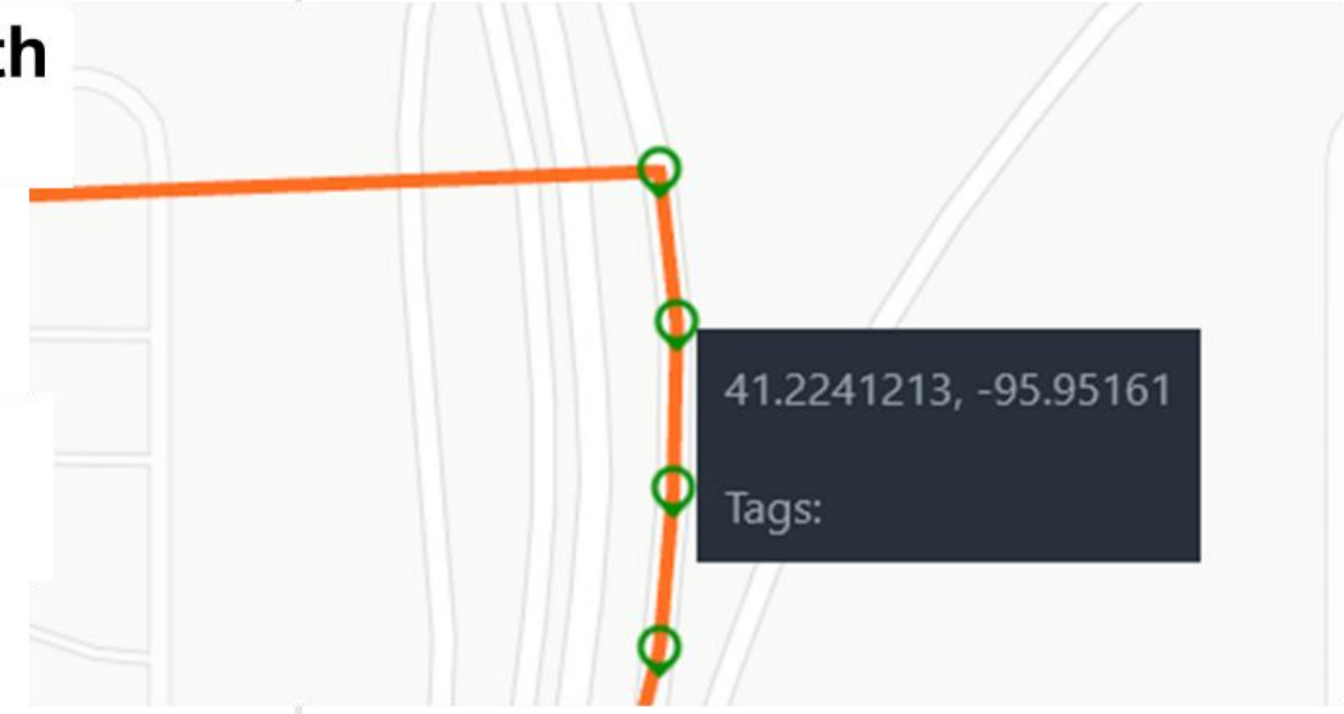
Menu Design
Creation and modification of routes and convoys with little obstruction of the map view



OSM and NBI Integration

View OSM and NBI data with the help of tags

Upcoming feature to view bridge structural data



NSF Award Number: 1762034 (Sep 2018 – Aug 2023) SMARTI

Transverse Crack Strain Analysis using U-Net on Concrete Bridge Dataset

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Summary

- Transverse cracks observed in concrete bridge elements can accelerate deterioration of bridge health
- Current system exclusively rely on data provided from human inspectors
- Many researched have been studied under restricted environments
- This project demonstrated the crack strain analysis using deep learning segmentation model with images collected from outdoor concrete bridges with UAVs

Data

Nebraska Concrete Bridge Dataset

- Outdoor concrete bridge deck images with cracks

Pedestrian bridge in Lincoln, NE

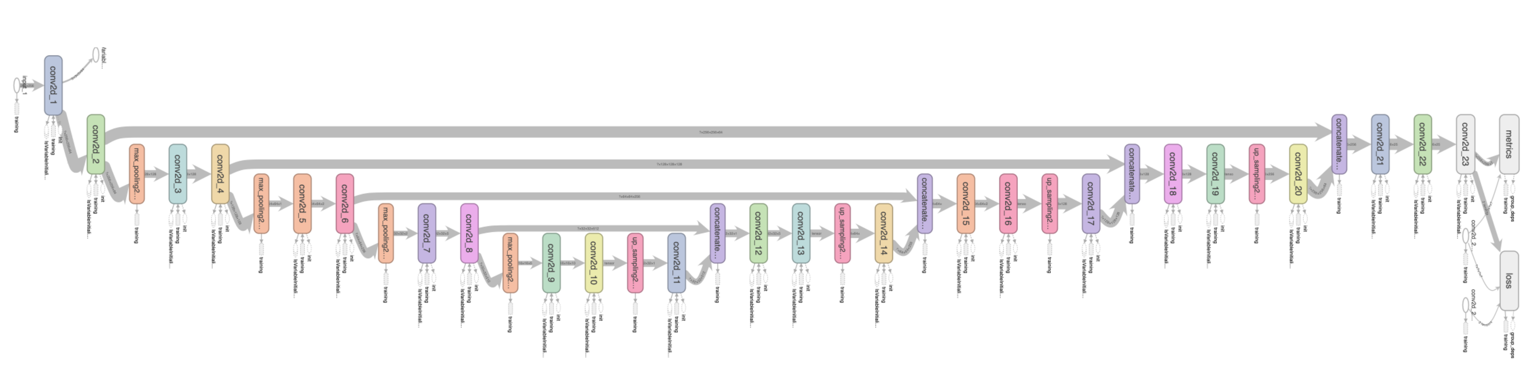
- Images collected with UAV
- UgCS software for automated image data collection for UAV
- Stitched with Pix4D software

Title (Location)	Keyword	Location	# of images (raw / augmented)
UAV19-1 (Elkhorn, NE)	• concrete overlay • construction marks • patches	Elkhorn, NE	13 / 3367
UAV19-2 (Elkhorn, NE)	• concrete overlay • tining marks	Elkhorn, NE	9 / 3266
UAV21 (Omaha, NE)	• concrete overlay • pier	Omaha, NE	219 / 2761
GV18 (Lincoln, NE)	• concrete overlay • expansion joints • tining marks	Lincoln, NE	260 / 3108
PD_DECK (Lincoln, NE)	• pedestrian bridge • deck	Lincoln, NE	100 / 100
PD_PIER (Lincoln, NE)	• concrete overlay • pier	Lincoln, NE	96 / 96

Detection Model

U-Net

- One of the SOTA methods for crack detection
- Semantic segmentation model with encoder and decoder based architecture
- Keras and Tensorflow based implementation

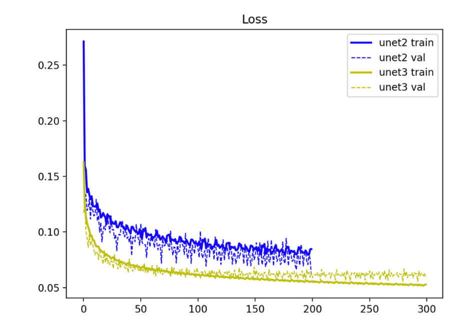


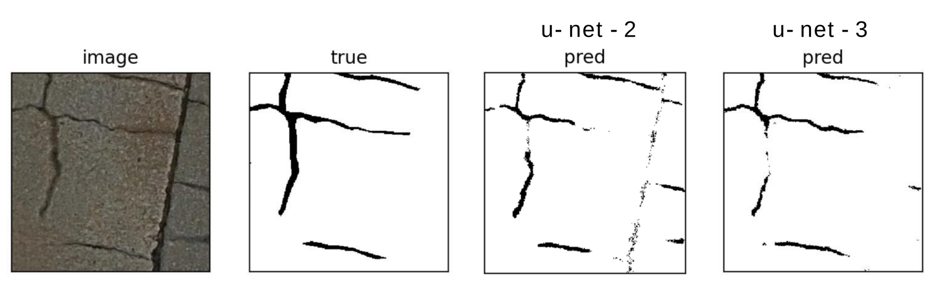
Crack Detection and Width Measurement

Training

- Model tuning for architectures and hyper-parameters
- Model performed best with 3M params

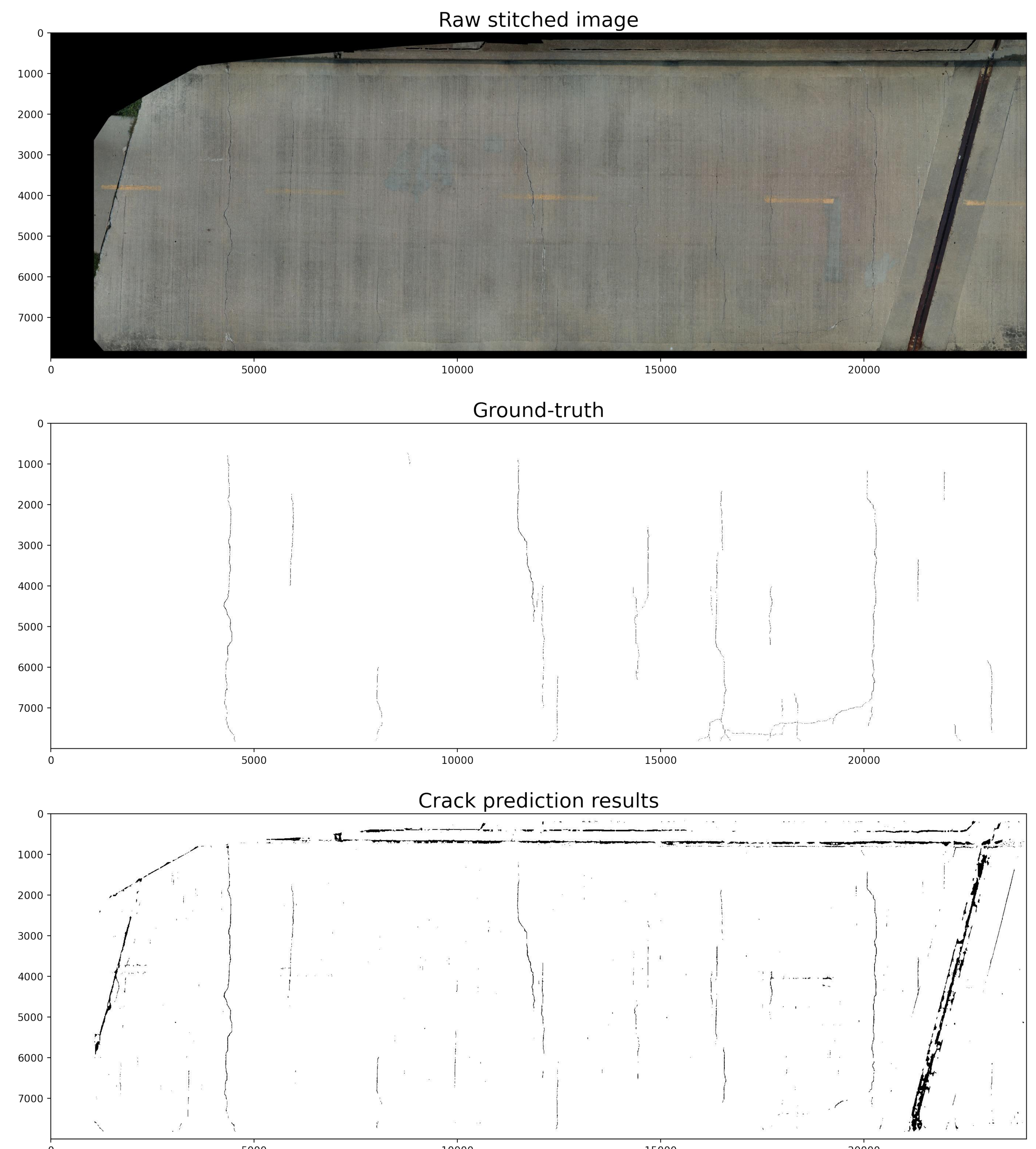
	U-net (baseline)	U-net-1	U-net-2	U-net-3
# of params.	2M	2M	3M	3M
Loss metric	F1	F1	IoU	F1
Precision	0.4184	0.4844	0.6408	***0.6762***
Recall	0.3358	0.4696	0.3978	***0.5734***
F1	0.3726	0.4020	0.4342	***0.5826***





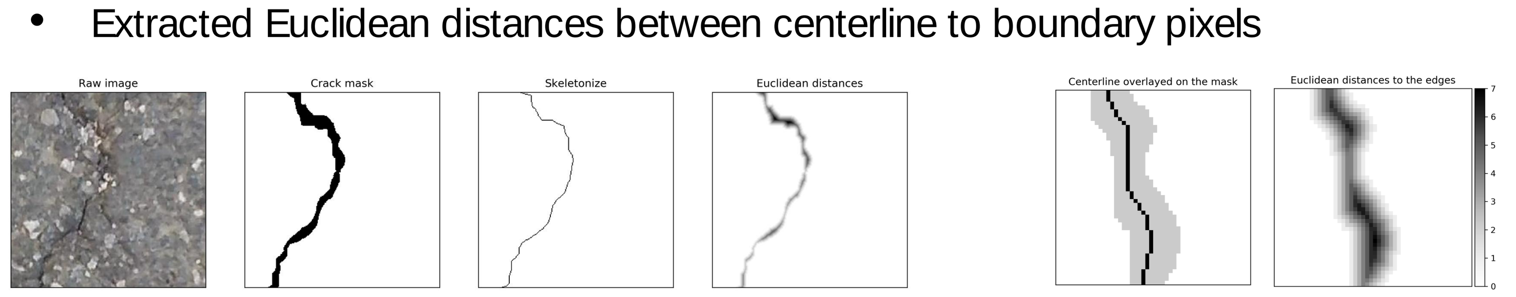
Inference

- Comparison to ground truth mainly focused on the apparent transverse cracks
- Tested for the first span of the pedestrian bridge image



Width Measurement

- Extracted Euclidean distances between centerline to boundary pixels



$$y = [\mu(\mathrm{dist}(\mathbf{b}, \mathbf{c})), \sigma(\mathrm{dist}(\mathbf{b}, \mathbf{c}))]$$

$$L_{1:smooth} = \begin{cases} |x| & \text{if } |x| > \alpha \\ \frac{1}{|\alpha|}x^2 & \text{if } |x| \le \alpha \end{cases}$$

Strain Analysis

Crack Width

- To provided perspective on the calculation of crack widths, it is necessary to consider a physical model of cracking
- For flexural cracking, the crack width at the level of the reinforcement can be calculated as follows

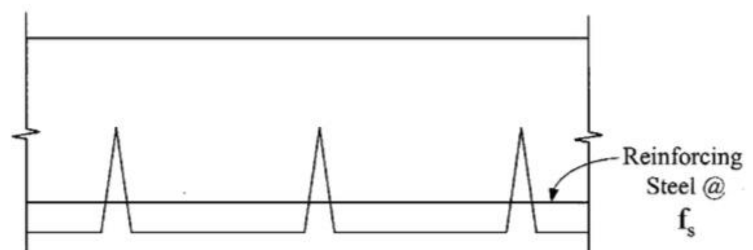


Fig. 2—Cracked section.

$$w_c = \varepsilon_s S_c \qquad \beta = \frac{\varepsilon_2}{\varepsilon_1} = \frac{h-c}{d-c}$$

where
w_c = crack width;
ε_s = reinforcing steel strain = $\frac{f_s}{E_s}$;
S_c = crack spacing;
f_s = reinforcing steel stress; and
E_s = reinforcing steel modulus of elasticity.

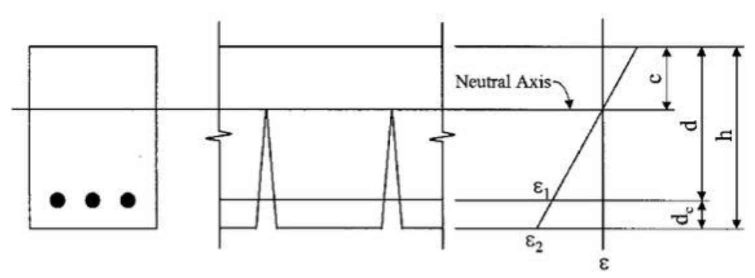


Fig. 3—Strain gradient.

$$w_c = 2\frac{f_s}{E_s}\beta\sqrt{d_c^2 + \left(\frac{s}{2}\right)^2}$$

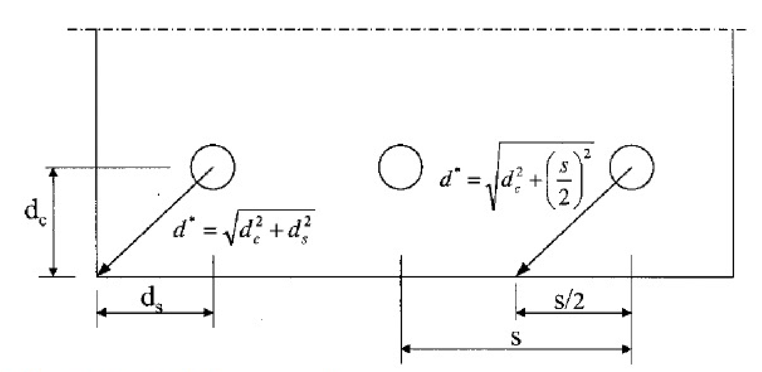


Fig. 4—Controlling cover distance.

where
s = maximum permissible bar spacing, in.;
w_c = limiting crack width, in.;
E_s = 29,000 ksi;
f_s = $0.6 f_y$, ksi;
β = $1.0 + 0.08d_c$; and
d_c = bottom cover measured from center of lowest bar, in.

Conclusion

- Mimicked the visual inspection performed with human inspectors by reading images, localizing cracks, and measuring crack widths for strain analysis
- Vision-based data analytics can provide useful information for bridge inspections and assist the health monitoring of aging concrete bridges

Reference

(a) SPH Engineering, Ugcs, https://www.ugcs.com, 2021.

(b) Pix4D, Pix4dmapper, https://www.pix4d.com/product/pix4dmapper-photogrammetry-software, 2021.

(c) Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18. Springer International Publishing, 2015.

(d) Frosch, Robert J. "Another look at cracking and crack control in reinforced concrete." *Structural Journal* 96.3 (1999): 437-442.

This study was financially supported by the NSF-BD Spokes Program (Award #1762034), NSF-IIS (Award #1925052), and MADS-OPP (Award #W912HZ21C0060). Their support is gratefully acknowledged.

Deep Learning Vision-Assistive Steel Bridge Inspection using Unmanned Aerial Vehicles

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[a] School of Computing, College of Engineering, University of Nebraska - Lincoln

[b] Department of Civil and Environmental Engineering, College of Engineering, University of Nebraska - Lincoln

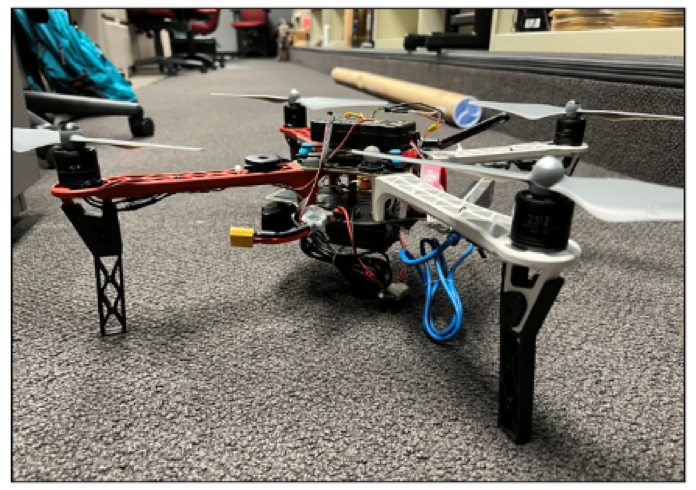
Summary

- Corrosion is one of the most typical bridge deficiencies shown in steel bridge members.
- Severely corroded members require further inspection than vision-based such as tactile inspection.
- Human-involved inspections can be a problem when some of the members are placed in a location where inspectors have to climb up or down
- This project proposes the inspection framework for steel bridge members using UAVs both in simulated and real-world scenarios

System Design

Steel bridge inspection using UAVs

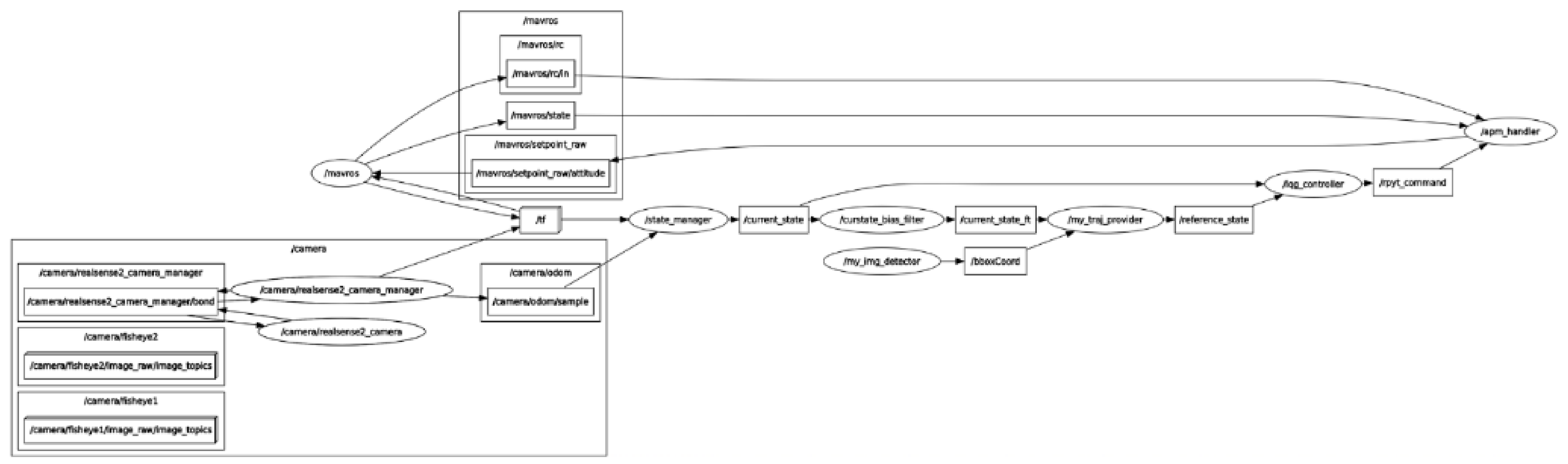
UAV Setup



Hardware Specification

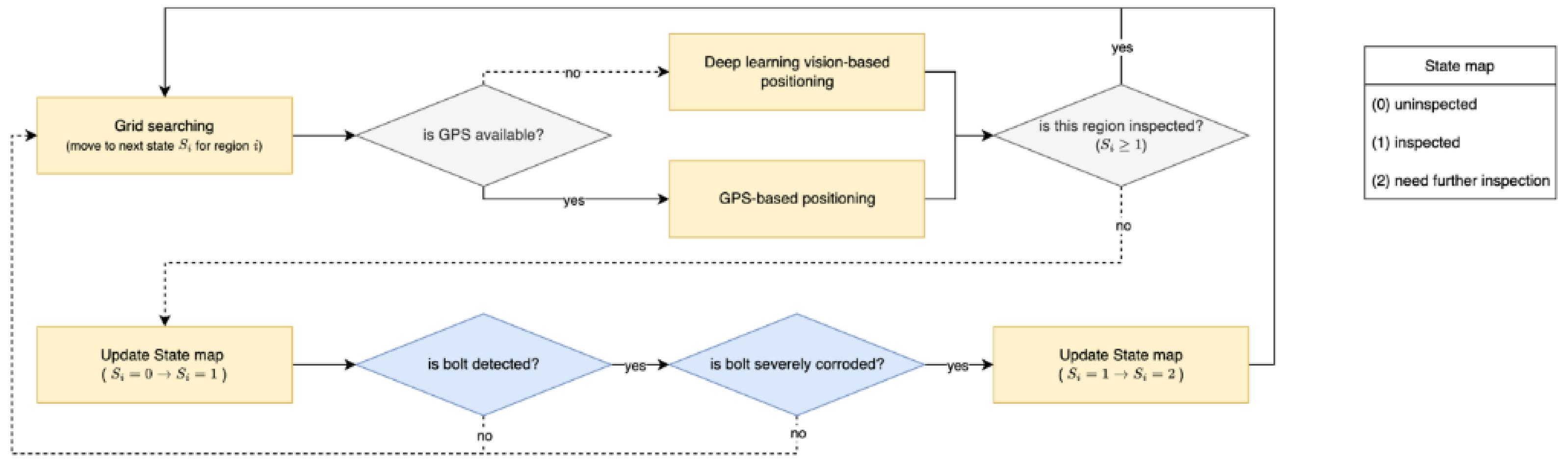
Part	Model	Weight (g)
UAV	F450 Quadcopter	282
Controller	Pixhawk PX4	38
Tracking camera	Intel Realsense T265	60
FPV camera	Logitech C920	182
Companion computer	NVidia Jetson Nano	140
Battery	5000mAh 11.1V LiPo	600

System graph in ROS



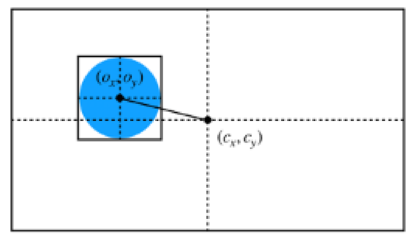
Inspection Algorithm

Algorithm Flowchart



Vision-assist Positioning for GPS Loss

- UAVs can easily lose GPS signal near the bridge site
- Design a positioning algorithm with deep learning vision with a FPV camera from a UAV
- Detect bridge members with the pre-trained model to focus on bridge sites in case of sudden GPS lost and stabilize UAV's current poses

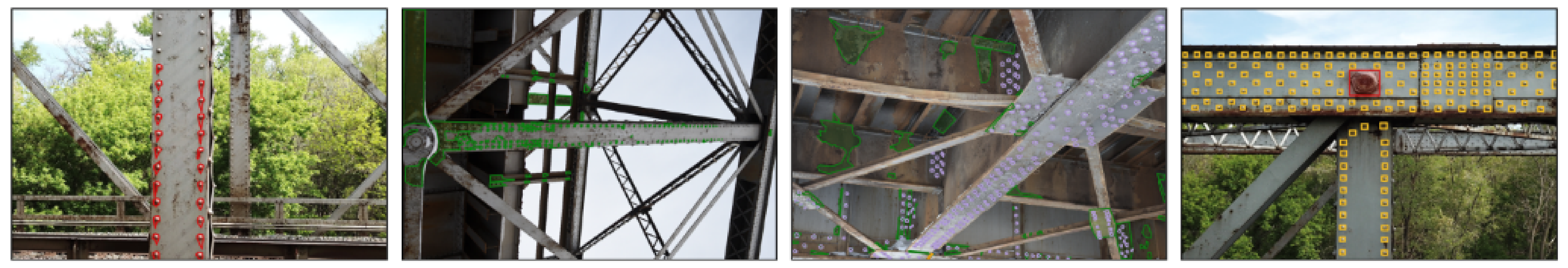


$$err = ((o_x - c_x) + (o_y - c_y))^{1/2}$$

Detection Model

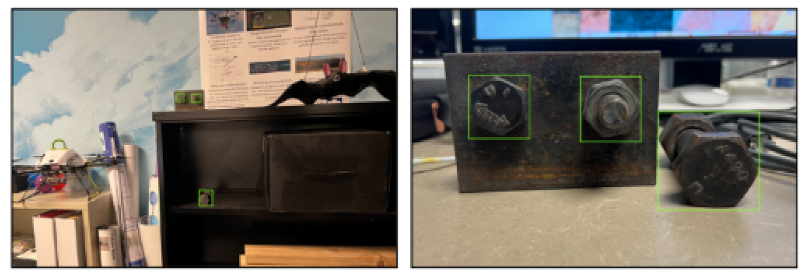
Data

- Collected and created varying types of labeled images
- Approximately 7000 rivets were labeled for bridge members



Tiny YOLO v3

- Light-weight and fast computing model (<30 convolutional layers) for real-time onboard detection on UAVs
- Identify and localize the target objects
- Train the model with bolt samples with light corrosion condition



Method	AP@.50	AP@.75	Time (FPS) (3000x4000px)
Mask R-CNN	0.87	0.45	0.2
YOLO v3	0.75	0.38	1

tested with Nvidia Tesla V100 PCIe

Experiments

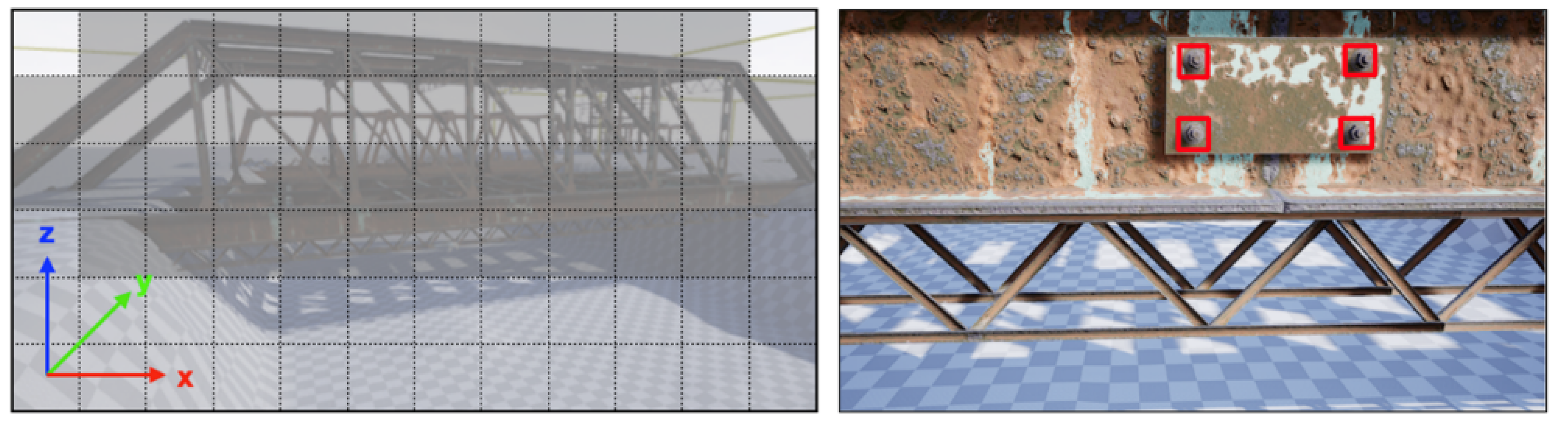
Experimental Setup

- Scan and inspect the side of the steel bridges with UAV's FPV camera
- Run onboard deep learning model on UAV's companion computer for real-time detection
- Wireless bi-directional communication between UAV and ground PC in real-time

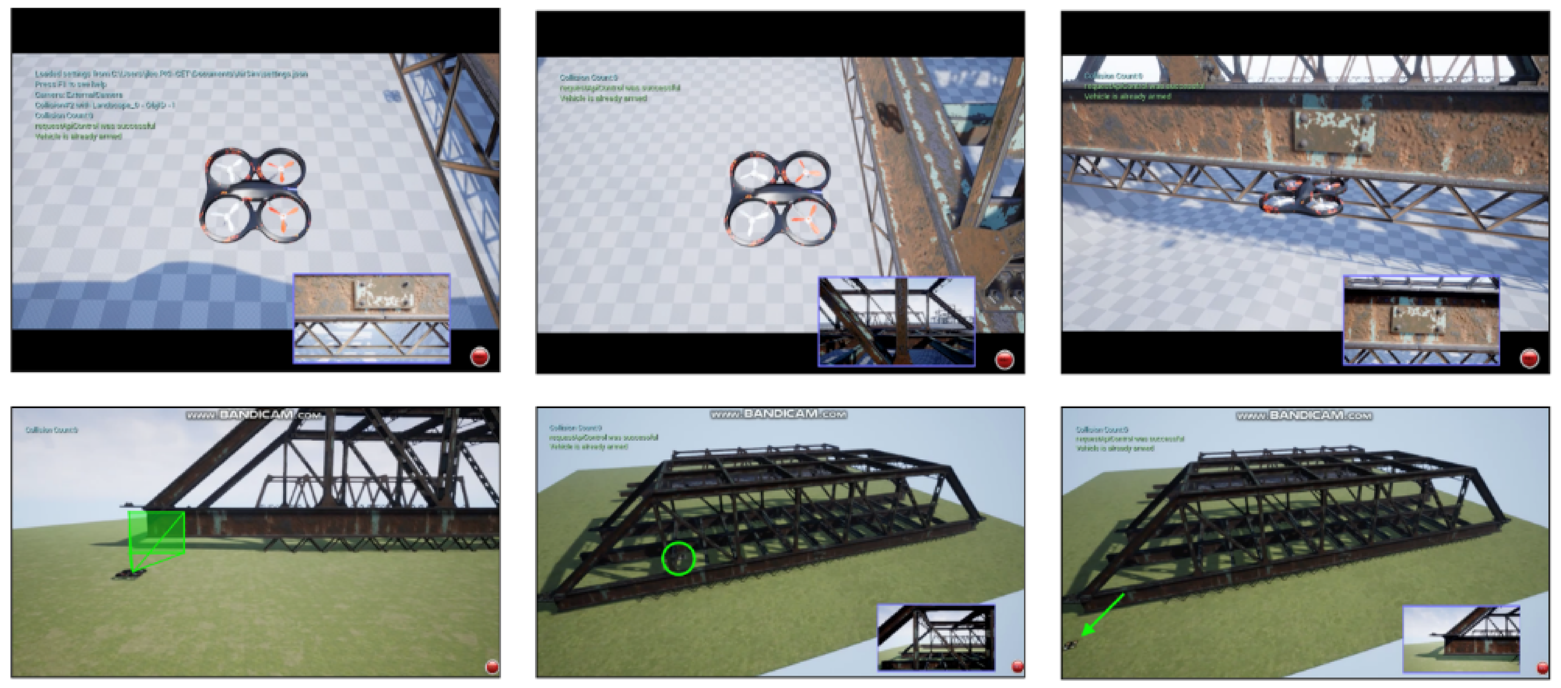
Simulation scenario

- Build a realistic simulated bridge environment using the Microsoft AirSim simulator
- A UAV with an FPV camera was used to perform the inspection with bolt detection

Inspection Environment in AirSim



Inspection Process for Bolt Detection



Real-world scenario

- The UAV system would be tested in the cage and the structural lab for the controlled testing environments
- The study is planning to be expanded in steel bridges located in Nebraska

Reference

(a) Redmon, Joseph, and Ali Farhadi. "Yolov3: An incremental improvement." *arXiv preprint arXiv:1804.02767* (2018).

(b) WeekendWarrior, Rusty Beams, https://www.unrealengine.com/marketplace/en-US/product/rusty-beams.

This study was financially supported by the **NSF-BD Spokes Program** (Award #1762034), **NSF-IIS** (Award #1925052), and **MADS-OPP** (Award #W912HZ21C0060). Their support is gratefully acknowledged.

An Output-Only Bayesian State Estimator for Partially Observed Structural Systems

Martin Masanes Didyk[a], Dr. Saeed Eftekhar Azam[a], Dr. Mohsen Ebrahimzadeh Hassanabadi[b]

[a] University of New Hampshire

[b] University of Sydney

OVERVIEW

- So, how do we monitor infrastructure if it is, in general, **large scale and with multiple DOFs**?
  - 1st idea is to completely monitor the structure, which is unpractical.
- 2nd idea might be a Virtual sensing technique, through a calibrated model or digital twin.
  - Through Recursive Bayesian Estimation techniques, we could estimate the response of unmeasured or unobserved locations of the system, using a limited number of measurements.
  - Also, the estimated quantities can then go back to the digital twin of the studied system to update the model.
- How is this different from other filtering techniques?: Unlike existing filtering techniques in the literature, for the state time update $\hat{x}_{k|k-1}$ at time k, observation y_{k-1} at t_{k-1} is adopted, and for state measurement update $\hat{x}_{k|k}$ at time k, observation y_k at t_k is adopted.

RECURSIVE ESTIMATOR

Initialization

$$\hat{x}_0, P_0$$

$$E_k = \left(H_k^T H_k\right)^{-1} H_k^T$$
$$\mathcal{G}_k = G_k E_k$$
$$\mathcal{A}_k = A_k - \mathcal{G}_k C_k$$

Time Update

$$\hat{x}_{k|k-1} = \mathcal{A}_{k-1}\hat{x}_{k-1|k-1} + \mathcal{G}_{k-1} y_{k-1}$$

$$P_{k|k-1} = \mathcal{A}_{k-1} P_{k-1} \mathcal{A}_{k-1}^T + \mathcal{G}_k R_k \mathcal{G}_k^T - \mathcal{G}_k R_k K_k^T \mathcal{A}_k^T - \mathcal{A}_k K_k R_k \mathcal{G}_k^T + Q_k$$

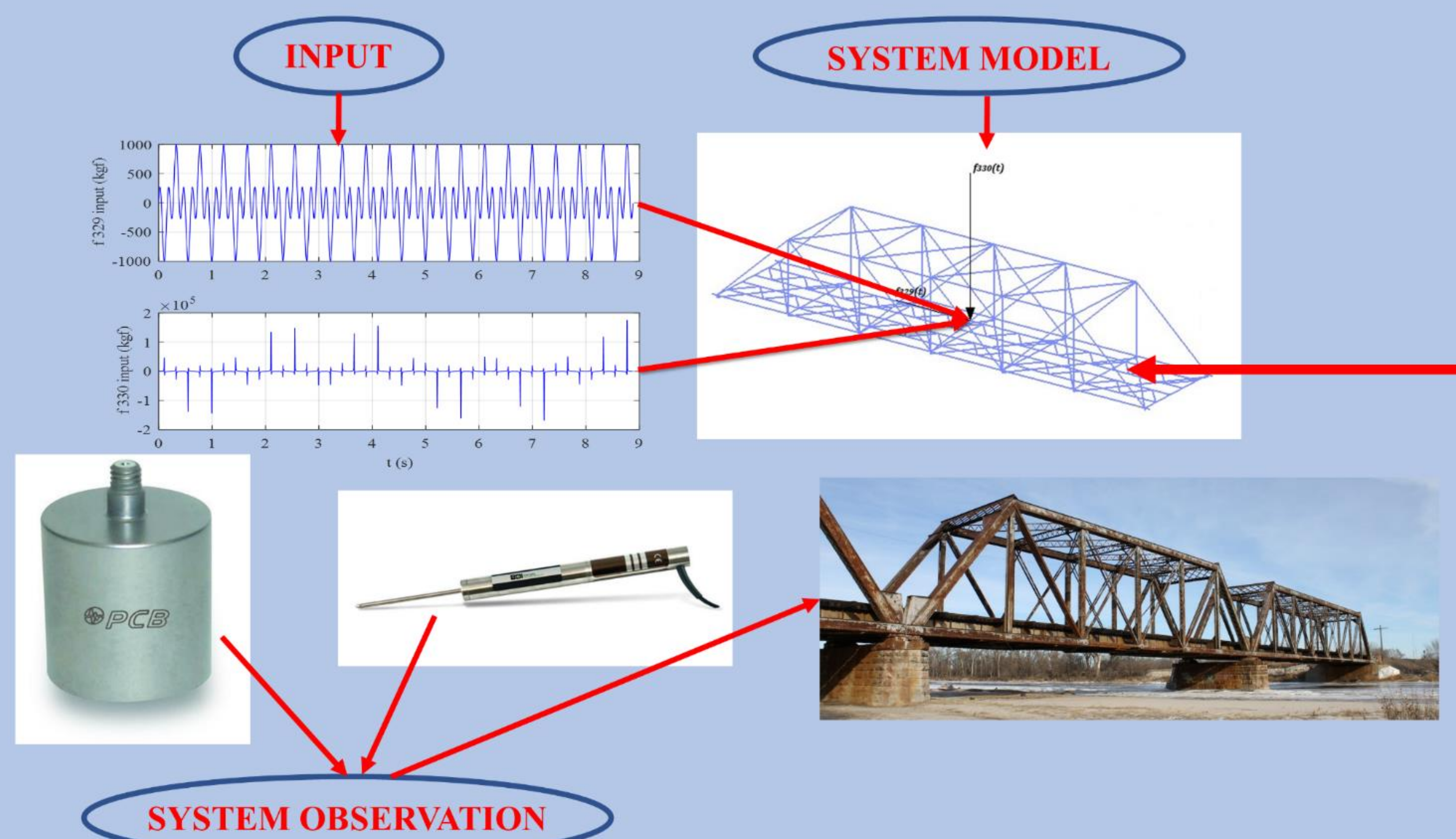
Measurement Update

$$D_k = I - H_k E_k$$
$$\Psi_k = U_k D_k \left(C_k P_{k|k-1} C_k^T + R_k\right) D_k^T U_k^T$$
$$\bar{\mathcal{K}}_k = P_{k|k-1} C_k^T D_k U_k \Psi_k^{-1}$$
$$\mathcal{K}_k = \bar{\mathcal{K}}_k U_k$$
$$K_k = \mathcal{K} D_k$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(y_k - C_k \hat{x}_{k|k-1}\right)$$
$$P_{k|k} = \left(I - K_k C_k\right) P_{k|k-1} \left(I - K_k^T C_k^T\right) + K_k R_k K_k^T$$

LITERATURE REVIEW

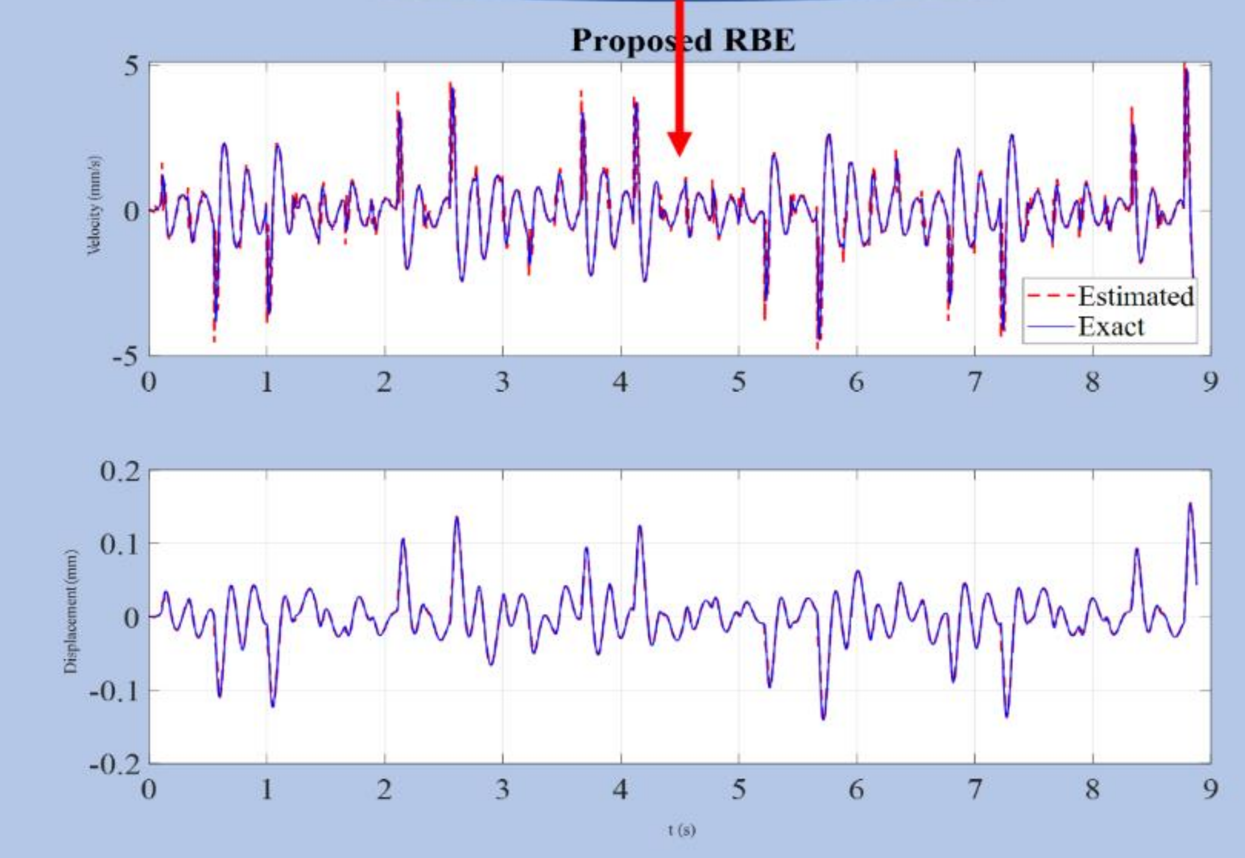
- Kalman Filter (KF) – 1969: needs input f_k
- Augmented Kalman Filter (AKF) – $f_{k+1} = f_k + v_k$
- Dual Kalman Filter (DKF) – 2015: $f_{k+1} = f_k + v_k$
- Gillijns and De Moor (MGDF) – 2012: no assumptions on input, prone to instabilities
- Solution: Eliminate the input
  - M. Hou and R. J. Patton: Discards parts of the observation
  - M. Darouach, M. Zasadzinski, and M. Boutayeb: Equivalent to GDF, and prone to some instabilities
  - P. K. Kitanidis : Only system w/o Direct feedthrough



MODEL UPDATING

VIRTUAL SENSING

STATES (*INPUT AND PARAMETERS*) ESTIMATION

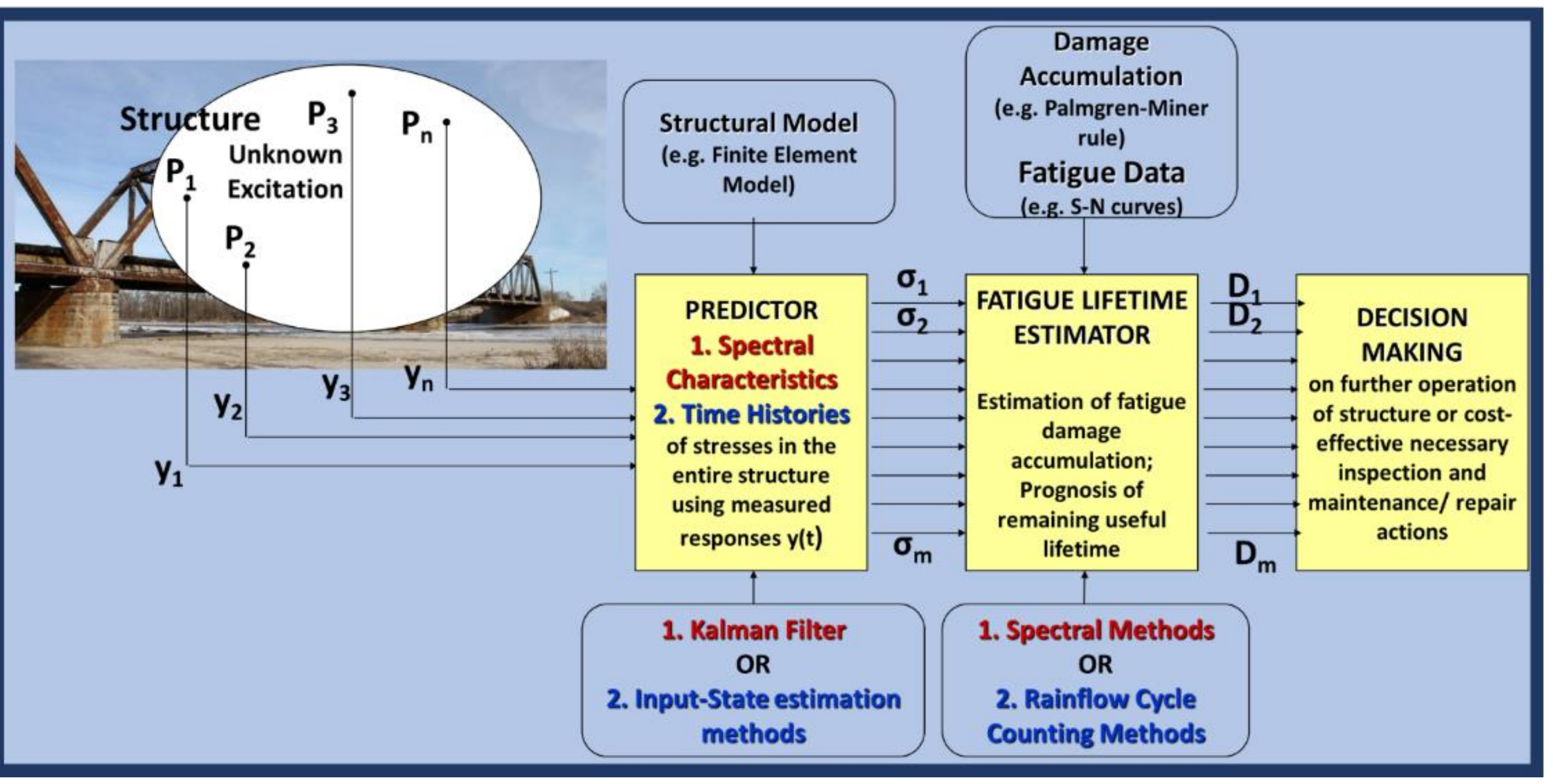


NOVELTY OF THIS WORK

- The proposed filter is a procedure for **eliminating input** from the estimation problem, and the Numerical instability is solved by analytical derivation of pseudo-inverse parameters.
- It's a **2-stage filter**, this is it has only a time and measurement stages, son there is no additional stage for the computation of the input
- In the case of it to be required, the **input can be reconstructed**.

FUTURE WORK

- Develop a **smoothing scheme** for the same algorithm to allow to an extended observation window.
- A **Non-linear extension** of the filter.
  - Nonlinear systems.
  - Parameter estimation.
- Application to bridges like **moving load input-state estimation**, without any knowledge about the characteristics of the input/load to the system.

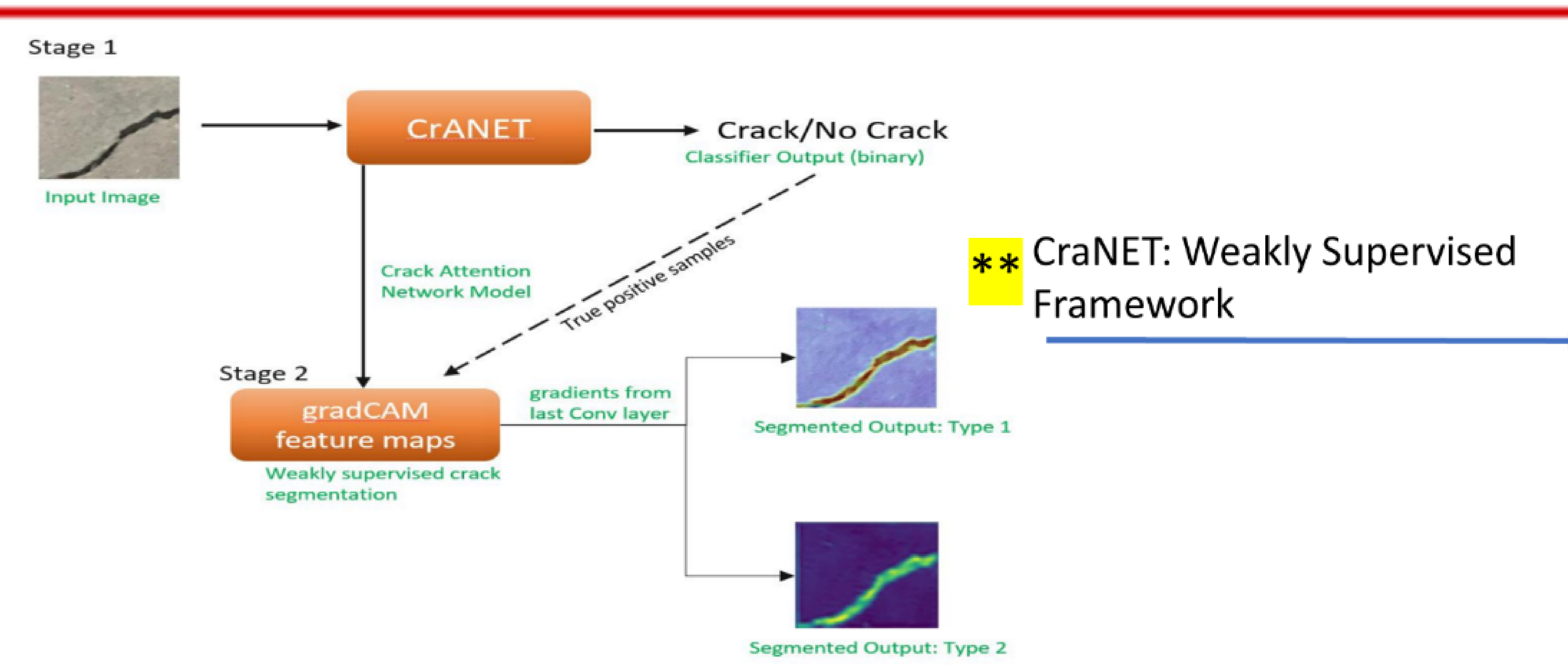


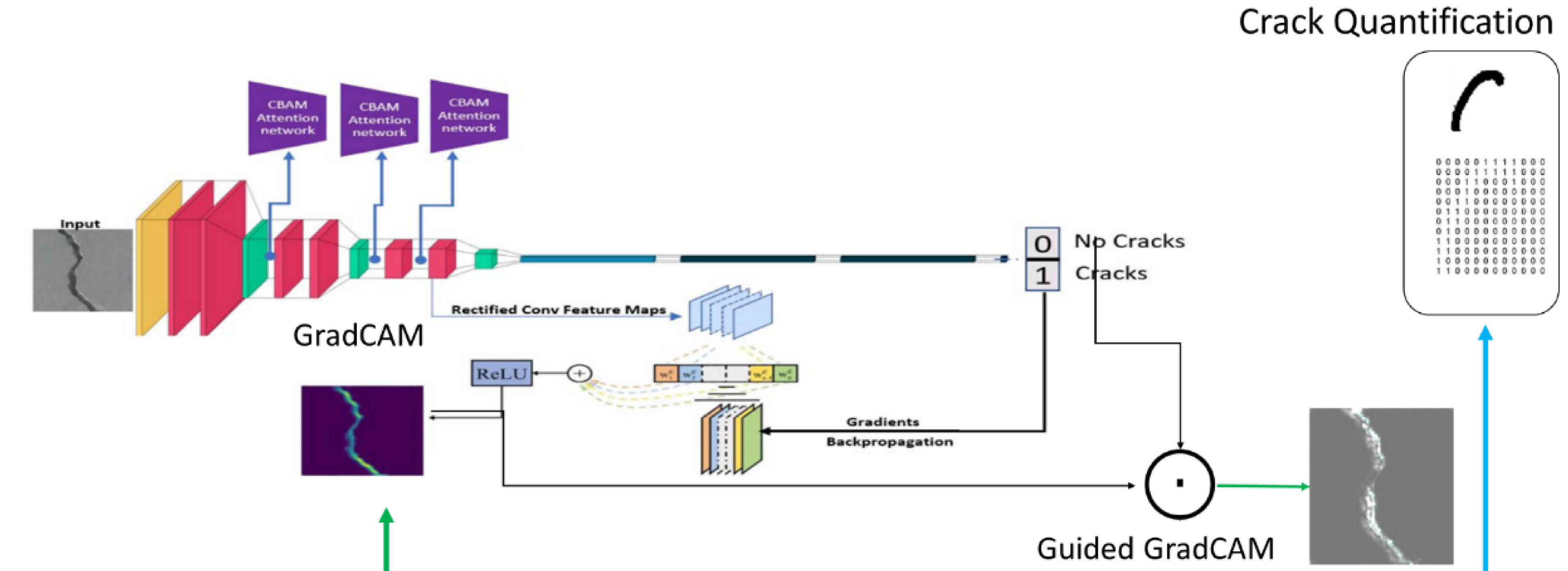
CEAIC: Cloud-Edge Adaptive Intelligence For Concrete Crack Detection and Quantification

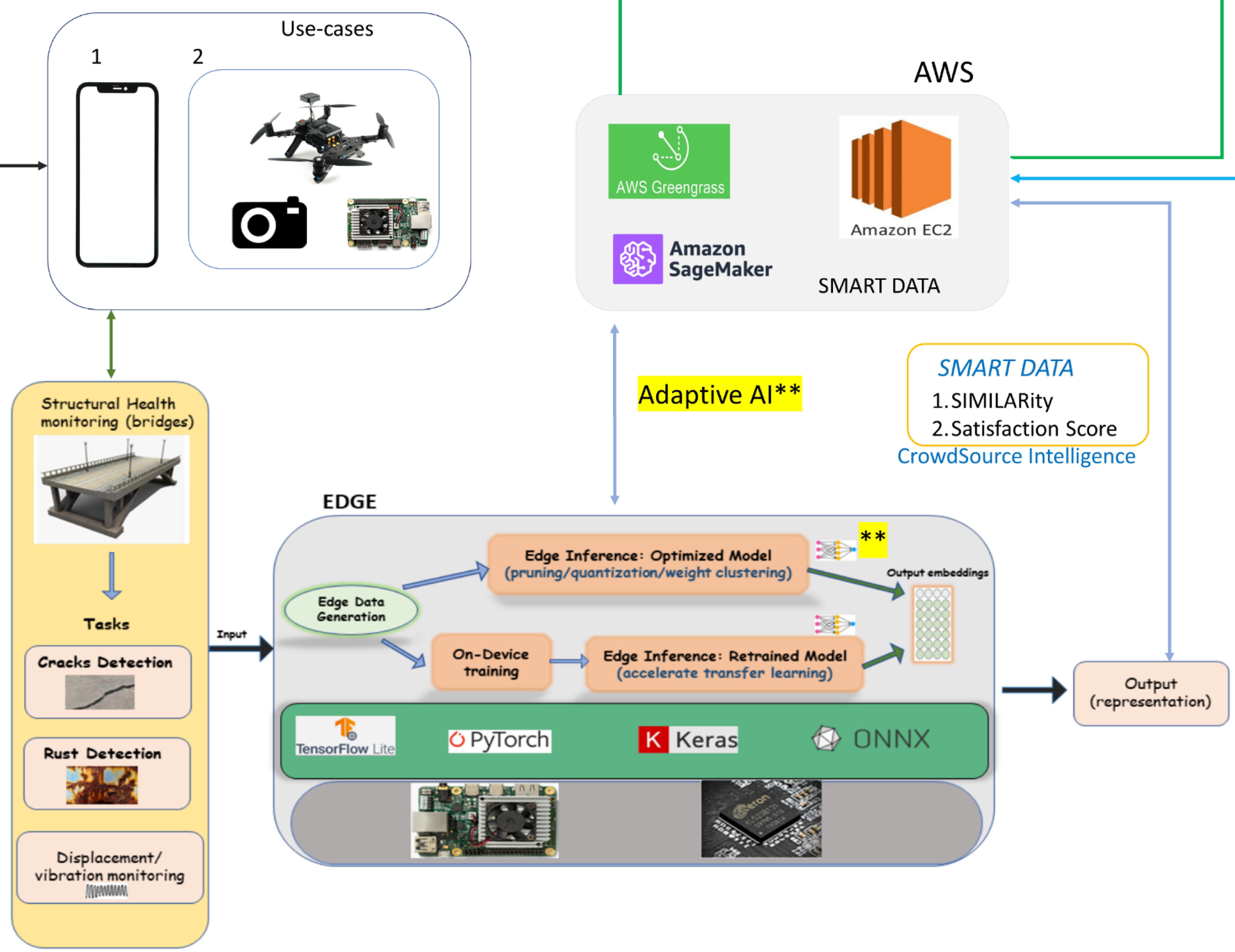
University of Nebraska at Omaha, College of IS&T

CONTRIBUTORS:

- Anoop Mishra
- Gopinath Gangisetti
- Deepak Khazanchi







AIM:

To perform real-time crack detection and quantification on concrete surface on unannotated images (weak labels) using weakly supervised learning

Proposed Methods on tasks:

1. Detection: CraNET, a weakly supervised framework (WSF)[2]
2. Quantification: Traversing binary connected components
3. Real-time inference: Cloud-Edge AI[1]

Conclusion:

- Proposed framework for label-free algorithms in SHM with minimum human-intervention that reduces cost and time
- Proposed Edge-AI framework to optimize latency for real-time inference and mobile use-cases
- Integrated Cloud-edge intelligence to adapt scenarios from crowdsource knowledge[3]

Table 1: Human validation study showing vote distribution on CraNET generated results

Qualitative Variable	Votes
Exactly Similar	224
Somewhat Similar	295
Neutral	61
Somewhat Dissimilar	100
Exactly Dissimilar	53
Total	733

Table 2: ML model performance

Model	Testing Accuracy	Avg Inference time (ms)
CNN + Attention (6 Conv)	99.4%	22
Edge CNN (3 Conv)	91%	15
Edge CNN (6 Conv)	92.3%	29

1. Mishra, A., Gangisetti, G., & Khazanchi, D. (2023). Integrating Edge-AI in Structural Health Monitoring domain. *arXiv preprint arXiv:2304.03718.*
2. Mishra, A., Eftekhar Azam, S., & Khazanchi, D. (2023). Weakly Supervised Crack Segmentation Using Crack Attention Network(CraNET) On Concrete Structures With Minimal Human Intervention *(under review)*
3. Mishra, A., & Khazanchi, D. (2023). Assessing Perceived Fairness from Machine Learning Developer's Perspective. *arXiv preprint arXiv:2304.03745.*

Acknowledgement: *This research is partially supported by NSF Award Number:1762034, Spokes: MEDIUM: MIDWEST: Smart big data pipeline for Aging Rural bridge Transportation Infrastructure (SMARTI) as well as US Army Crops of Engineers, Engineering Research and Development Center grants W912HZ21C0060 – Multilevel Analytics and Data Sharing for OPerations Planning (MADS-OPP) and W912HZ23C0005 – SMART Analytics for Critical*

National Infrastructure Analytics Portal – Breaking Down Silos

Sahithi Anne[1], Surya Rajalakshmi Muthiah[1], Dr Sachin Pawaskar[1]
[1]College of Science and Technology, University of Nebraska at Omaha

Problem Statement

- Multiple systems exist in silos for maintenance and monitoring of critical structure health. Can we bring disparate systems together?
- Huge datasets from National Bridge Inventory (NBI) is available and needs to be processed efficiently. (Approximately 7.5 GB)
- Need an integrated solution that offers better visualization and analytics of huge datasets.

NIA Portal

- The National Infrastructure Analytics (NIA) web portal offers a framework of analytical methods, visualization techniques, and tools.
- NIA hosts data-driven models to comprehend bridge maintenance and efficiency. Additionally, NIA includes references to the compilation of various datasets, cleaning, analysis, and transformation of bridge inspection records into time-series formats for all states and all previous years.
- The NIA framework enables users to extract useful insights from the data and facilitates users to identify critical information and predict patterns which help the federal government to plan to fund improvements in infrastructure .

Features

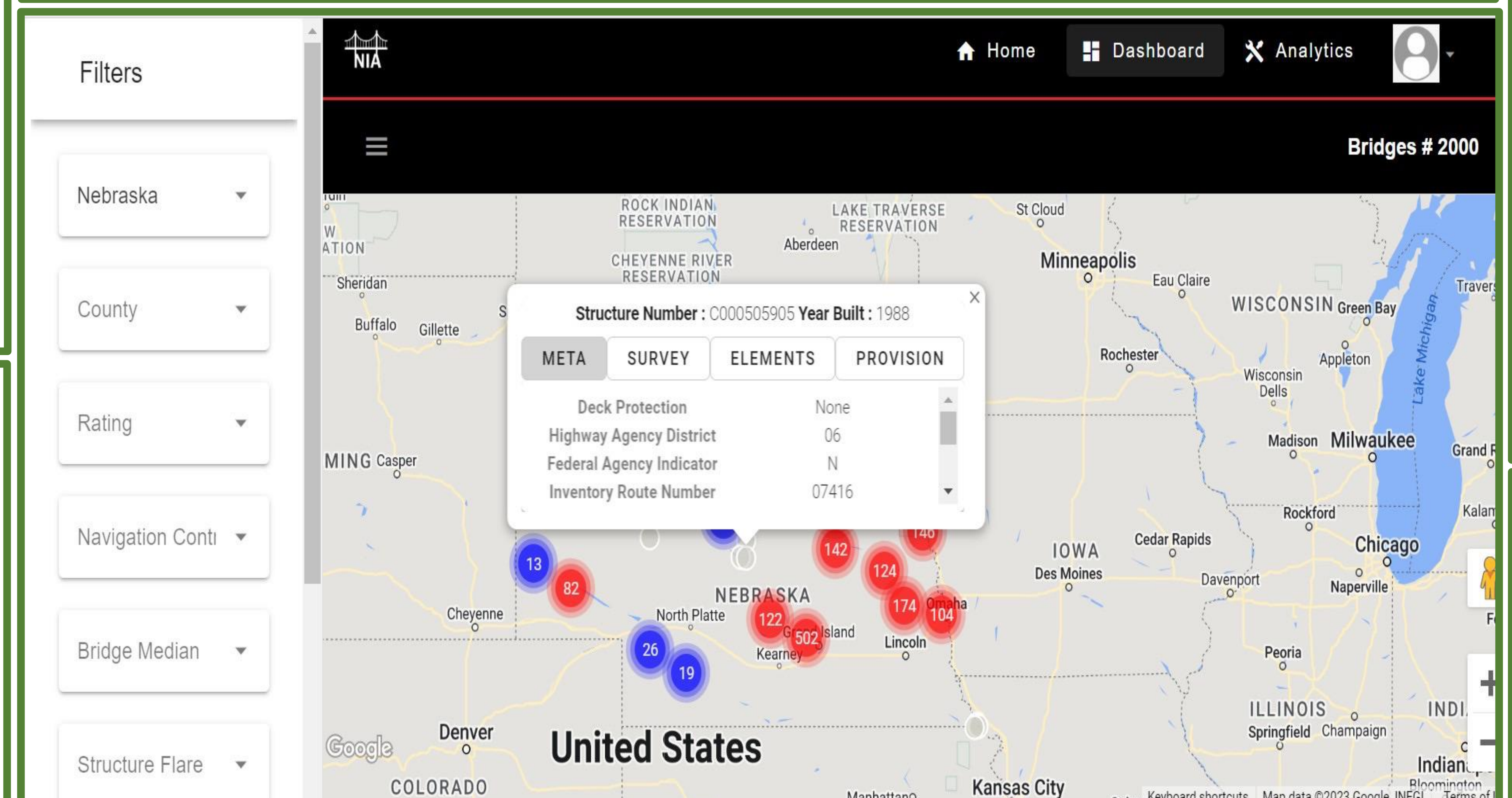
- Framework for Integrated Eco-system
- Data visualization for actionable insights
- Data analytics for predictive maintenance
- Flexibility to extend to other critical infrastructure
- Ability to view metadata for each bridge like location, surveyed information, individual elements conditions, etc.
- Provisions available on a bridge can be viewed.

Techniques

- Data preprocessing
  - Download data from FHWA data sources, analyze it and convert it to the desired format.
- Database and Cloud Integration
  - Database on Heroku, schema design and load
  - Optimization
- Data Visualization
  - Implemented using Google Maps, Django REST API and Vue JS for UI
- Data Analytics and Machine Learning (Future Work)
  - Predict critical information like patterns, trends, etc.
  - Integrate Data Analytics into the tool.

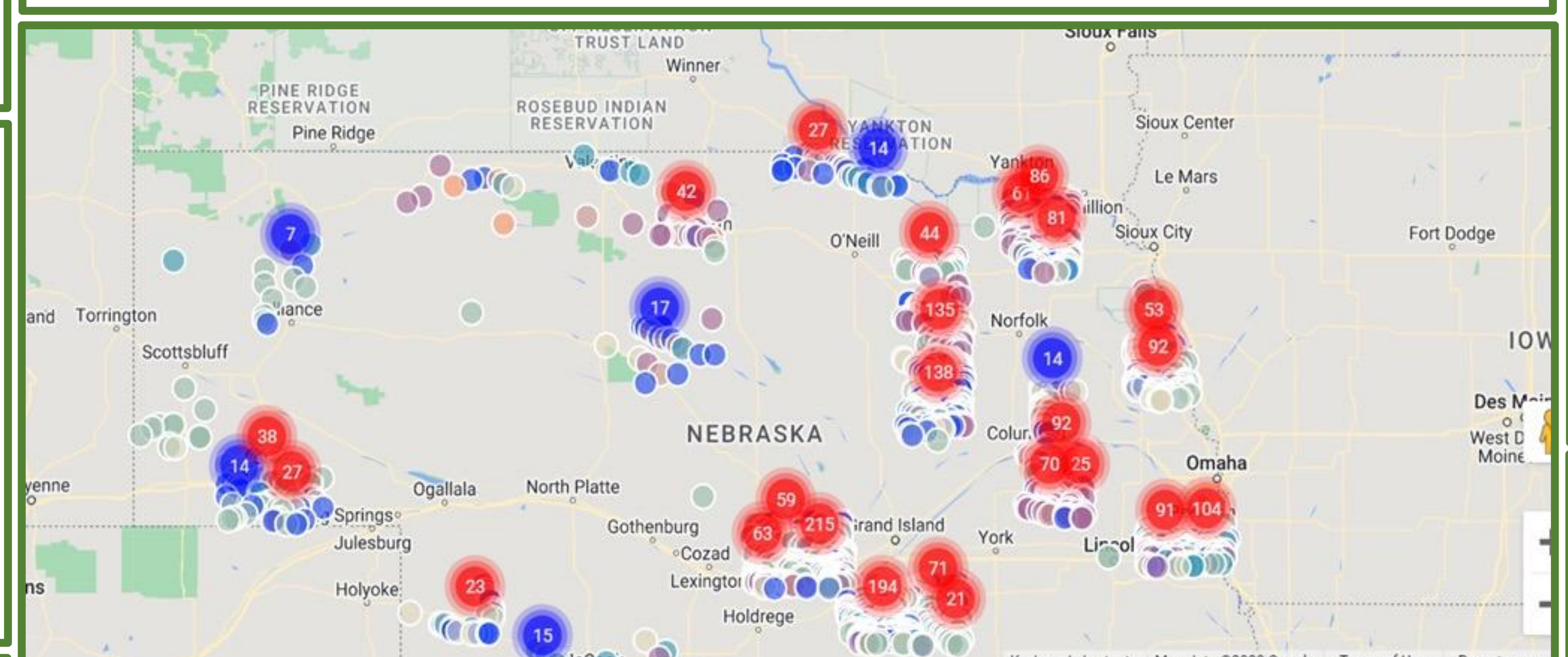
Infrastructure Mapping

The below image shows the NIA dashboard with the metadata bubble expanded. Various filters are provided on the sidebar.

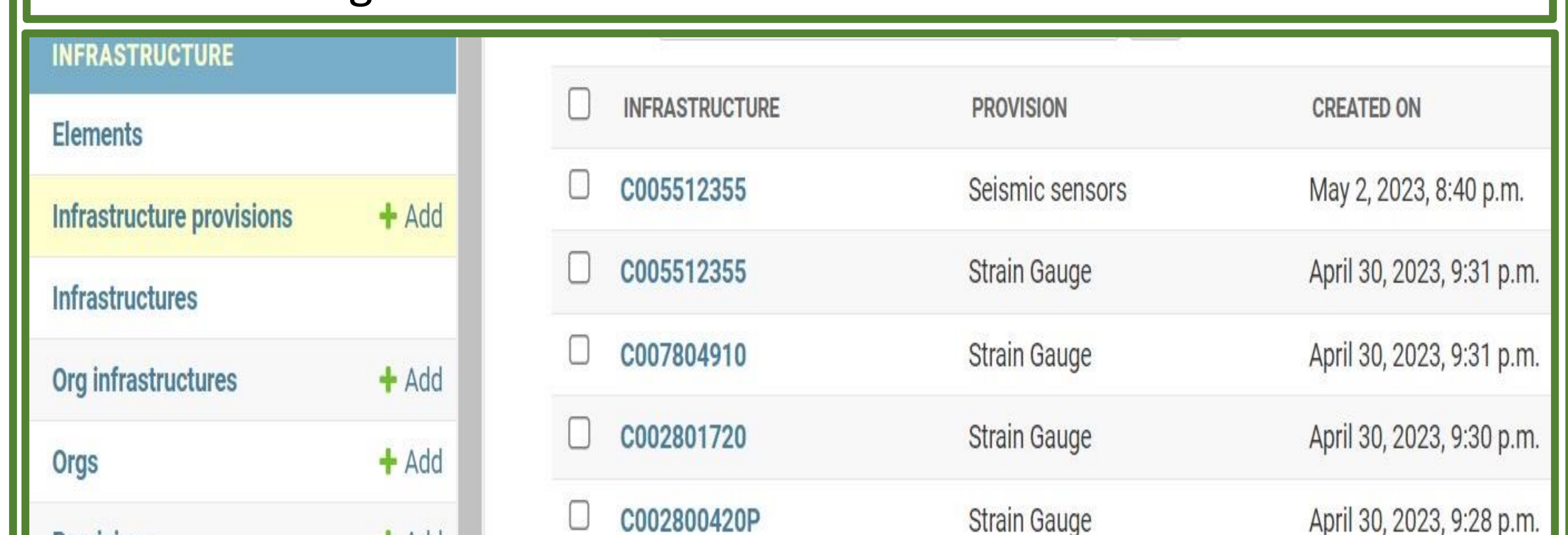


Nebraska Bridge infrastructure

The below image shows the bridges in Nebraska. These data points are colored according to the bridge ratings. For example, bridges marked bright red represent bridges that are in critical condition.

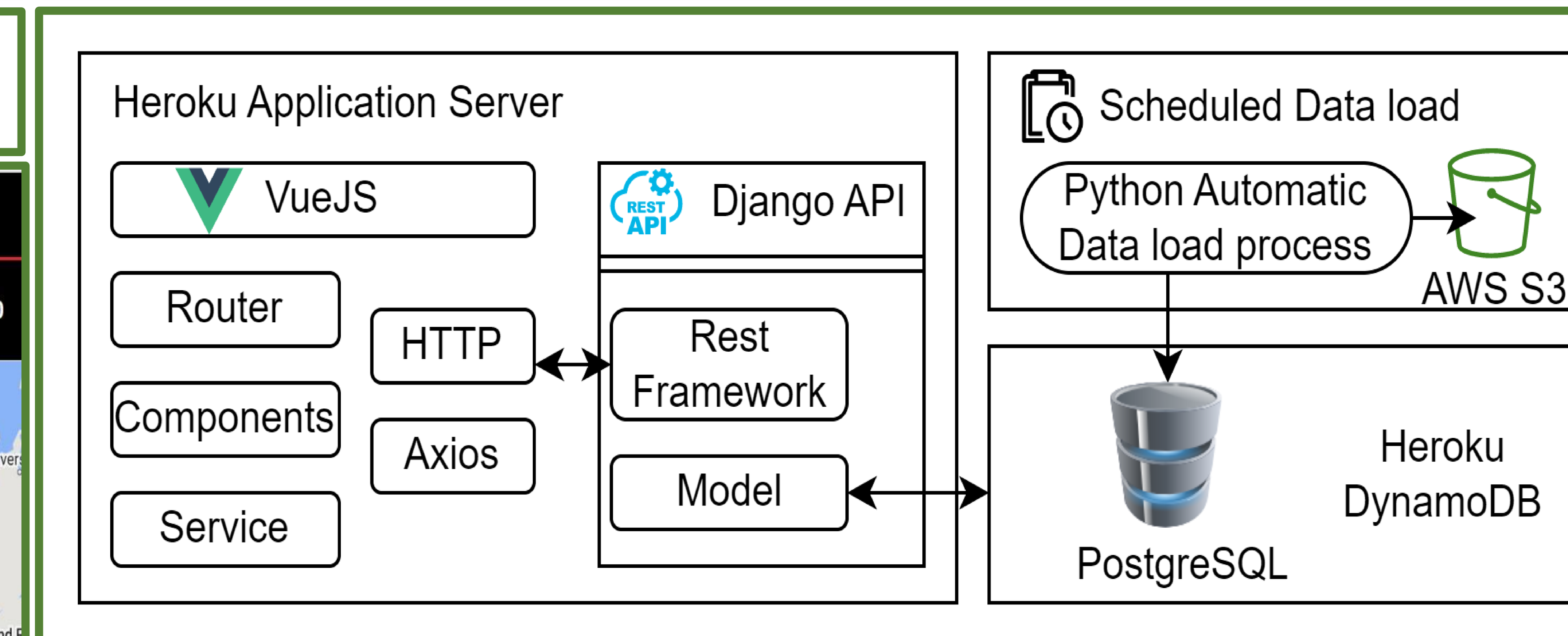


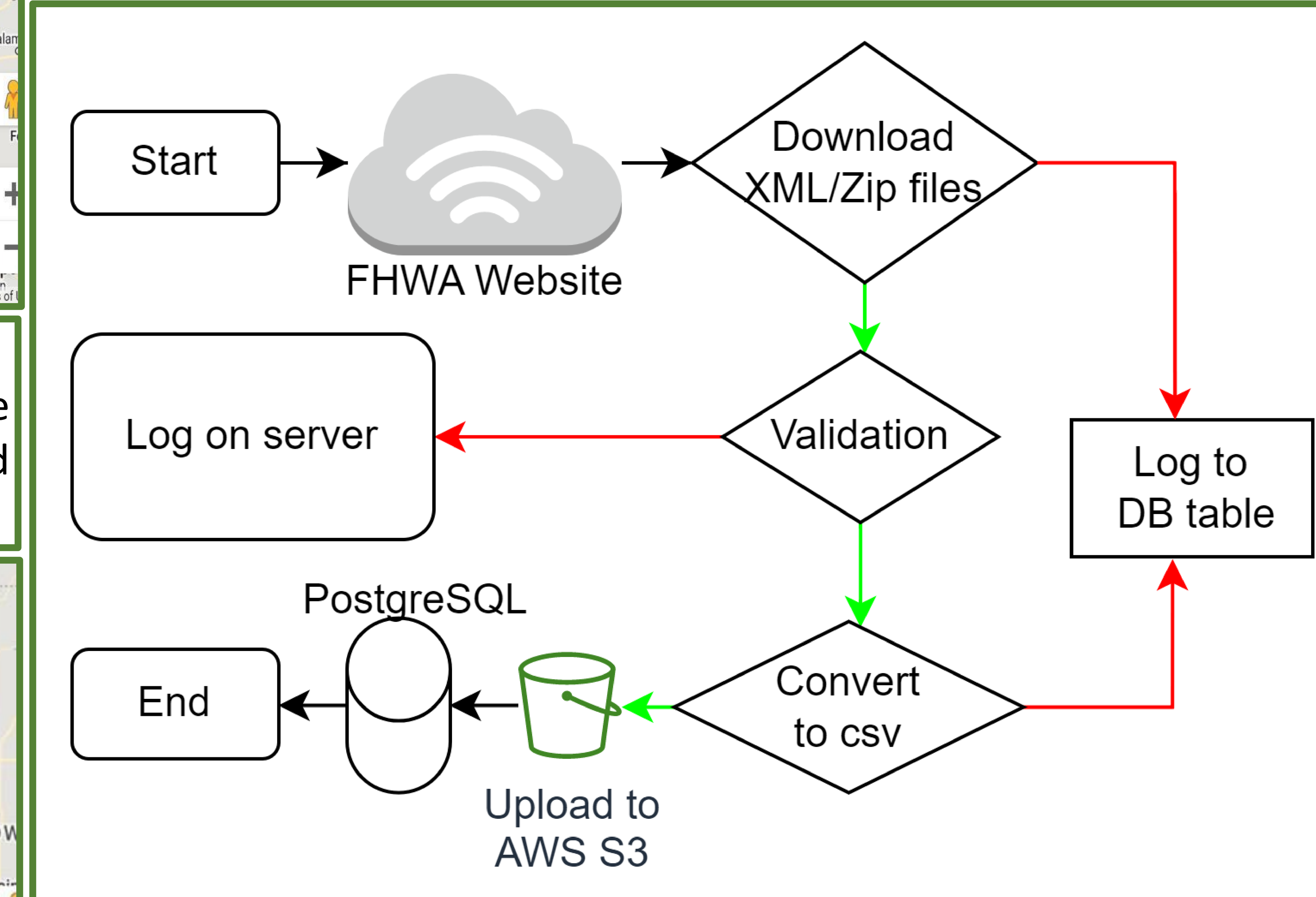
The below image is a snippet from the admin page where infrastructures can be provisioned for various elements. Here infrastructure C005512355 has been provisioned for Seismic sensors and Strain Gauges.



INFRASTRUCTURE	PROVISION	CREATED ON
C005512355	Seismic sensors	May 2, 2023, 8:40 p.m.
C005512355	Strain Gauge	April 30, 2023, 9:31 p.m.
C007804910	Strain Gauge	April 30, 2023, 9:31 p.m.
C002801720	Strain Gauge	April 30, 2023, 9:30 p.m.
C002800420P	Strain Gauge	April 30, 2023, 9:28 p.m.

Architectural Diagram





Applications of NIA

- NIA is a one-stop shop that integrates data from a wide range of data sources.
- NIA can be used by bridge engineers to analyze the condition of bridges over the years.
- NIA can be used to predict trends which can be used for improving current bridge conditions and in the construction of new bridges.

This project is partially supported- by

NSF Award Number:1762034, Spokes: MEDIUM: MIDWEST: Smart big data pipeline for Aging Rural bridge Transportation Infrastructure (SMARTI)

US Army Corps of Engineers, Engineering Research and Development Center grants W912HZ21C0060 – Multilevel Analytics and Data Sharing for OPerations Planning (MADS- OPP) and W912HZ23C0005 – SMART Analytics for Critical Infrastructure inside a Resilient Data Fabric (SMART-RDF).

Non-contact Bridge Response Measurement: Monitoring Nebraska's Closed County Bridges

Roya Nasimi, Ph.D., Mubarak Abu Zouriq & Daniel G. Linzell, Ph.D., Department of Civil & Environmental Engineering, University of Nebraska-Lincoln, Lincoln, NE

Introduction

Bridges in Nebraska

- Nebraska has over 15000 bridges
- More than 9% of the county bridges are in poor condition[1]
- They are regularly being monitored for safe operations
- Over 7% of the bridges are closed due to safety concerns
- Commonly, they are being inspected visually by the trained engineers
- Traditionally, bridge assessments are done visually by experts or via using contact sensors

[1] "Nebraska Department of Transportation"

Traditional Bridge Inspections

Limitations of Traditional Inspection Methods and Contact Sensors:

- Access to the bridge
- Needs to be fixed and be installed properly
- Safety
- Installation cost

Cameras for inspections:

- Cameras are low-cost and accessible
- They are light and easy to use
- They have become popular for bridge inspections
- Data recording and storage is easy

Smartphones and low-cost cameras options for bridge inspections

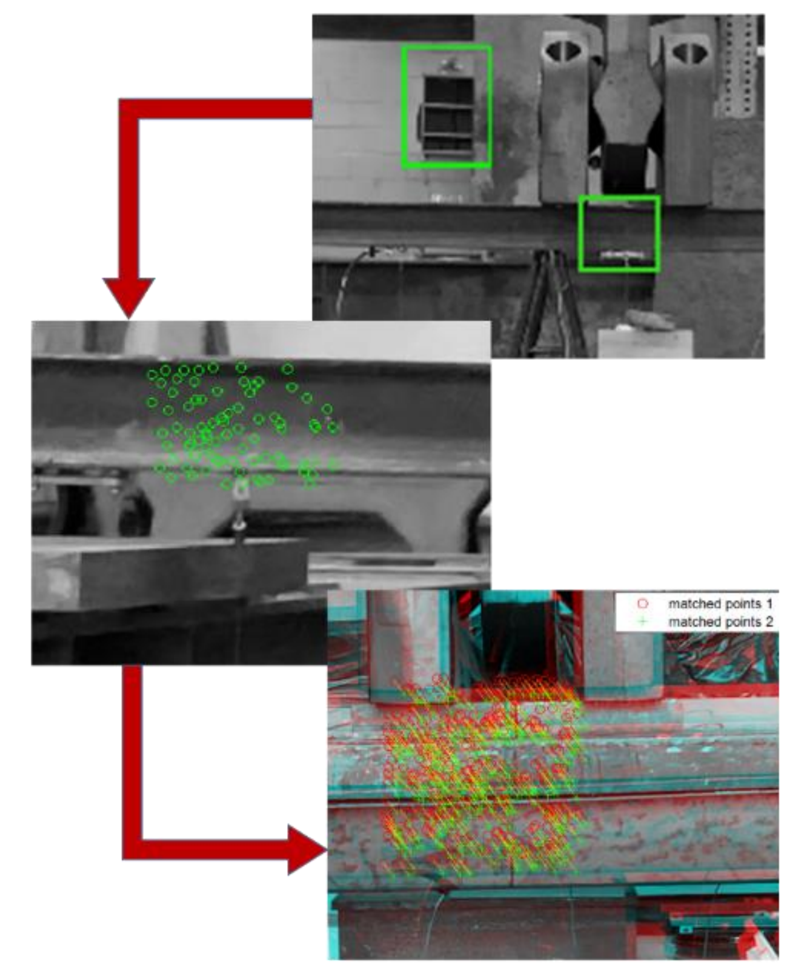
Computer Vision for Motion Tracking

Extraction of Displacement Using Cameras

- Computer vision methods can find different information from the video frames, including displacement
- Displacement estimation can be accomplished using targets or without adding any target to the structure

Steps for Extraction of Displacement from Cameras

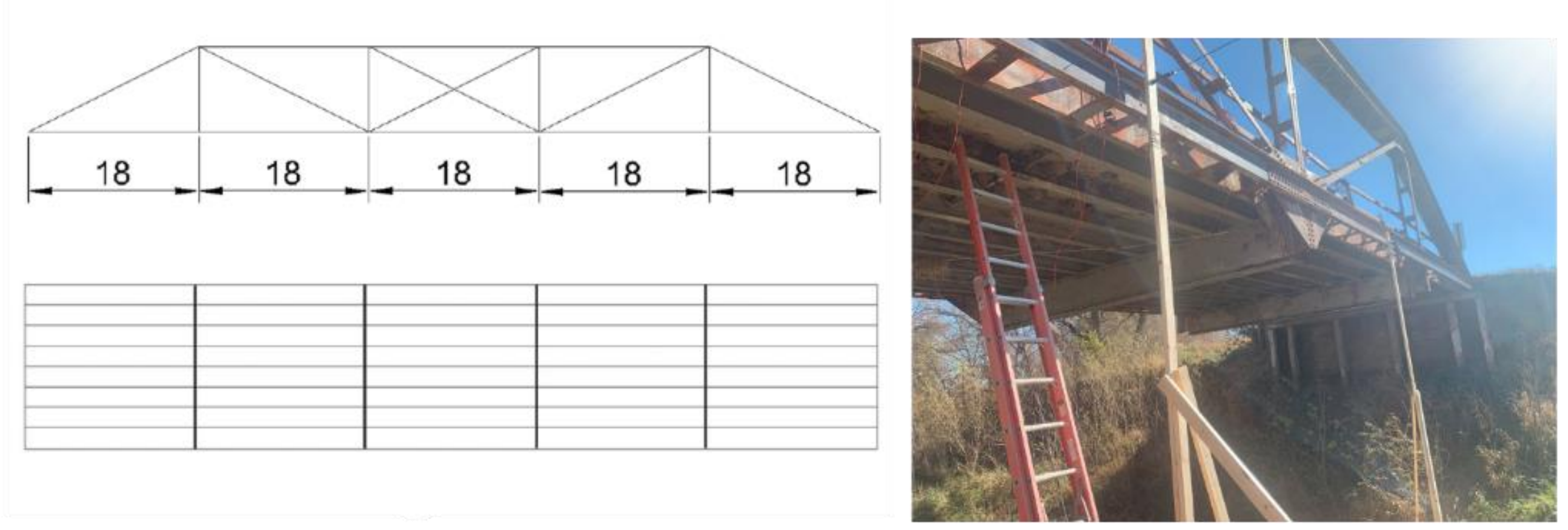
- Identify regions of interests
- Detect feature points
- Track motion by matching feature points across frames
- Convert measurements to world coordinates



Feature points extraction and matching

Selected Bridge (D041) and Sensors

- An out of commission bridge was selected
- The bridge is a 90 ft steel truss bridge with a concrete deck
- The bridge and the site were instrumented with contact and non-contact sensors/cameras
- Dynamic loading was imposed on the bridge using a 26 ft U-Haul truck
- 48 strain transducers and 4 accelerometers were mounted on the bridge for contact-based health assessment and damage detection



(a) (b)

Selected bridge's (D041): (a) elevation and plan view; (b) bridge site.

Bridge Test

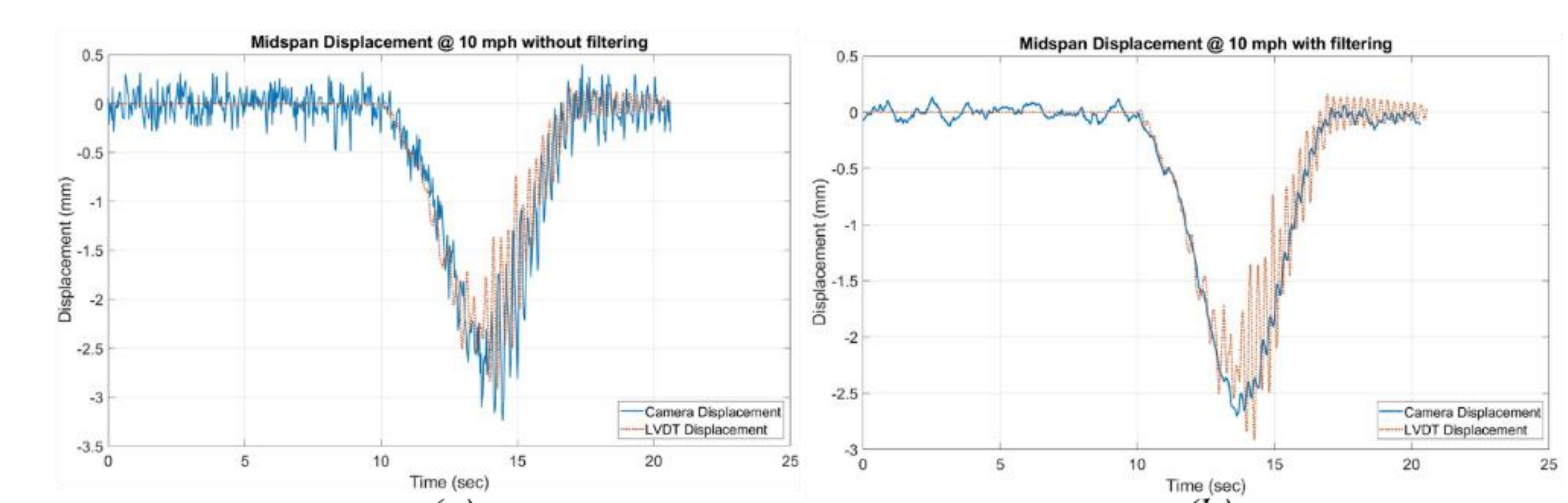
- Three cameras were set up at distances of 18', 20', and 37' on west side of the bridge
- Ground truth values were measured using LVDT on the west side of the bridge

Bridge instrumentation and experiment

Displacement Estimation

- Sample of results for camera and LVDT measurements at Midspan point.
- The U-Haul truck crossing the bridge with 10 mph speed.
- Data filtration applied using Simple Moving Average (SMA) filter:

$$Disp_{filtered}(n) = \frac{1}{w}\sum_{i=n}^{n+(w-1)} Disp_{UnFiltered}(i) \qquad w\text{: window size}$$



(a) (b)

Measured Displacements using Camera and LVDT: (a) With Filtering; (b)without Filtering

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Bridging Big Data Convoys:

Calculation and Visualization of Novelty Index in AWS

Nethakani Rahul Kumar

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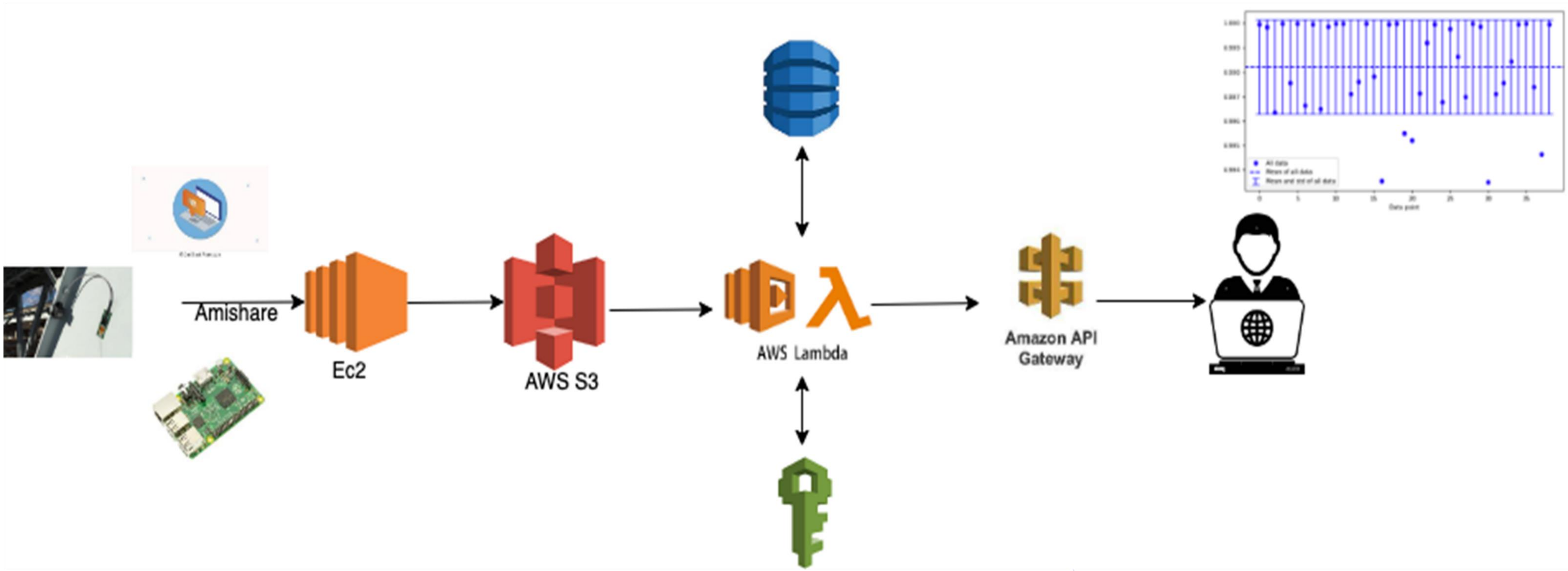
University of New Hampshire: *Dr. Yashar Eftekhar Azam Kinnami: Jim Burke*



- Generates TDMS File from sensor data.
- Store data in Rasberry-pie using aws green grass.
- Transfer files to Ec2 instance through Amishare.

- Mount S3FS file system in Ec2 instance and move to S3 Bucket
- Generate Novelty Index and store then in DynamoDb using lambda Functions
- Restrict lambda access by adding necessary IAM permissions.
- Generate end-point using Api-gateway for front-end to access

- Web access to Client to view damage Index
- Flexibility to use filters to see only necessary data

Building Explainable Machine Learning Lifecycle:

Model Training, selection, and deployment with Explainability

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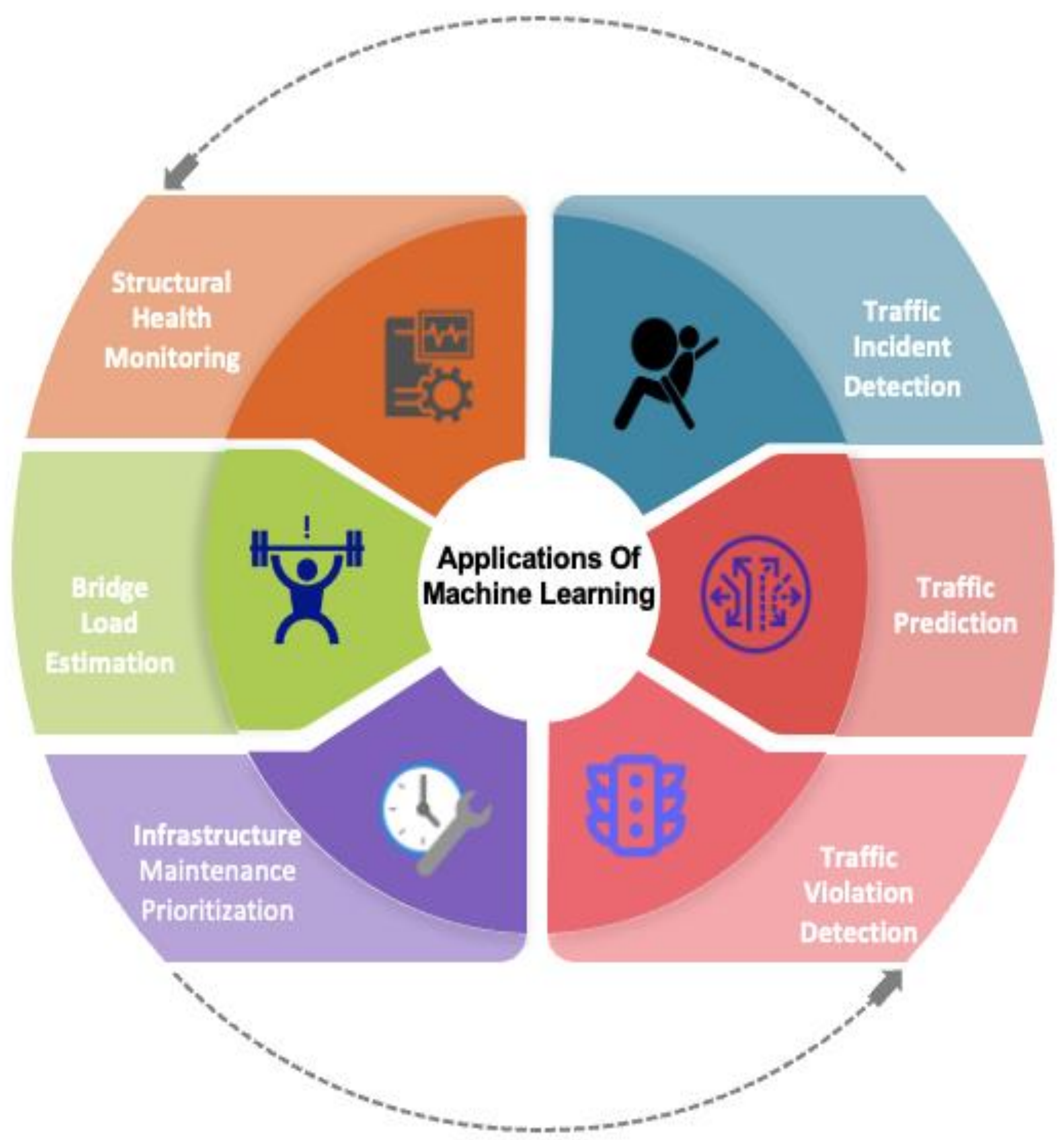
Machine Learning

Machine learning has rapidly gained popularity in recent years and has become an essential component of numerous domains, including critical domains such as infrastructure maintenance and monitoring. In order to build effective machine learning models, it is essential to have a deep understanding of the end-to-end pipeline and the tools and platforms available for building it.



machine learning in different domains

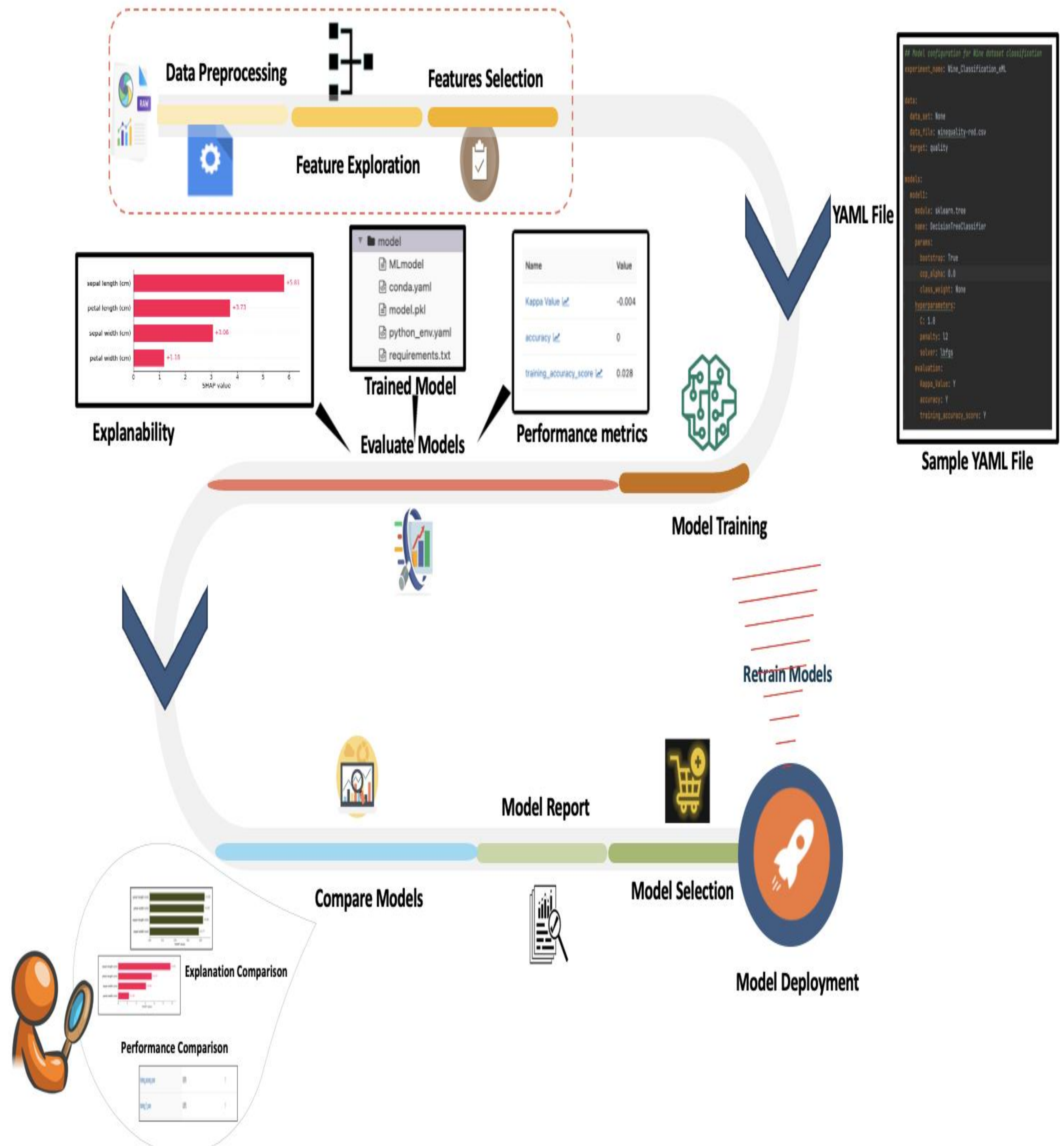
State-of-the-art open-source MLOps platforms

mlflow
Apache Airflow
Kubeflow
Pachyderm
DVC

Machine Learning Lifecycle

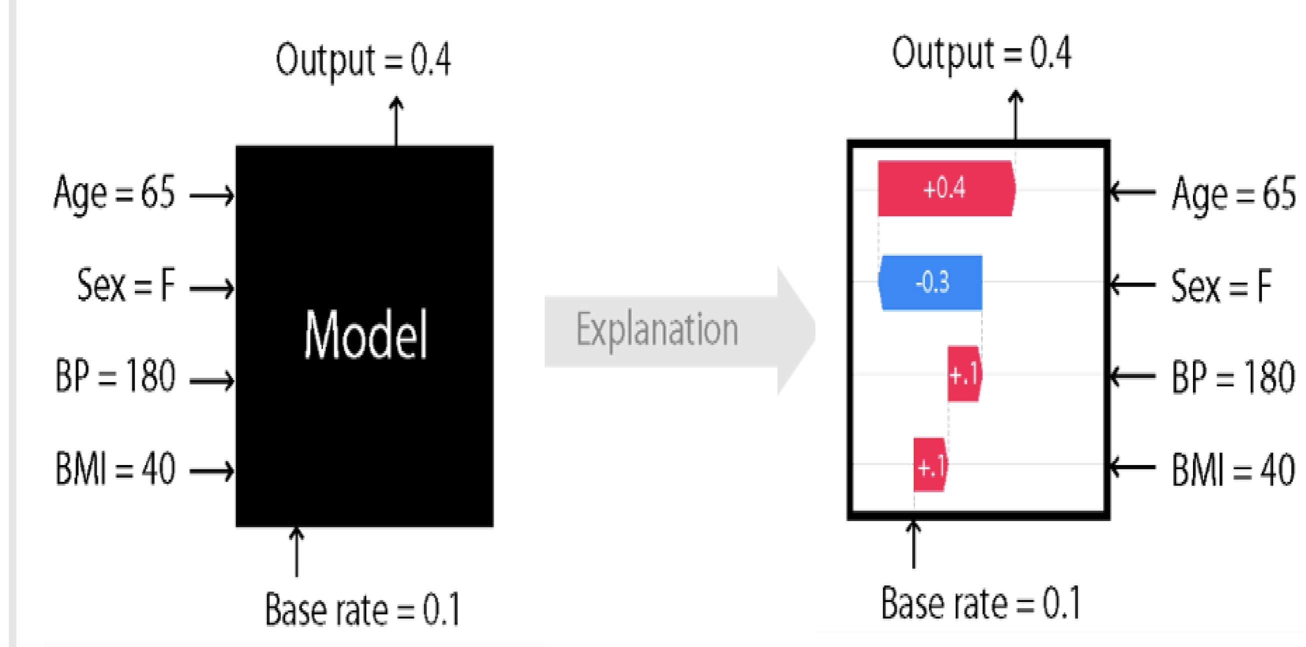
A set of interrelated stages for training and deploying machine learning models. It is divided into phases, each with its own set of activities and needs. It needs an important component – Explainability.

Building Explainable Machine Learning lifecycle with MLflow



Why add Explainability in ML Engineering

Explainable models help build trust in machine learning systems, as users and stakeholders can better understand the rationale behind the model's predictions or decisions. This transparency is particularly important in sensitive domains like healthcare, finance, infrastructure, and traffic, where the consequences of model decisions can be significant .



Model explanations [3]

Acknowledgements

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[3] Shap documentation, Retrieved May 5,2023,from https://shap.readthedocs.io/en/latest/index.html

University of Nebraska Omaha

Progress in a New Visualization Strategy for ML Models

A Mid-Project Summary of Design and Ongoing Problems

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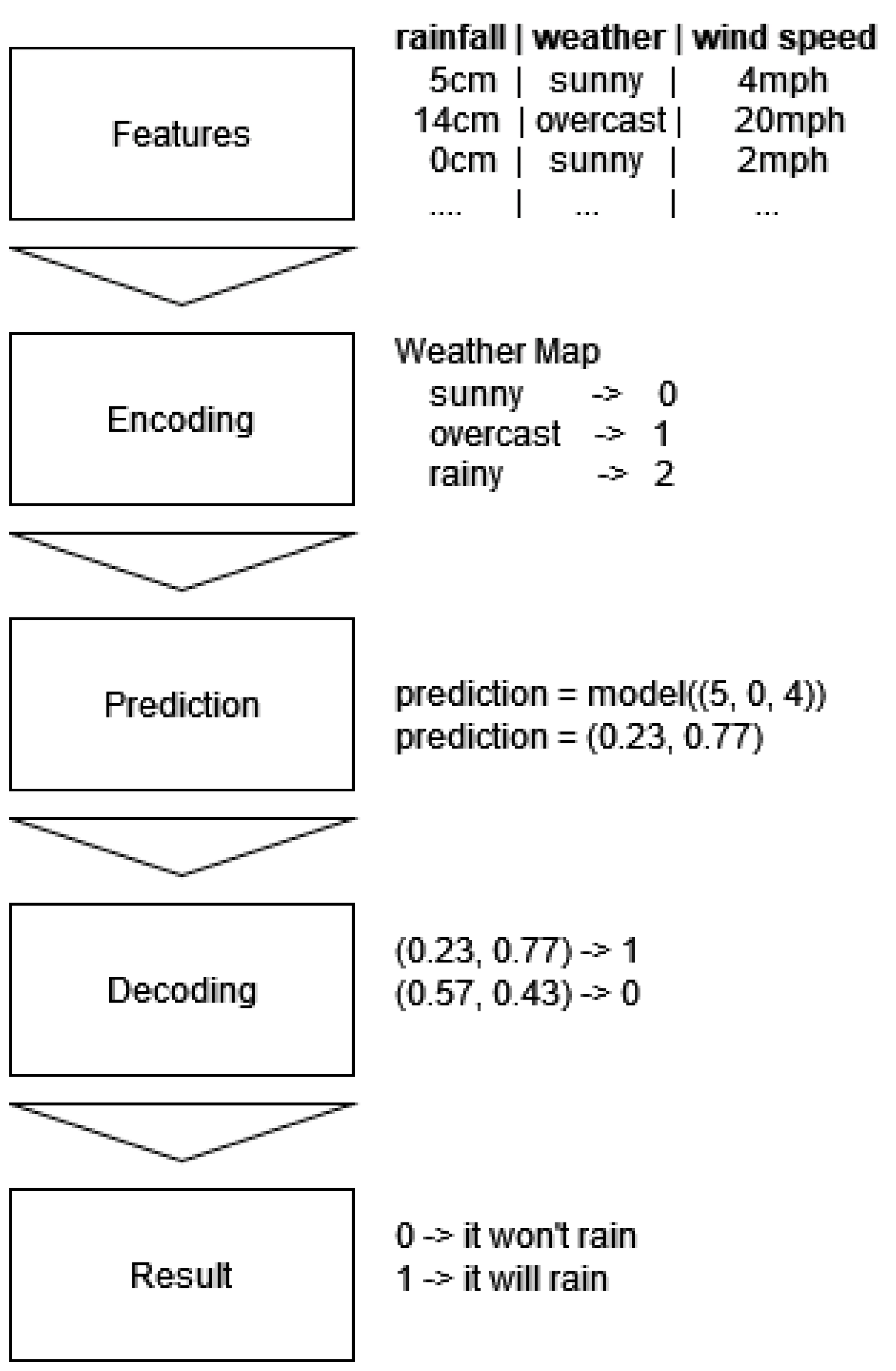
Background

Overview of ML Models

Machine Learning Models are trained on datasets which are encoded into numbers. The models are then evaluated for effectiveness, eventually yielded a model which can somewhat accurately make predictions based on correlations from the input.

Machine Learning Models take a set of features, or categories of data, and encode them into numbers; a model then is able to be sent information to make predictions. After a prediction is made, it must be interpreted via decoding. This then leads to a result.



The above graphic shows a model deciding whether it will rain or not given recent amount of rainfall, wind speed, and the current whether condition.

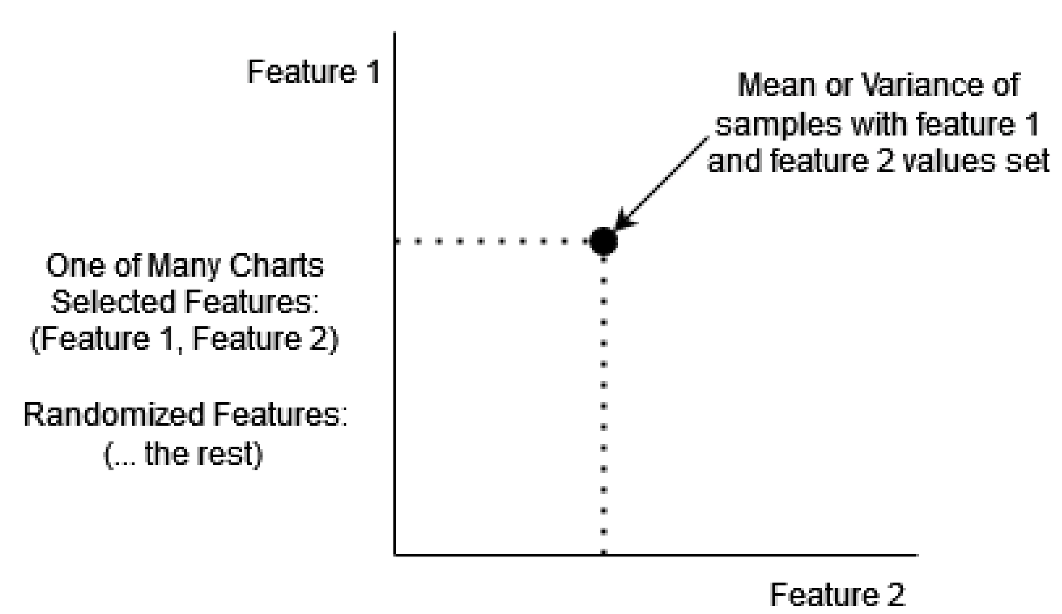
Visualization

Main Idea

This visualization strategy takes two selected features and draws a graph with the model's output embedded in a color gradient.

At a coordinate (feature 1, feature 2), the model can be ran by generating random, acceptable values for additional features. The model is polled a number of times, each time with the selected features remaining the same, but other features randomly generated. Model output is aggregated in a arithmetic mean value.

This mean value is used as the third dimension in the graph, the color gradient.

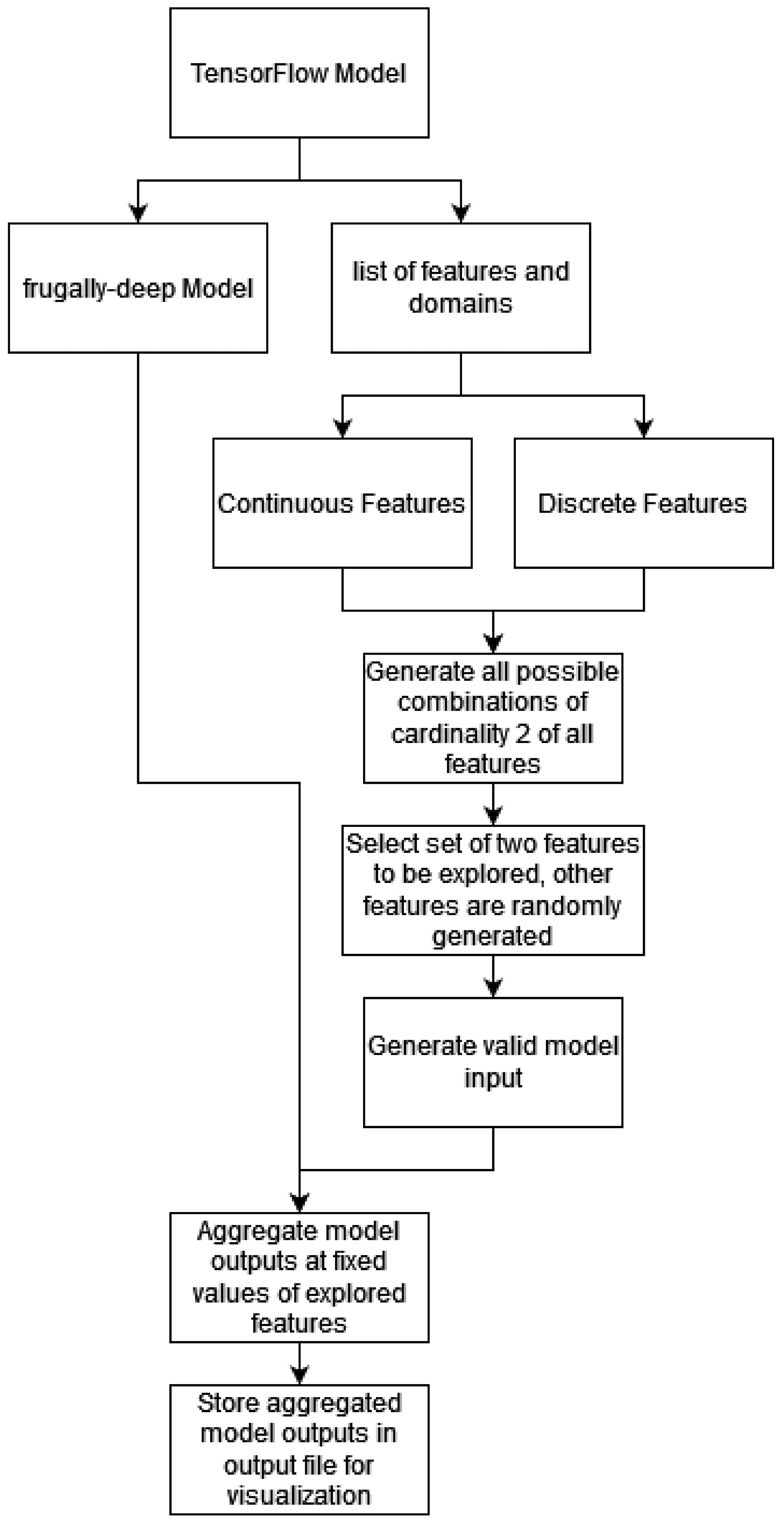


Usefulness of Visualization

Explores Model's Learned Boundary Lines

Decision Tree models create linear, single-axis boundaries, but most other models, including deep-learning models create non-linear boundaries. The goal of this visualization is to find and show those boundary lines as they exist in a relation between two features.

Design



Visualization

D3.js is used to create a heatmap, a cell a coordinate whose color is determined by a linear interpolation along a gradient using the mean.

Challenges

- Achieving linguistic performance and memory control when models originate from Python-based Tensorflow programs
  - Resolved with the frugally-deep github repository and using C++ to generate visualization data
- Learning about ML and how it's organized just before and just after a prediction is made
  - Talking with my team members and experimenting with the model in Python and C++ has given me a better understanding of machine learning
- .Managing different types of input (Discrete vs Continuous)
  - An incremental approach was used to explore the continuous space, represented using floating-point values. The discrete values are only calculated once if not matched with a continuous, saving runtime

Work In-progress

- Incremental Variance Algorithm alongside arithmetic mean
- Expanding visualization technique beyond binary models
- Managing inter-feature constraints during random generation and feature selection
- Usage of this visualization technique to explore a model trained on the Iris dataset

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