

BBD 2023 Lightning Talks

This slide deck contains the slides used in the Bridging Big Data 2023 Workshop.

Note that the name title slides have been removed for conciseness.

Note also that some of the posters were updated after they were added here.

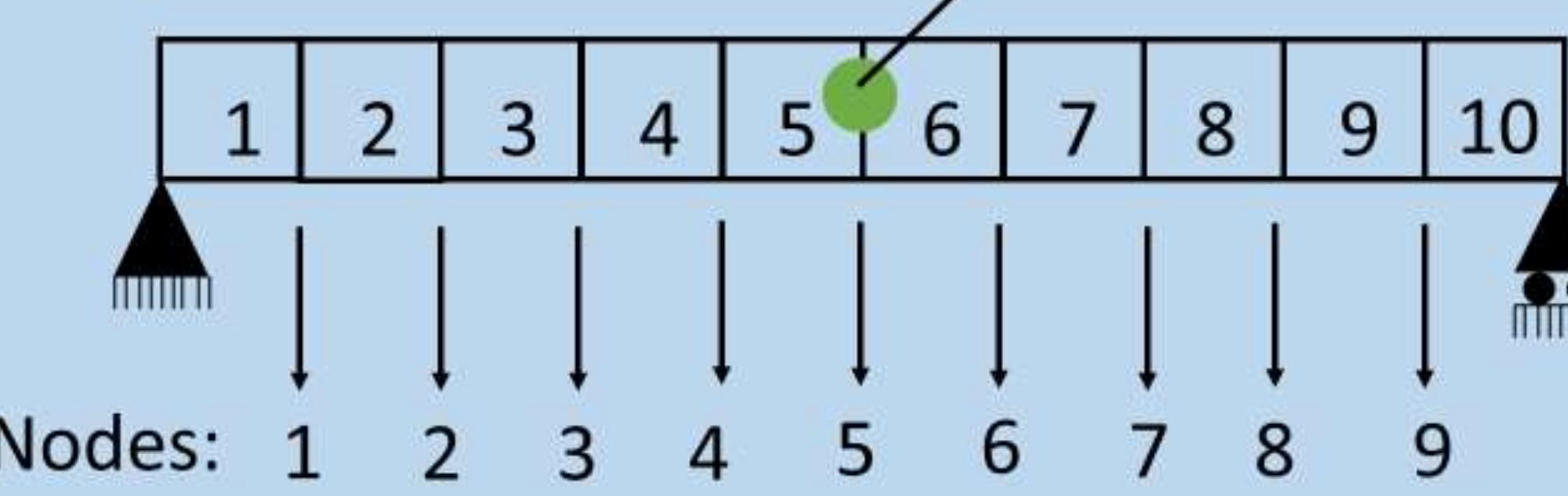
Bridging the Gap with Machine Learning Techniques: Structural Damage Detection Framework in Bridges

Burak Duran¹, Saeed Eftekhar Azam¹¹Department of Civil and Environmental Engineering, University of New Hampshire, Durham, NH

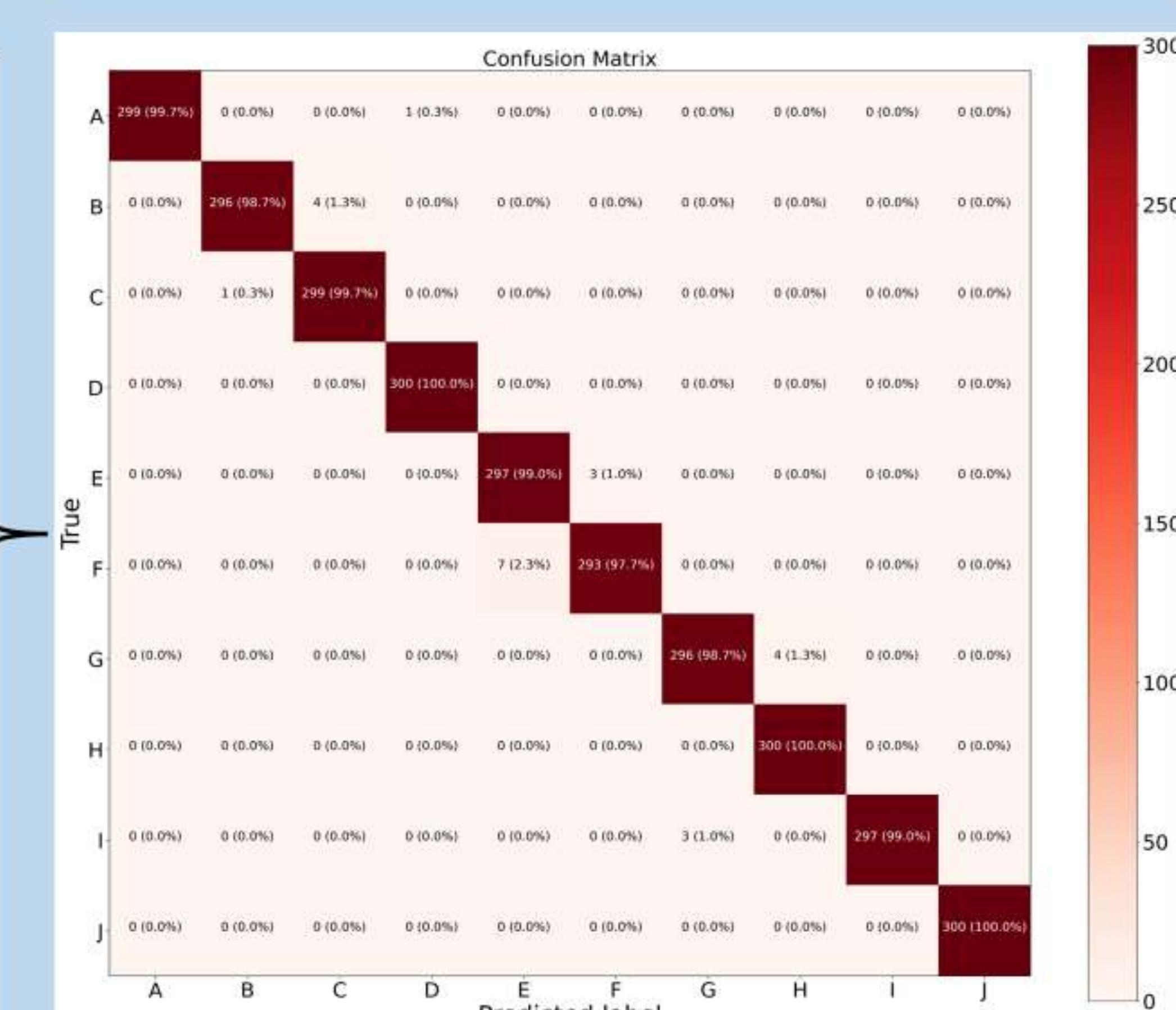
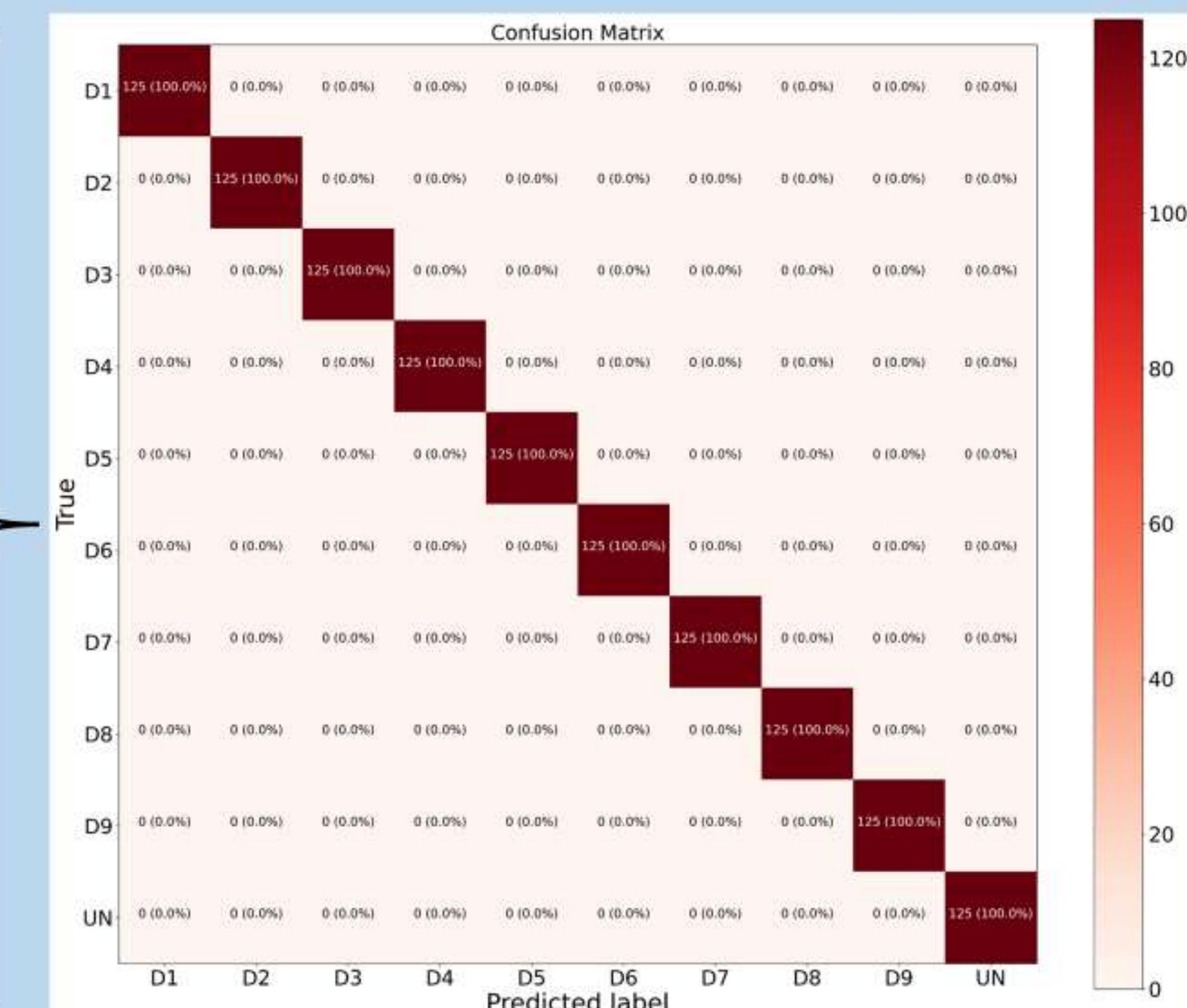
Supervised Technique: Deep Learning-based Two-step damage detection using Convolutional Neural Network

Step-1 Identification of damage severity

Apply load time-history

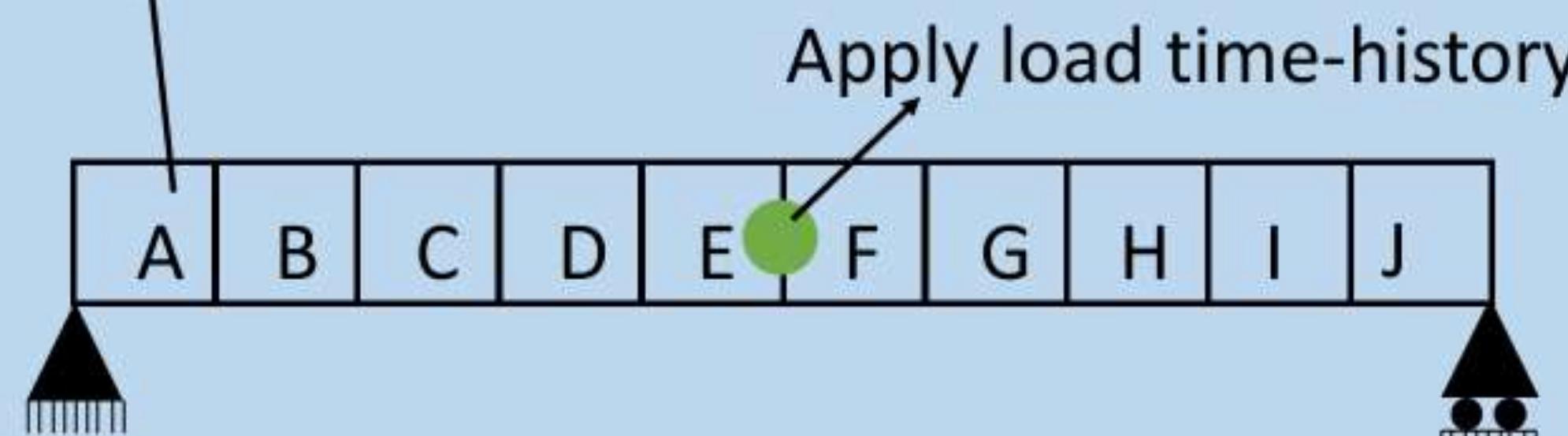


- Damage is represented by EI reduction (10%, 20%, ..., 90%) at Member-5
- D1 is the heavily damaged case whereas the UN is the healthy case.
- Obtain the acceleration response at the nodes and convert them into gray-scale images
- %100 testing accuracy

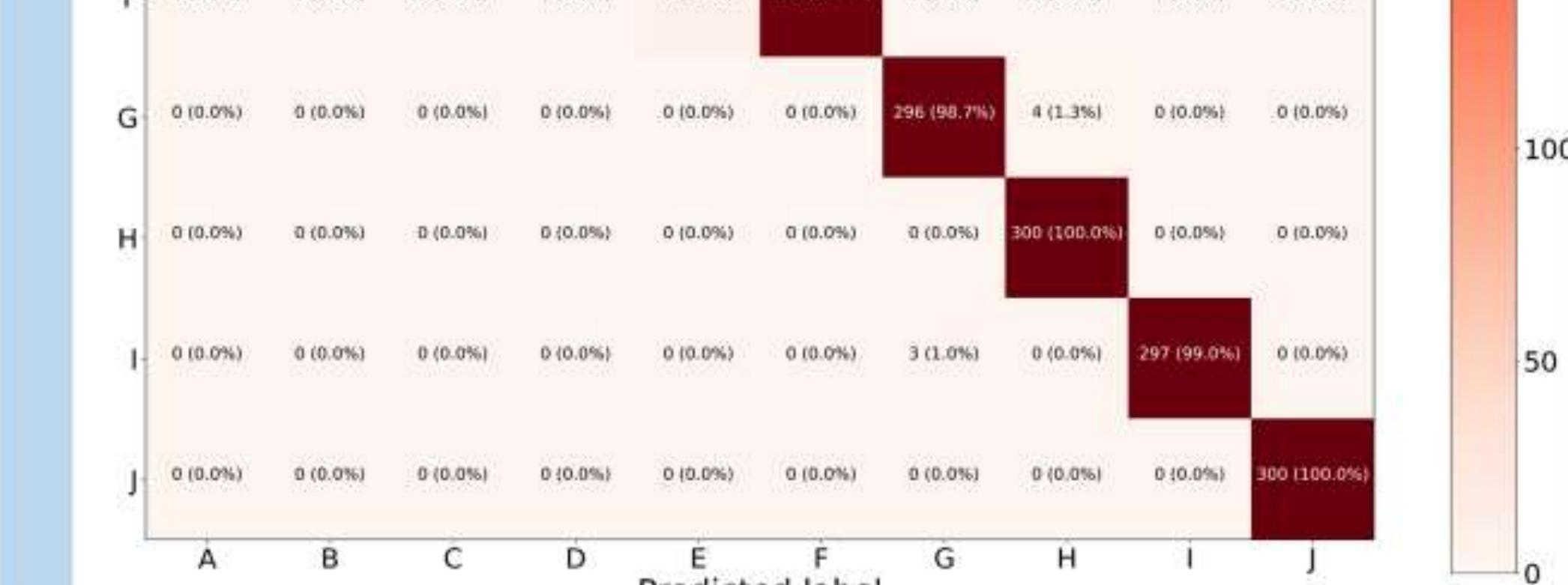


Step-2 Identification of damage location

EI varies within each location along the beam

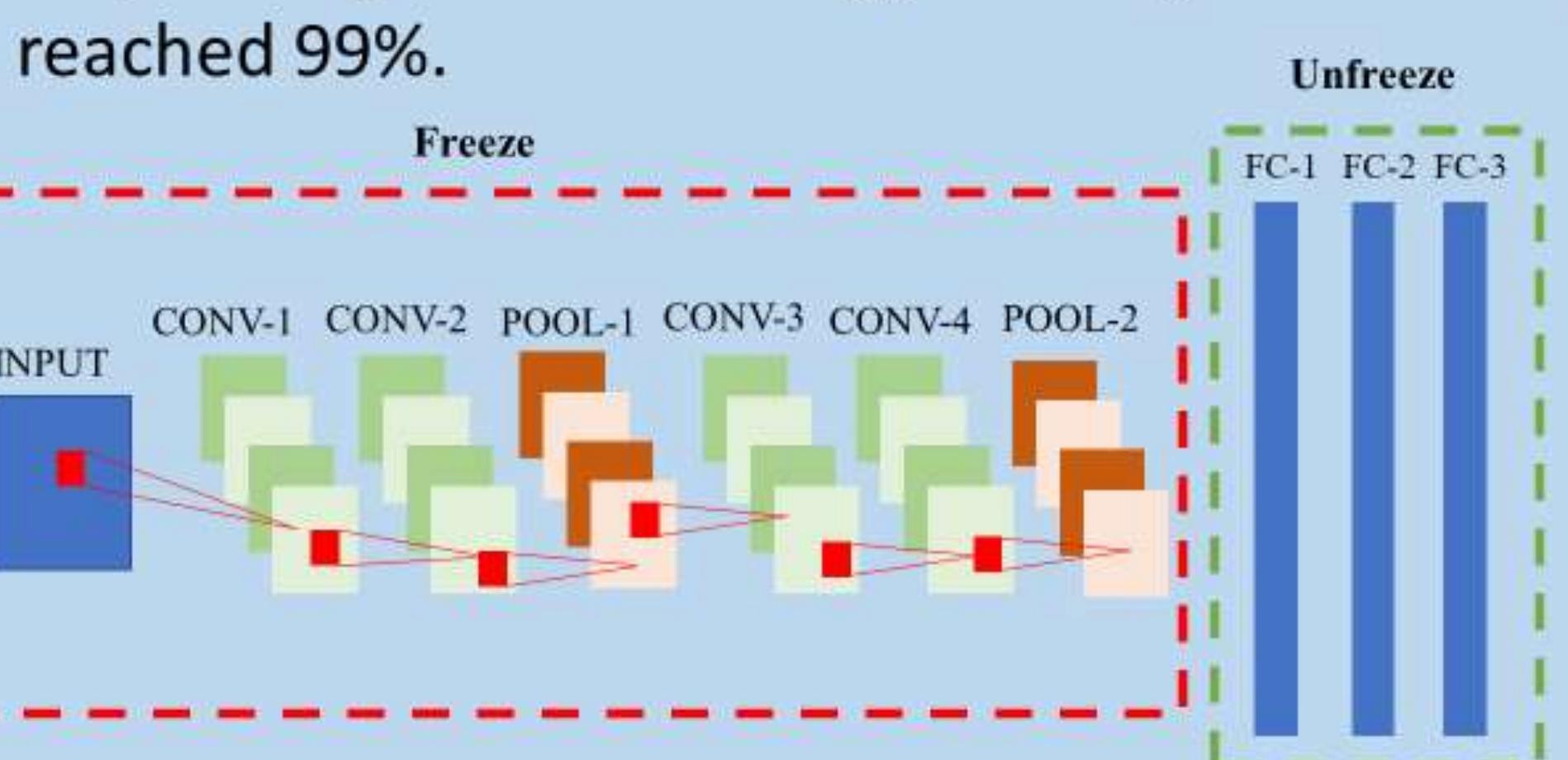


- Collect acceleration sensor data at each node for each corresponding load time history and EI value.
- Convert the data into gray-scale images for the CNN implementation.
- %99 testing accuracy

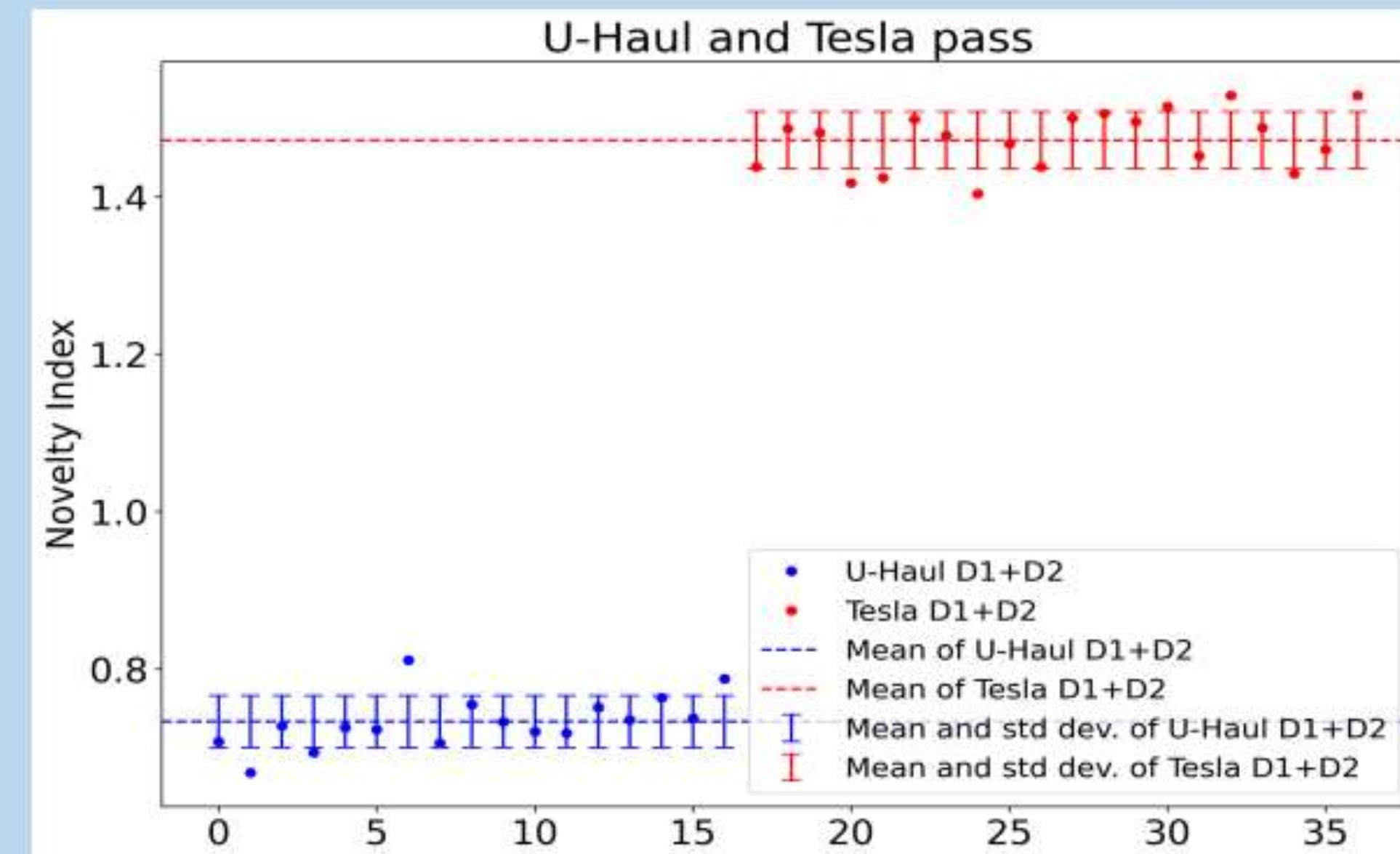
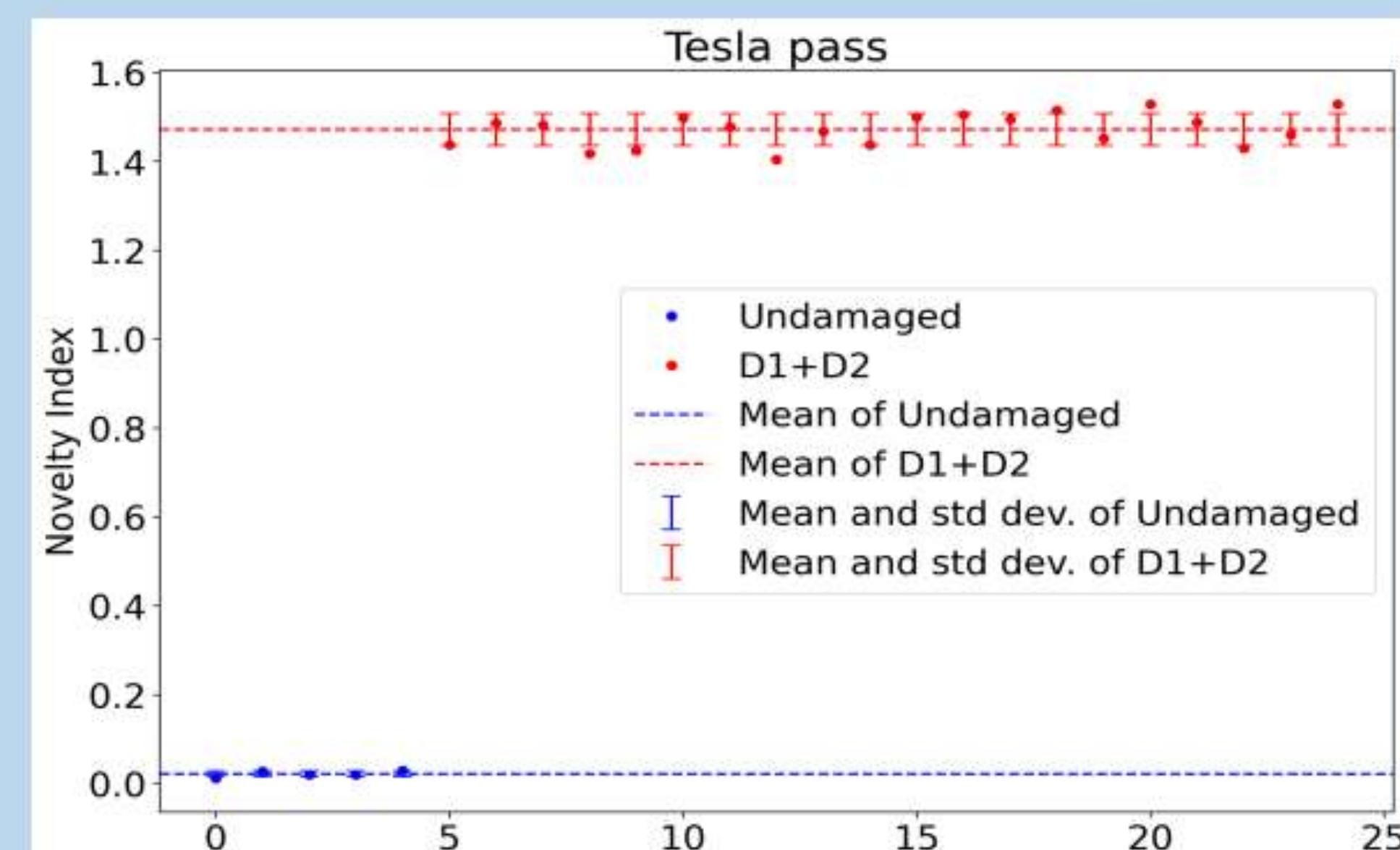
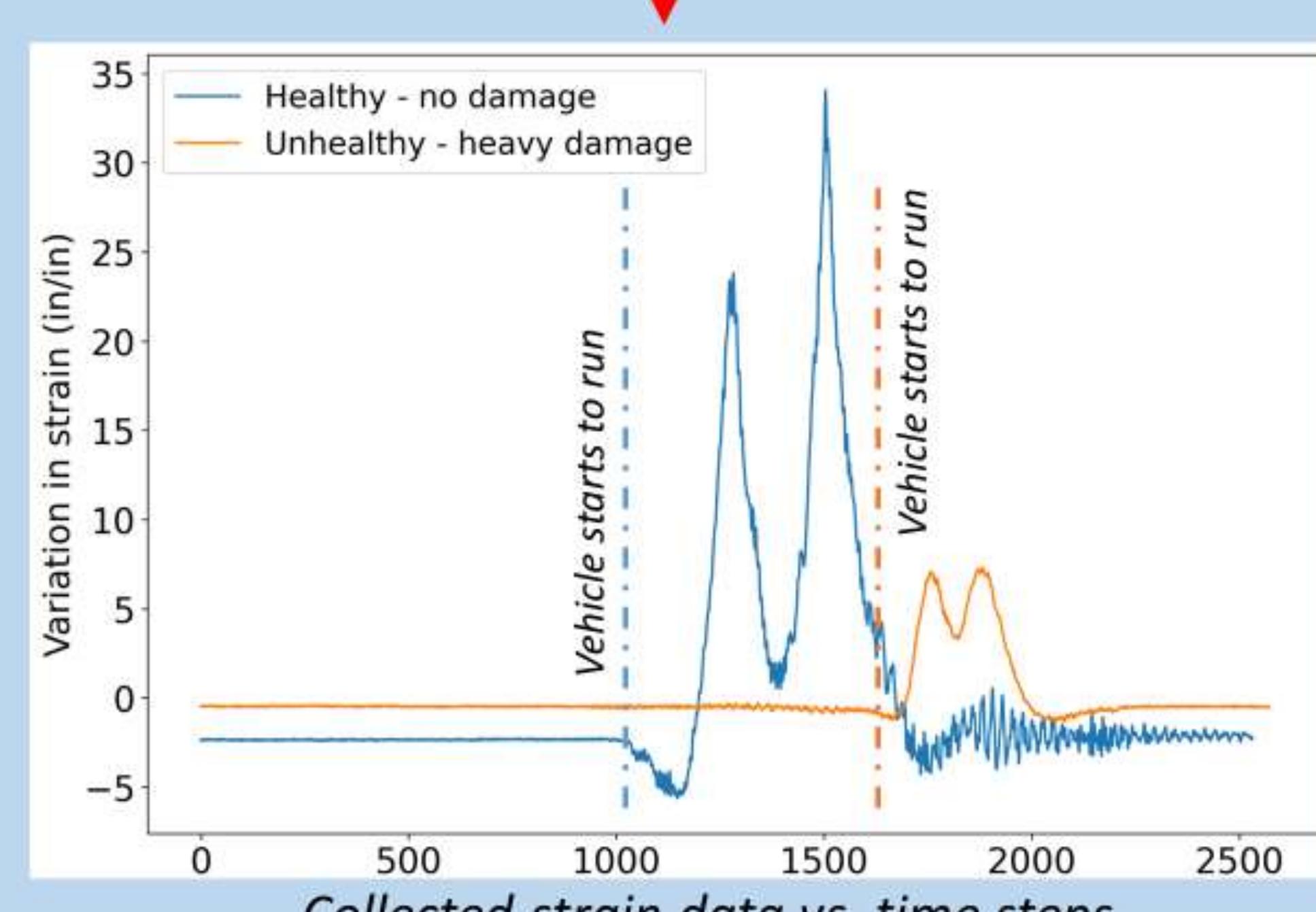


Transfer Learning: Re-weighting

- 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



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 Corps of Engineers, Engineering Research and Development Center grants W912HZ21C0060 – Multilevel Analytics and Data Sharing for Operations Planning (MADS-OPP) and W912HZ23C005 – SMART Analytics for Critical

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

Rola El-Nimri, Daniel Linzell

Department of Civil and Environmental Engineering, University of Nebraska-Lincoln, Lincoln, NE, USA



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.



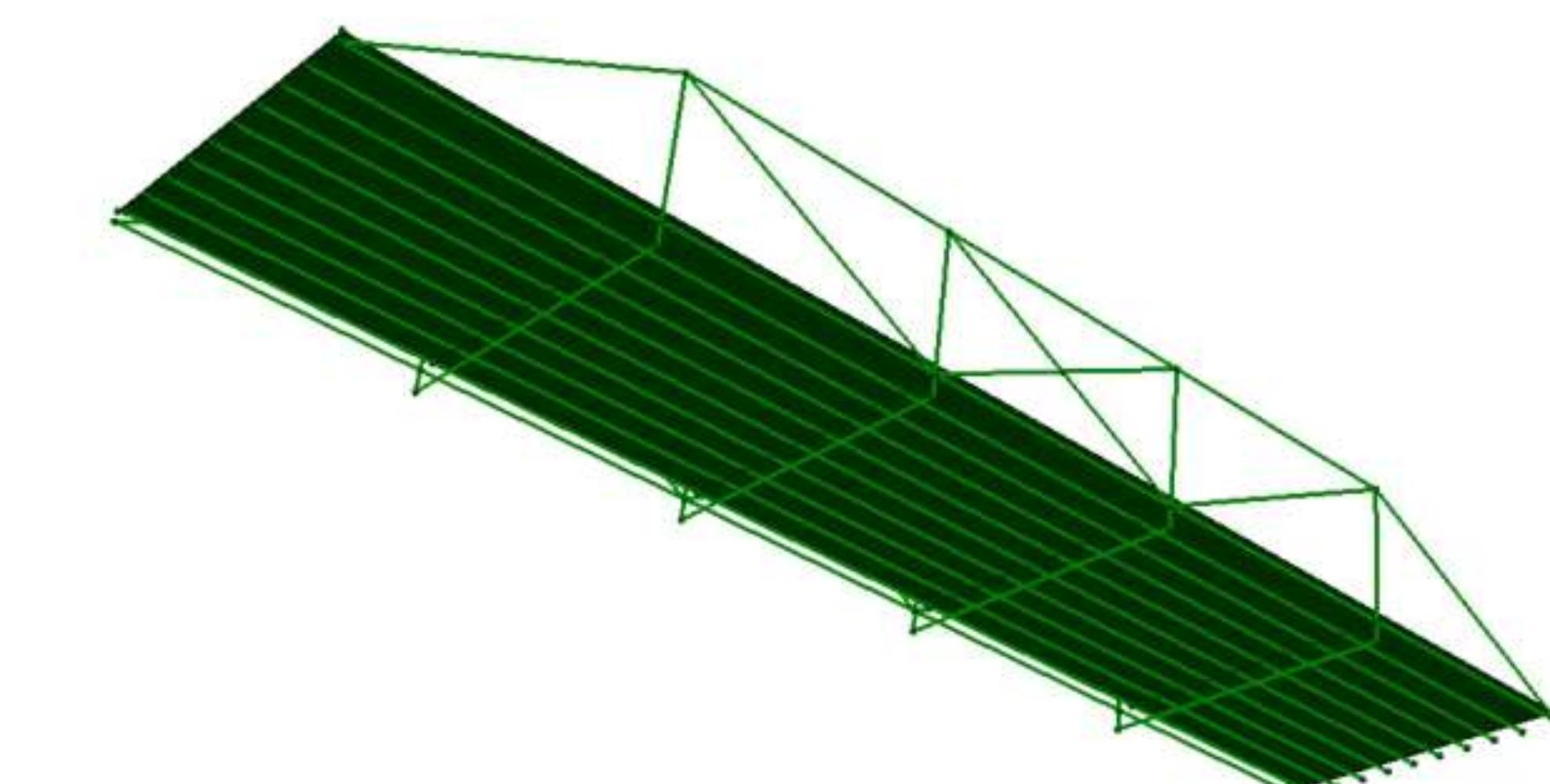
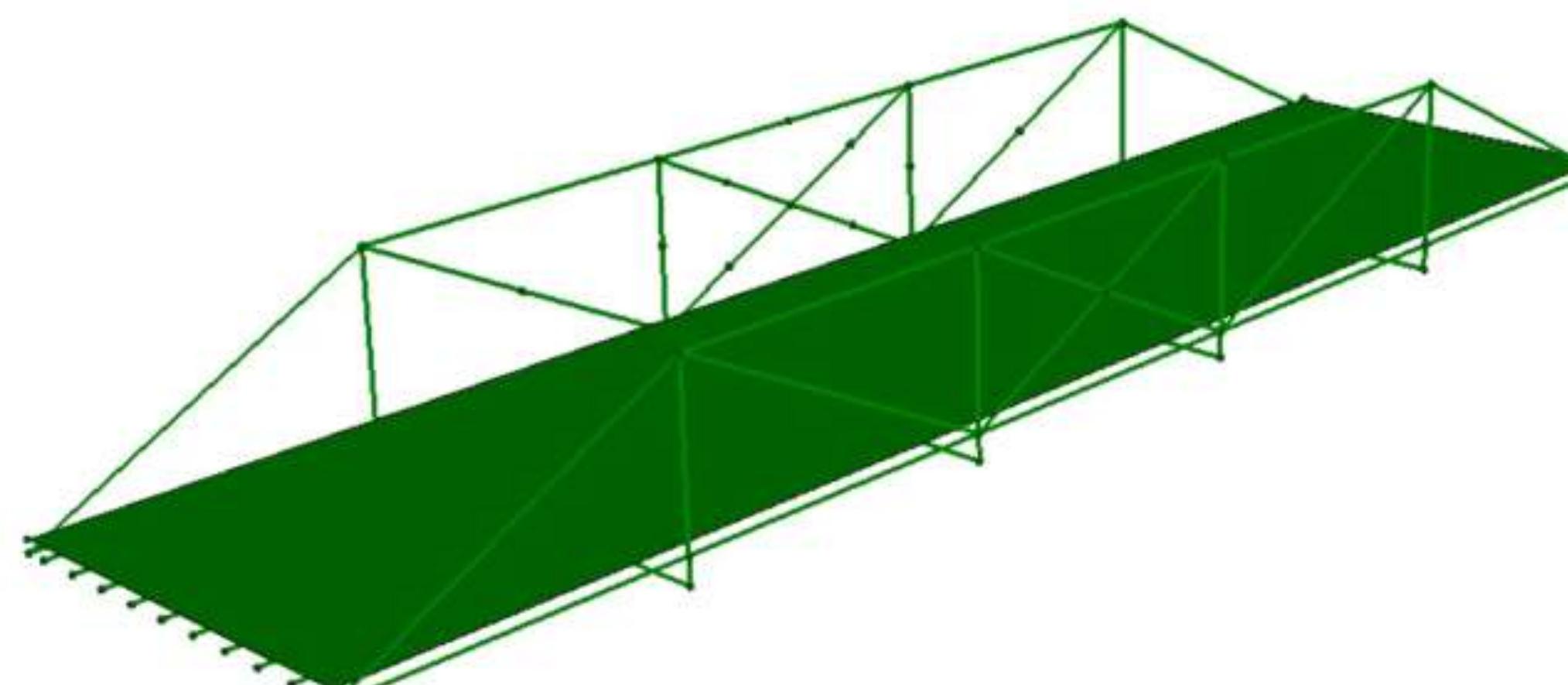
Tests:

- 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.

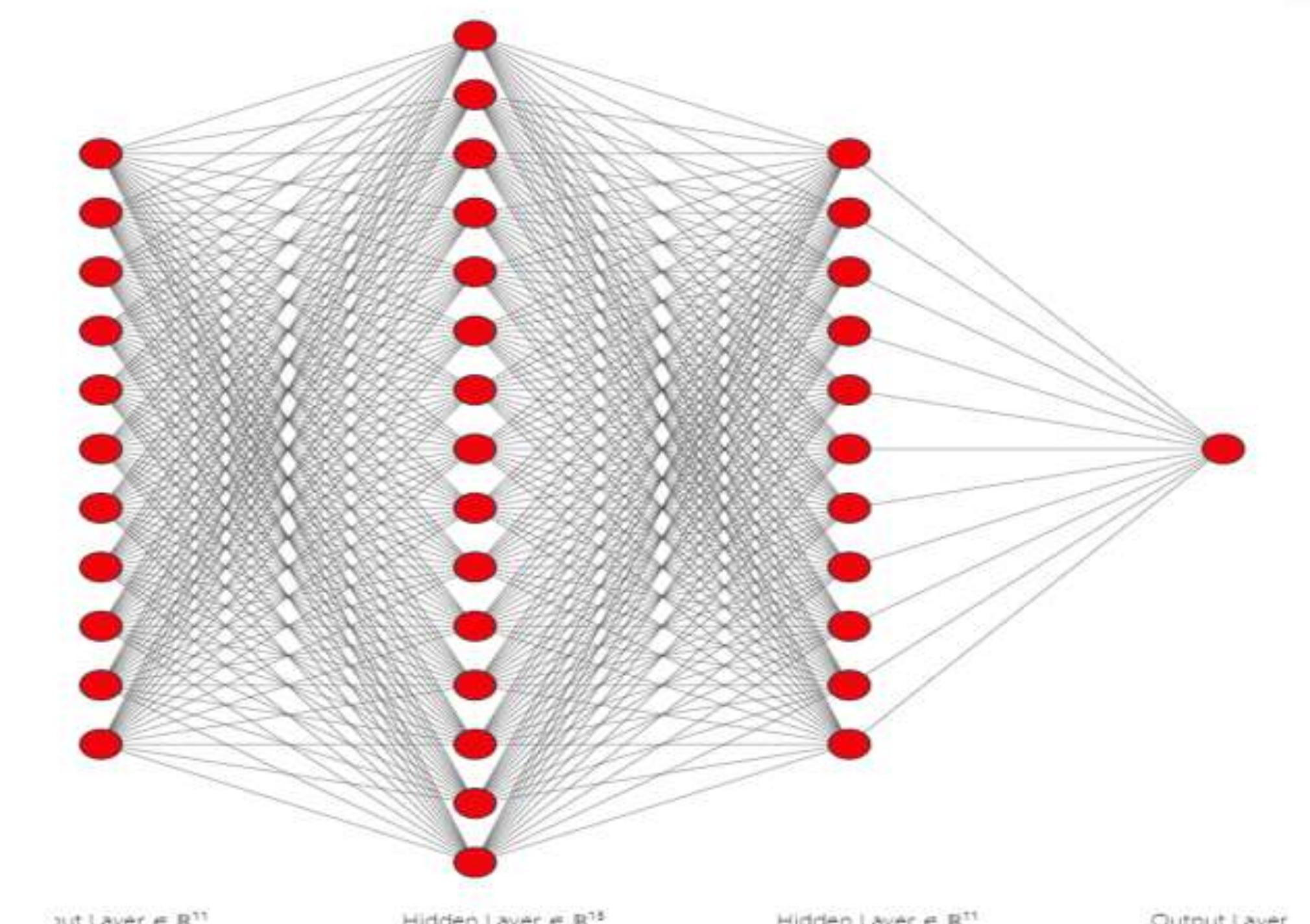


POD-ANN Damage Identification

- Modelling the bridge using OpenSees.

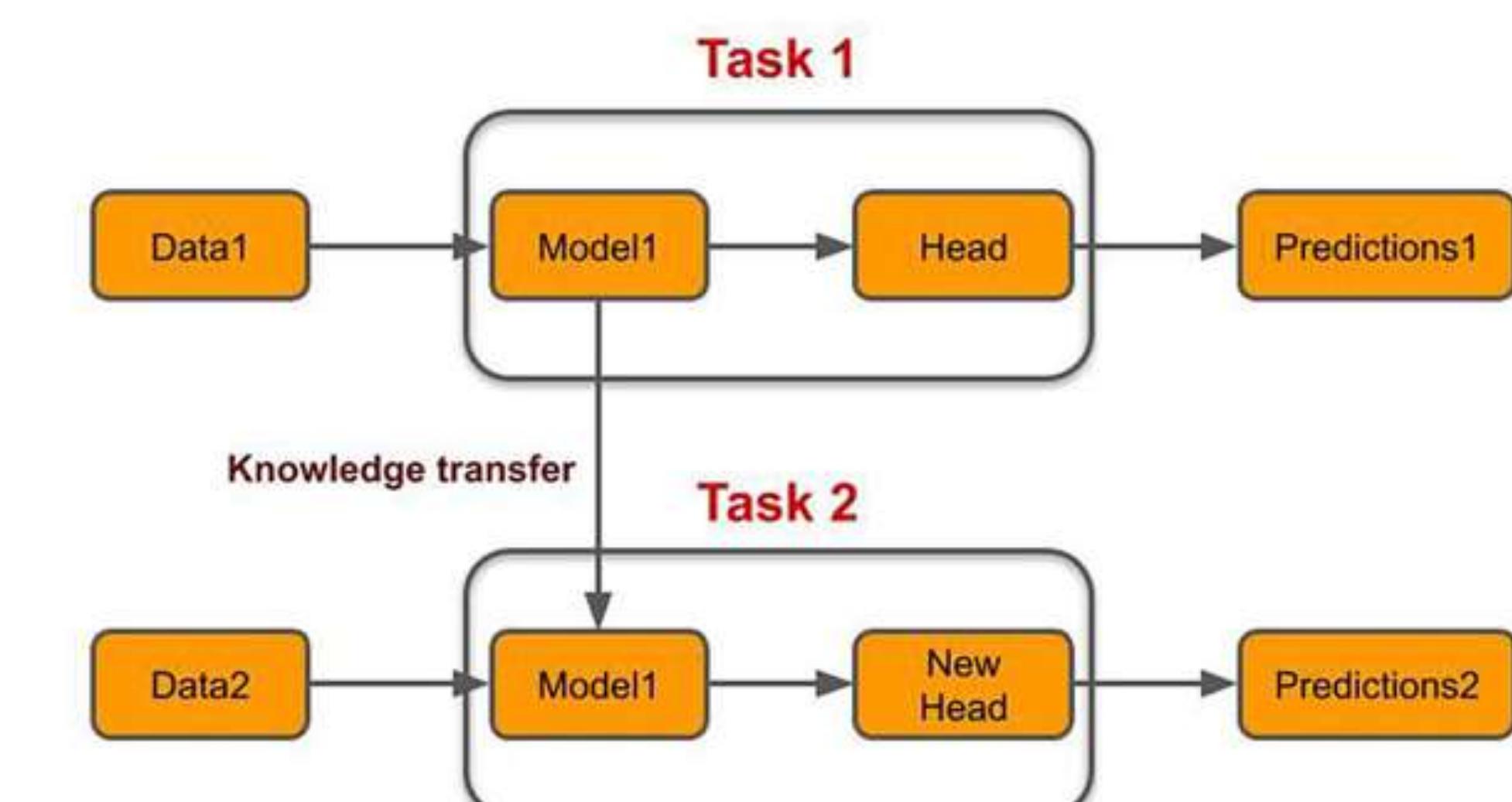


- Generating strain data for healthy and damage scenarios (matching the field).
- Performing the POD and obtaining POMs for the numerical data.
- Training an ANN to detect the POMs – Supervised Learning.
- Performing the POD on the field data and obtaining the POMs.



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.



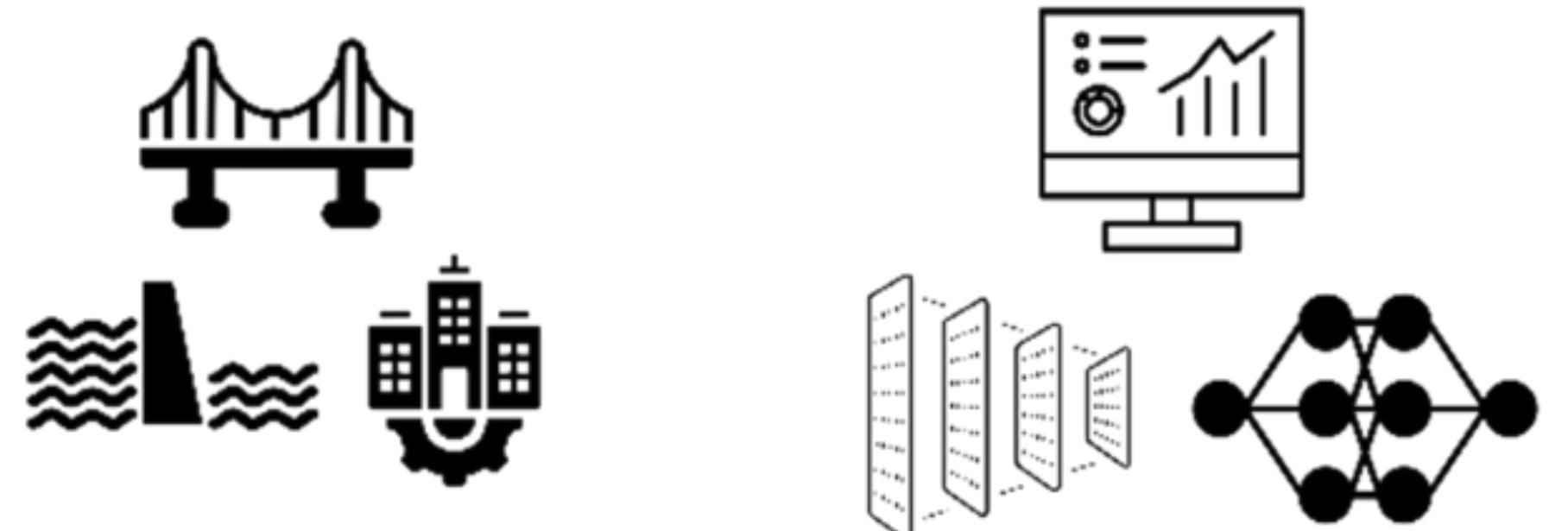
Securing Machine Learning at the Edge for Autonomous Structural Health Monitoring (SHM)



Sheikh Muhammad Farjad (sfarjad@unomaha.edu), Robin Gandhi, George Grispos

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?

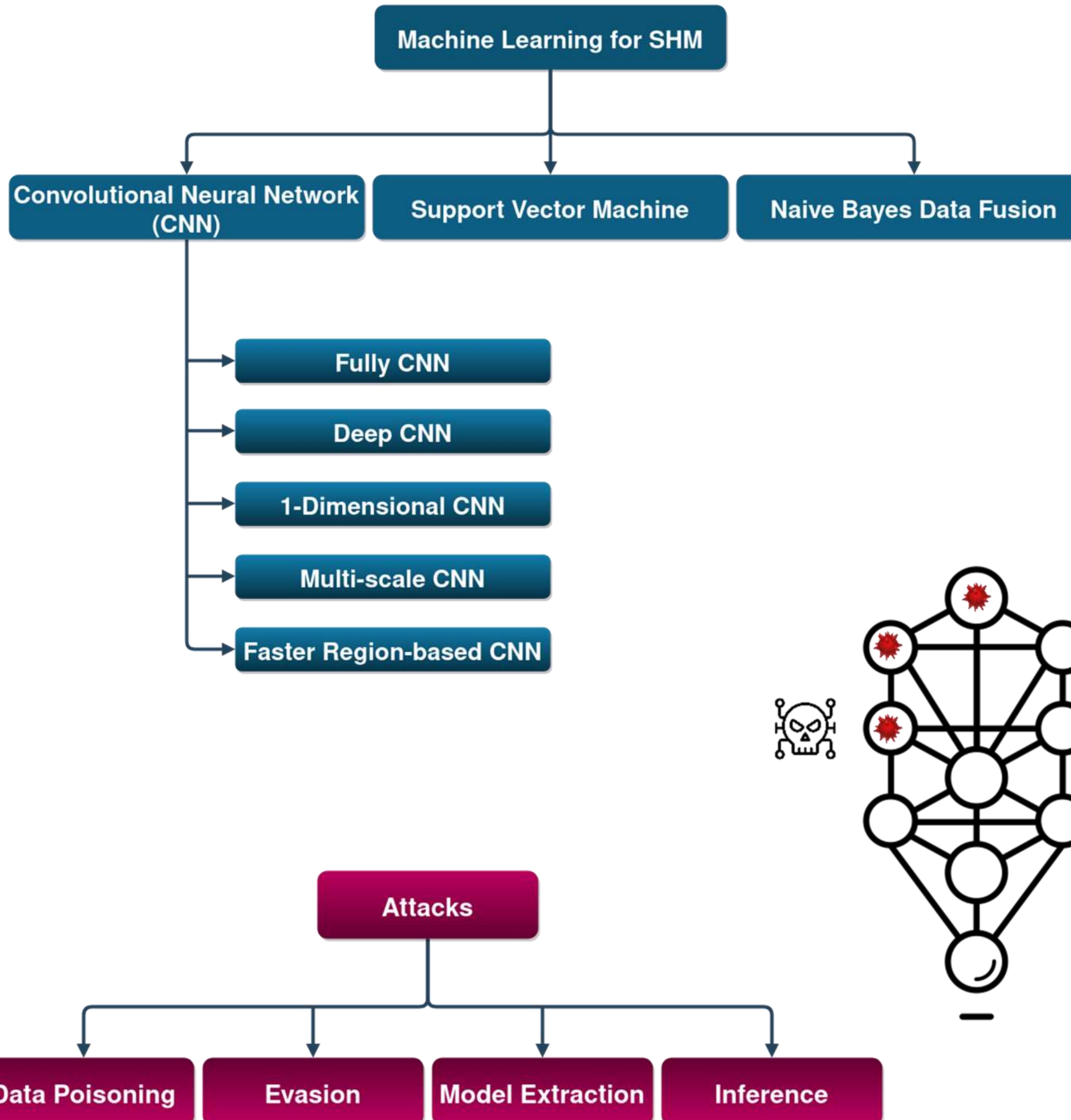
Methodology

- Identify usecases for **ML-based approaches** for SHM.
- Conduct a **security analysis** of studied approaches.
- Propose** a framework to study the effects of security threats on autonomous SHM operations.
- Evaluate** the proposed framework using real world solutions.

Data Collection for SHM

- Contact-based Approach
- Vision-based Approach

Machine Learning for SHM



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 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).



References

- 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>
- 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>.



Deep Reinforcement Learning based Approaches for Bridge Structural Health Monitoring

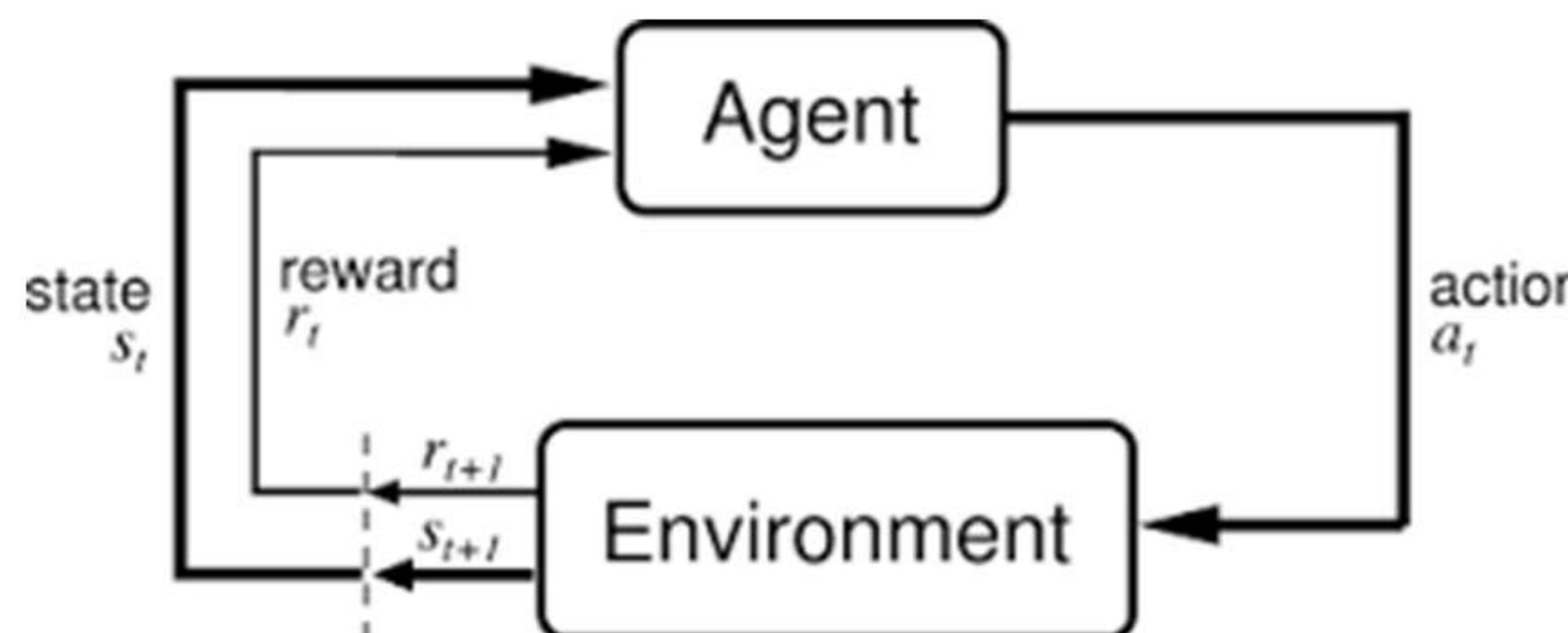
University of Nebraska at Omaha

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

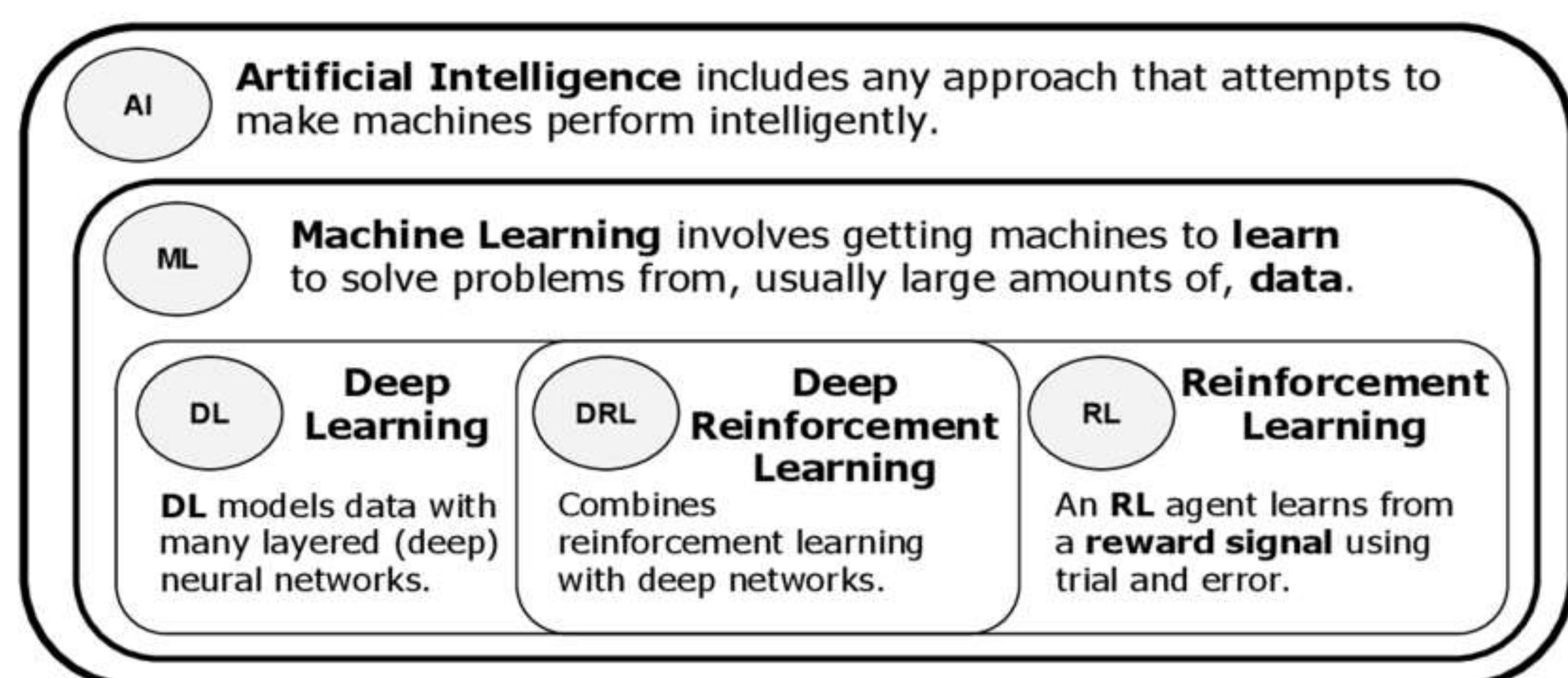


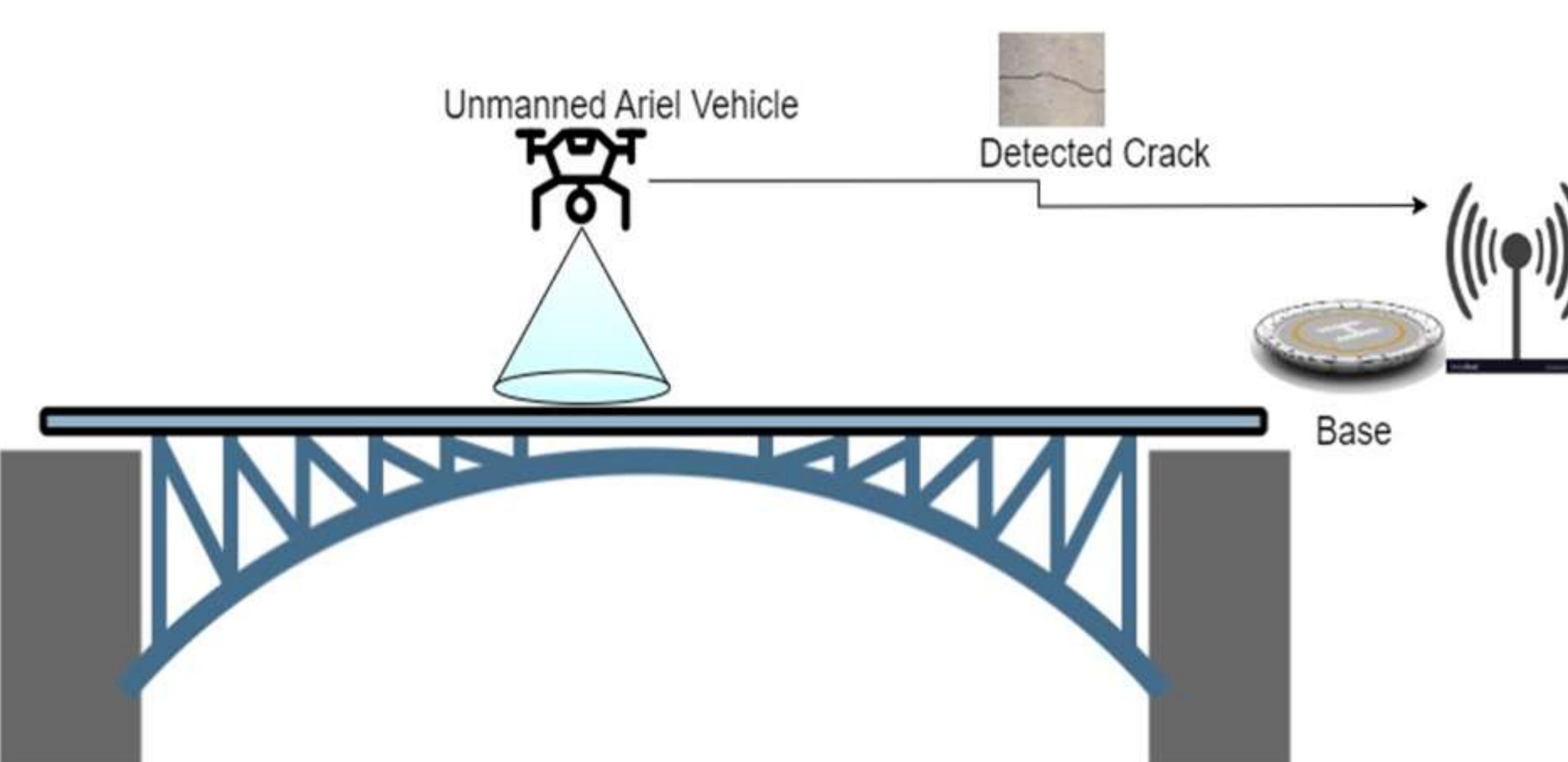
Image Source: Whittlestone, Jess et al. "The Societal Implications of Deep Reinforcement Learning." *J. Artif. Intell. Res.* 70 (2021): 1003-1030.

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

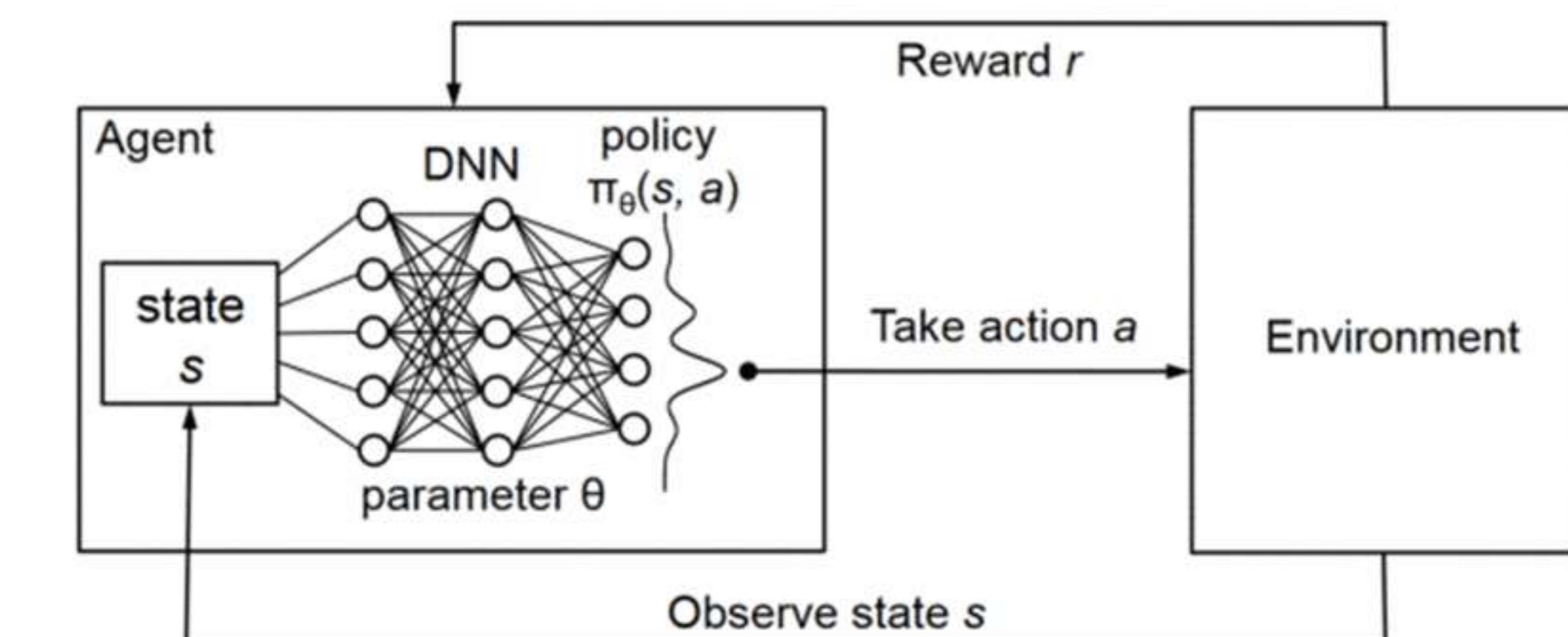
- Maintenance Schedules take too long and recordings are prone to errors
- Frequent surveying helps detection of new cracks and check the condition of old ones



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 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

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

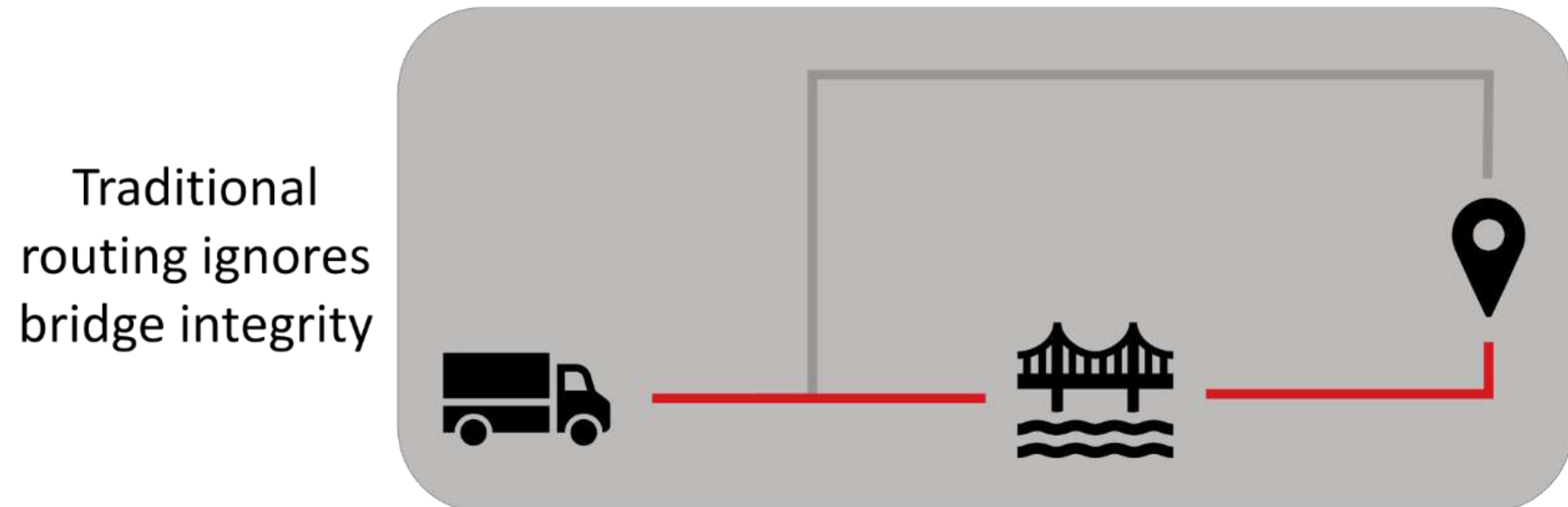
1. Mnih, Volodymyr, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves et al. "Human-level control through deep reinforcement learning." *nature* 518, no. 7540 (2015): 529-533.
2. Yi, Lingzhi, Xianjun Deng, Laurence T. Yang, Hengshan Wu, Minghua Wang, and Yi 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.

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

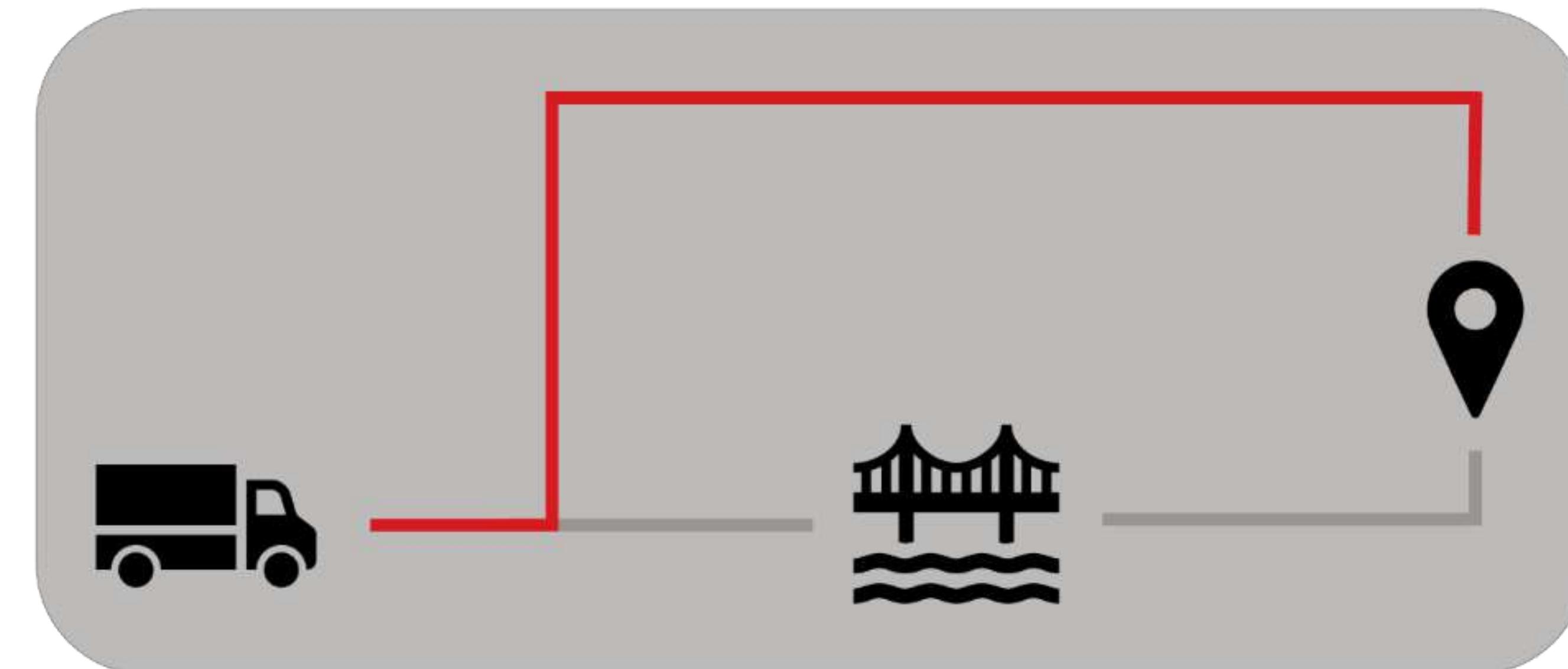
William Heller, Brian Ricks, Yonas Kassa, Rahul Kamar Nethakani, Brandon Lacy
University of Nebraska at Omaha

Goal

Traditional Routing



Bridge-observant Routing



Architecture

+

Big Data



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



- 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



- 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



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



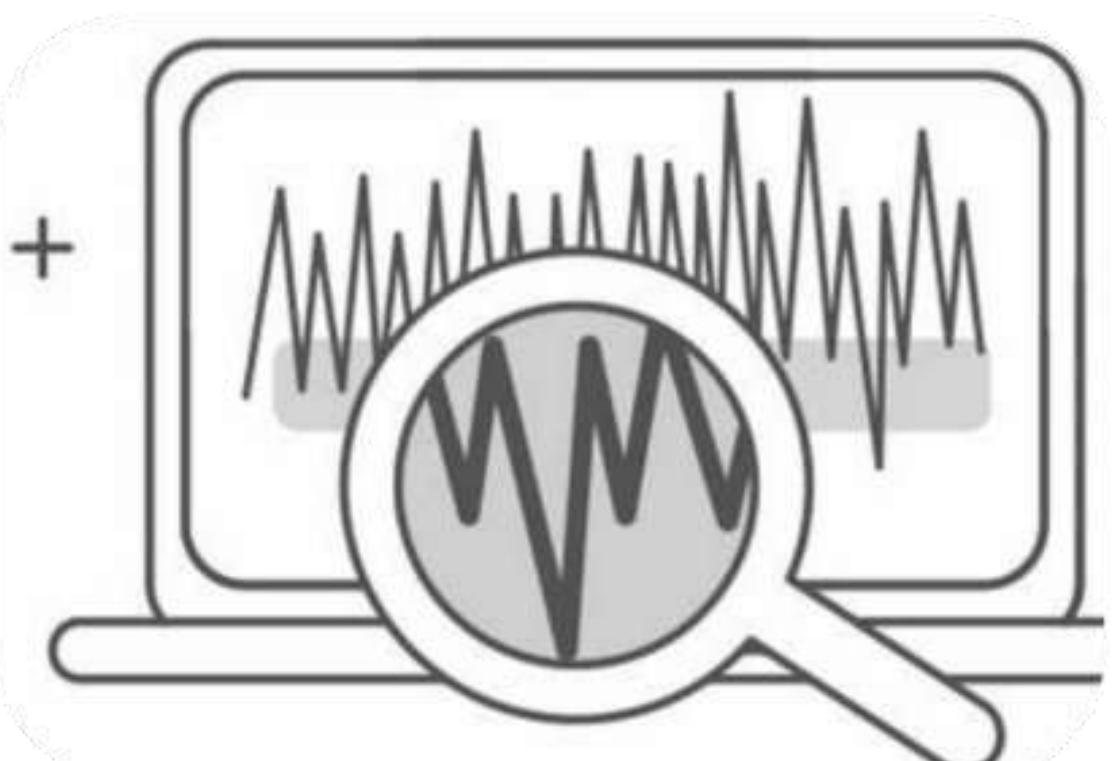
Secure communication

- Employ secure lightweight protocol



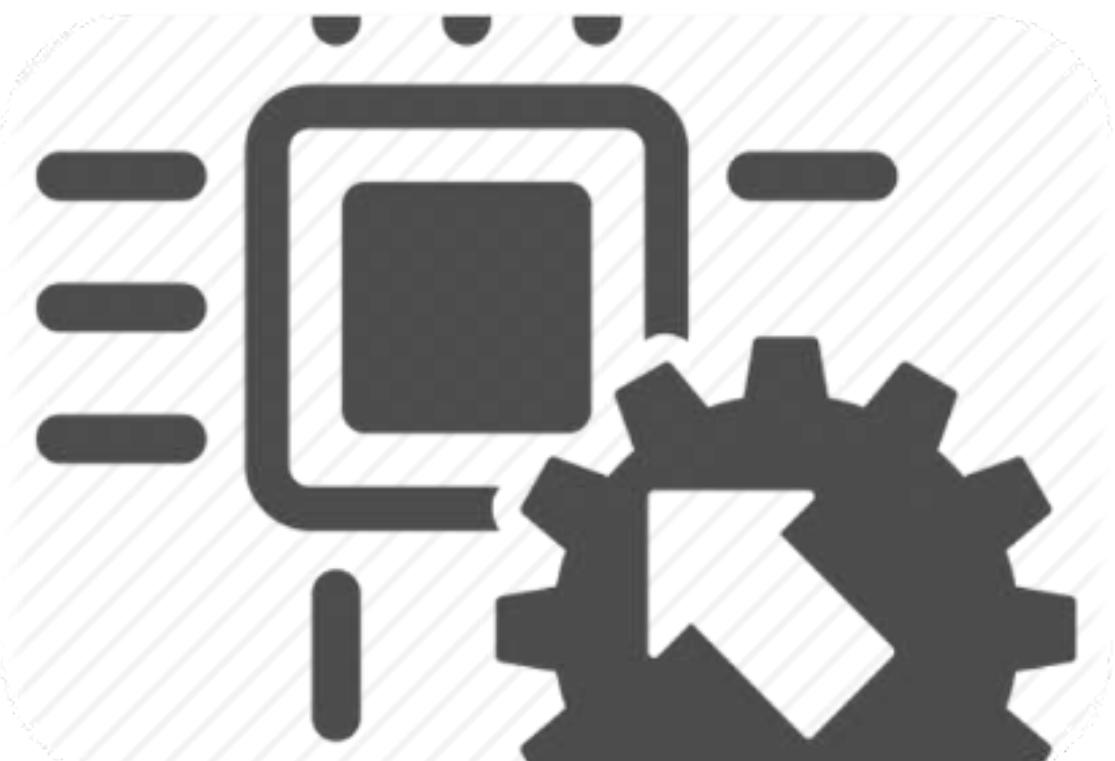
Robust authentication and access control

- OAuth 2.0
- X.509 certificate



Real time anomaly detection

- ML and statistical analysis analysis



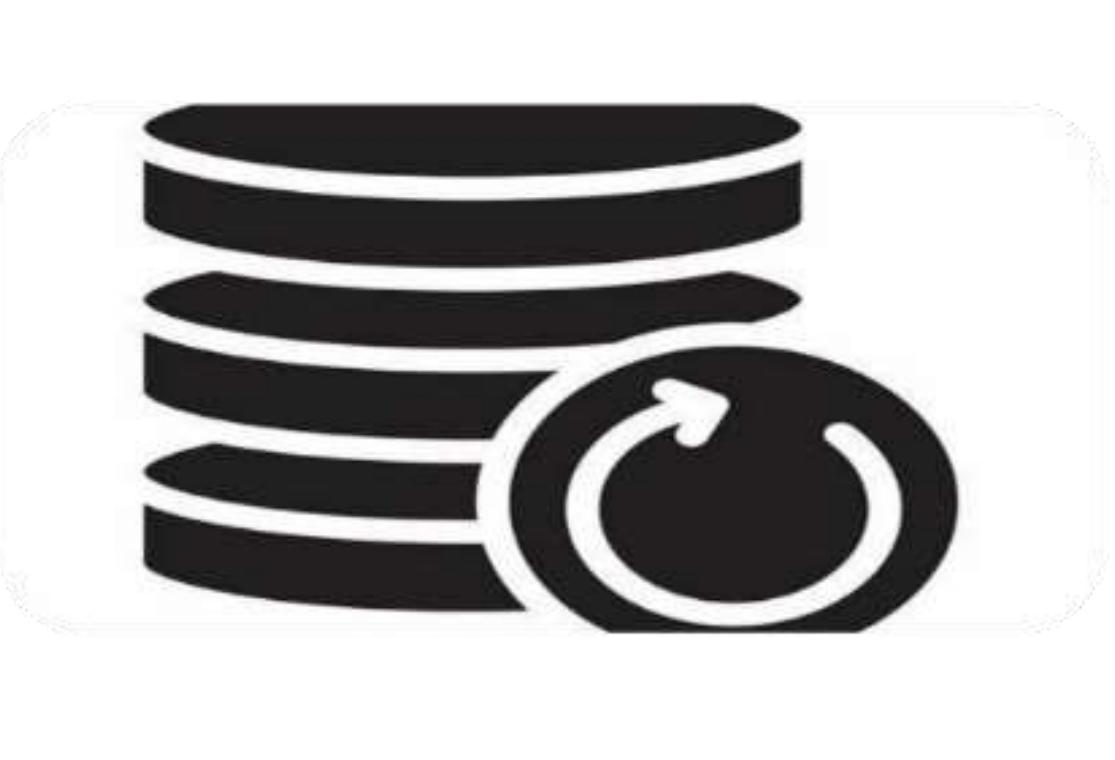
Secure firmware and software updates

- 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 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).



References

[1] Sadeghi, Ahmad-Reza, et al. "Security and Privacy Challenges in Industrial Internet of Things." *Proceedings of the 52nd Annual Design Automation Conference*, 2015, <https://doi.org/10.1145/2744769.2747942>

[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>.

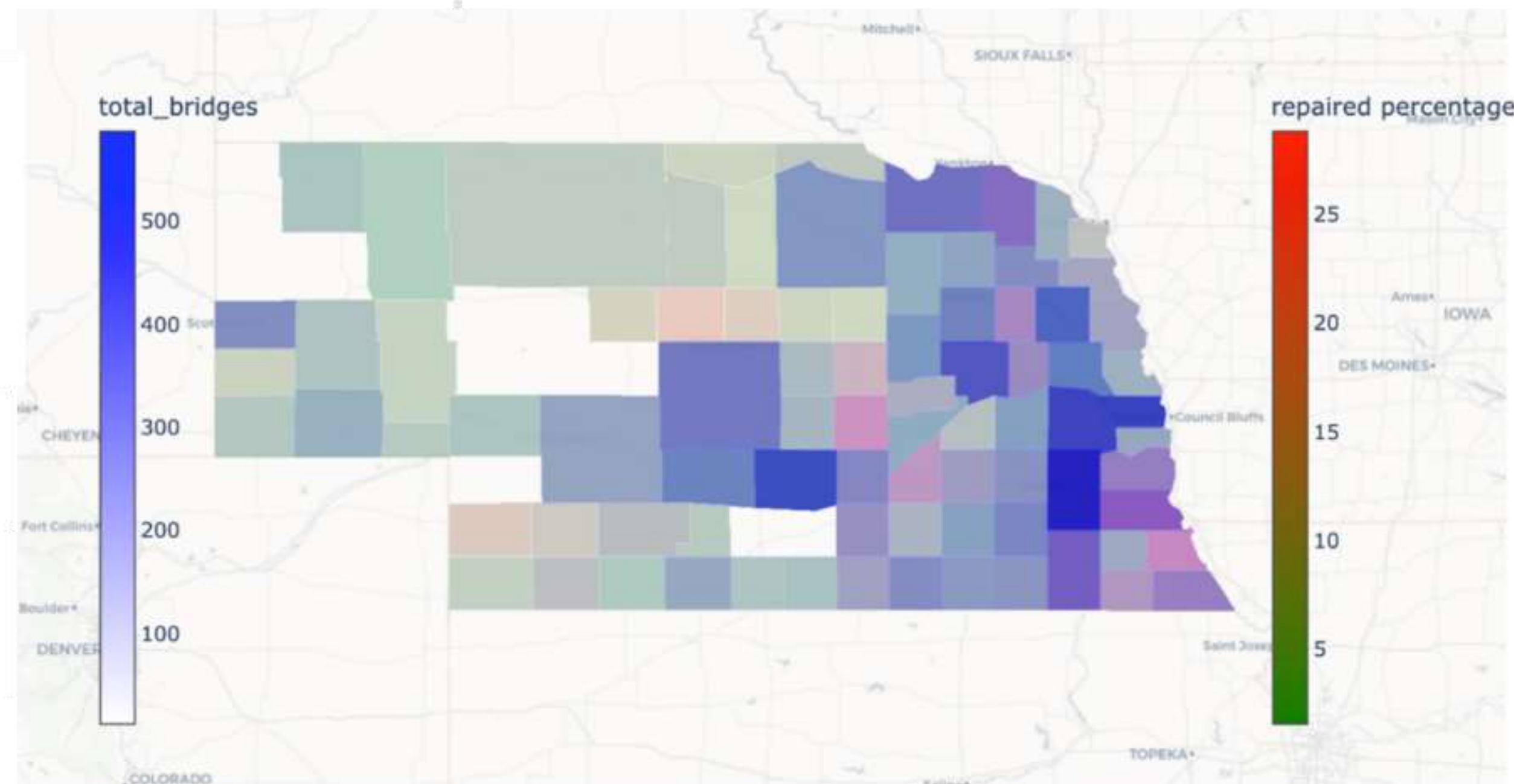


How to Select Simple-Yet-Accurate Model for Bridge Maintenance?

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

Background

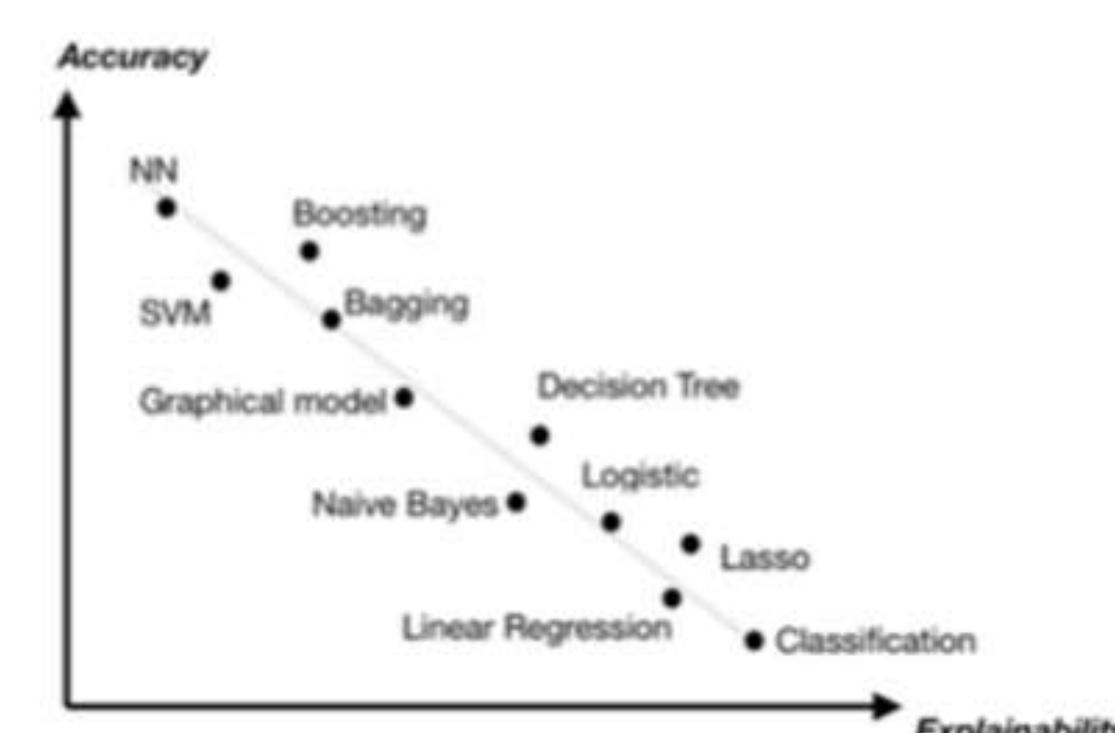
15,376 Bridges
NBI and LTBPP
28 Bridge Features
8 ML Algorithms



Challenge

Challenge 1:

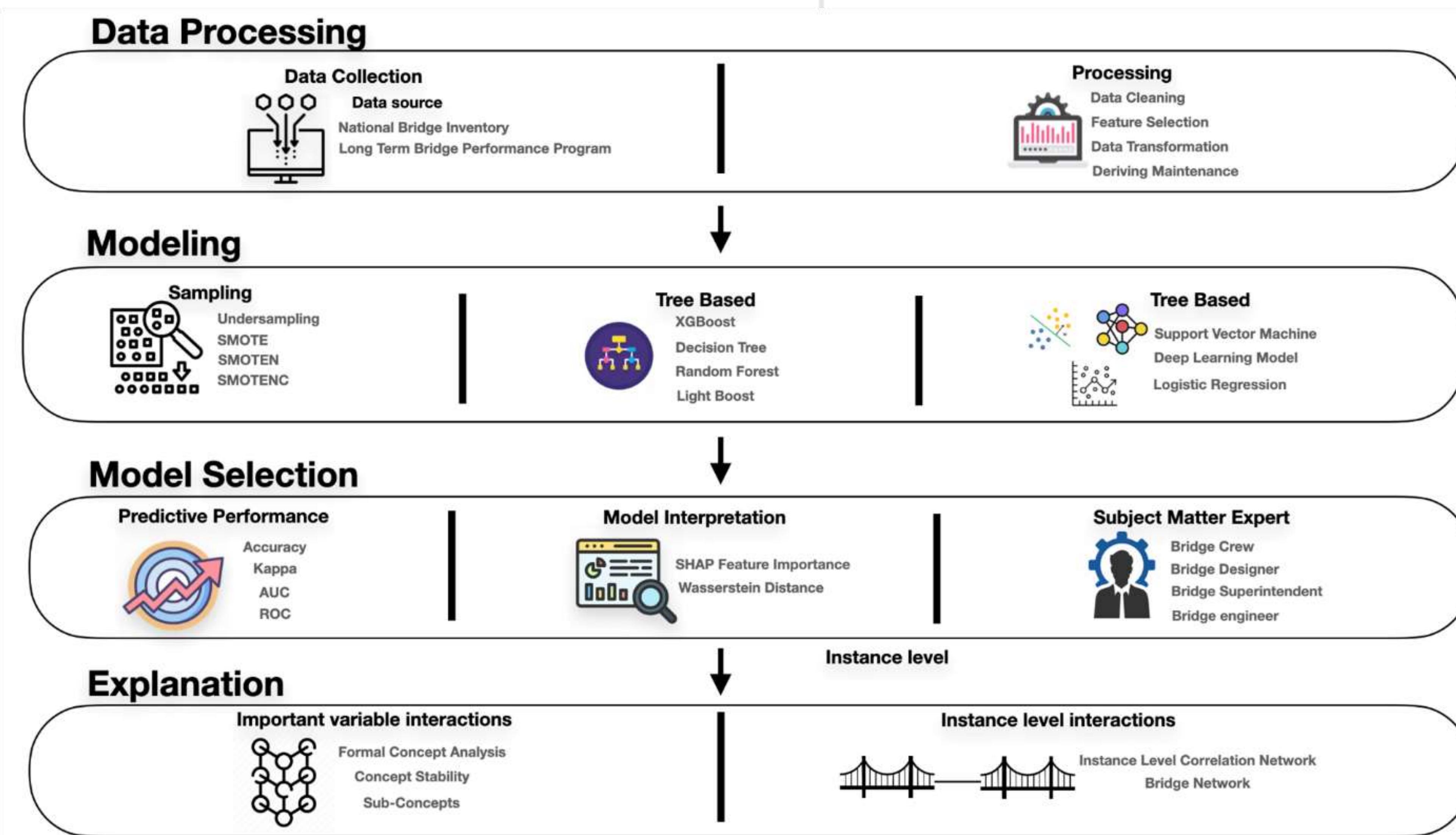
Explainability is inversely proportional to accuracy Every model tells a different story about bridge health



| Method | Physical | Region | Structural and material | Environmental | Service |
|---|----------|--------|-------------------------|---------------|---------|
| Case-based reasoning (Mortouros et al. 2002) | ✓* | — | ✓* | ✓* | ✓* |
| Cox hazards model with LASSO & stepwise regression (Westach-Glossner et al. 2020) | — | ✓* | ✓* | ✓* | ✓* |
| Linear regression and Monte Carlo simulation (Hassan and Elwakil 2020) | — | ✓* | ✓* | ✓* | ✓* |
| Bayesian hierarchical model (Schmidbauer 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 | ✓* | ✓* | ✓* | ✓* | ✓* |

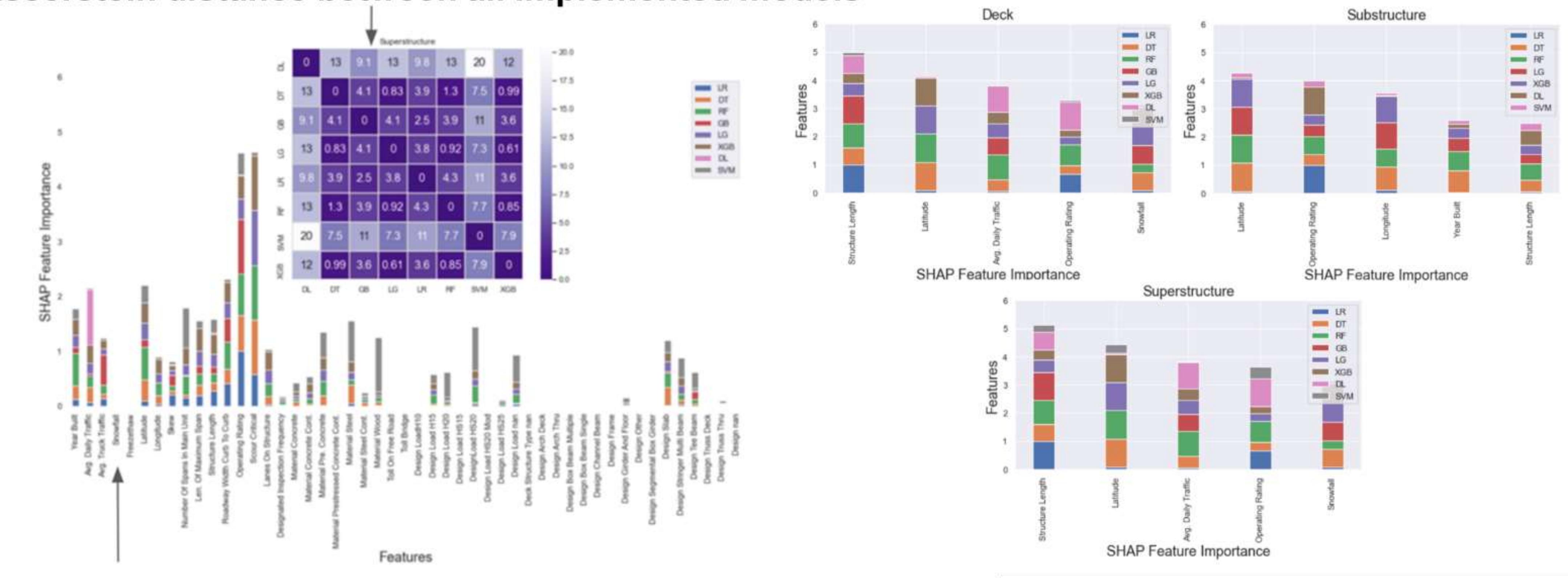
Note: A check mark indicates factor category tested; an asterisk indicates the factor category found to be influential. The text with the bold font is the proposed method in this manuscript.

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

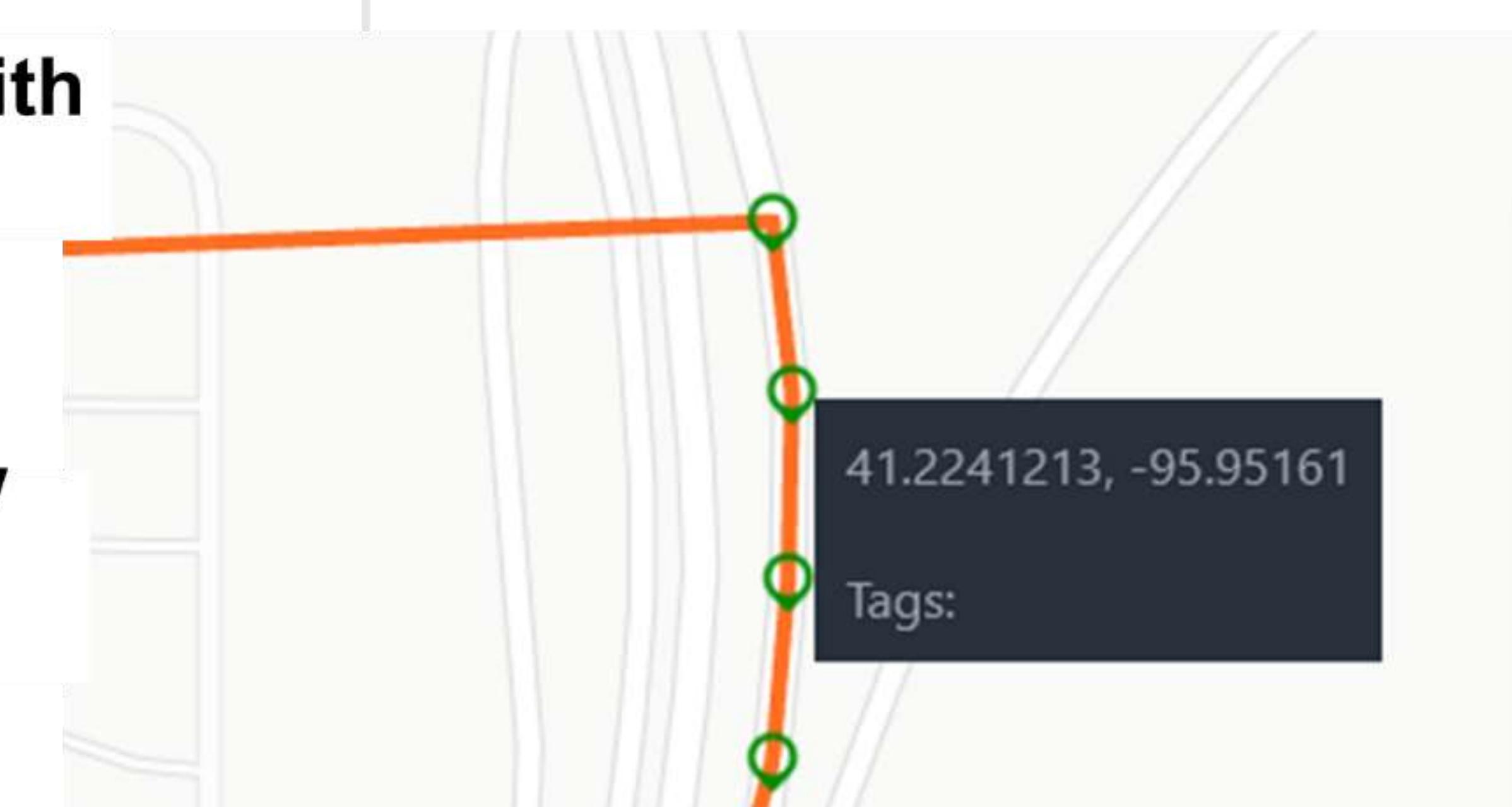
Save Routes and Convoys for later use

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

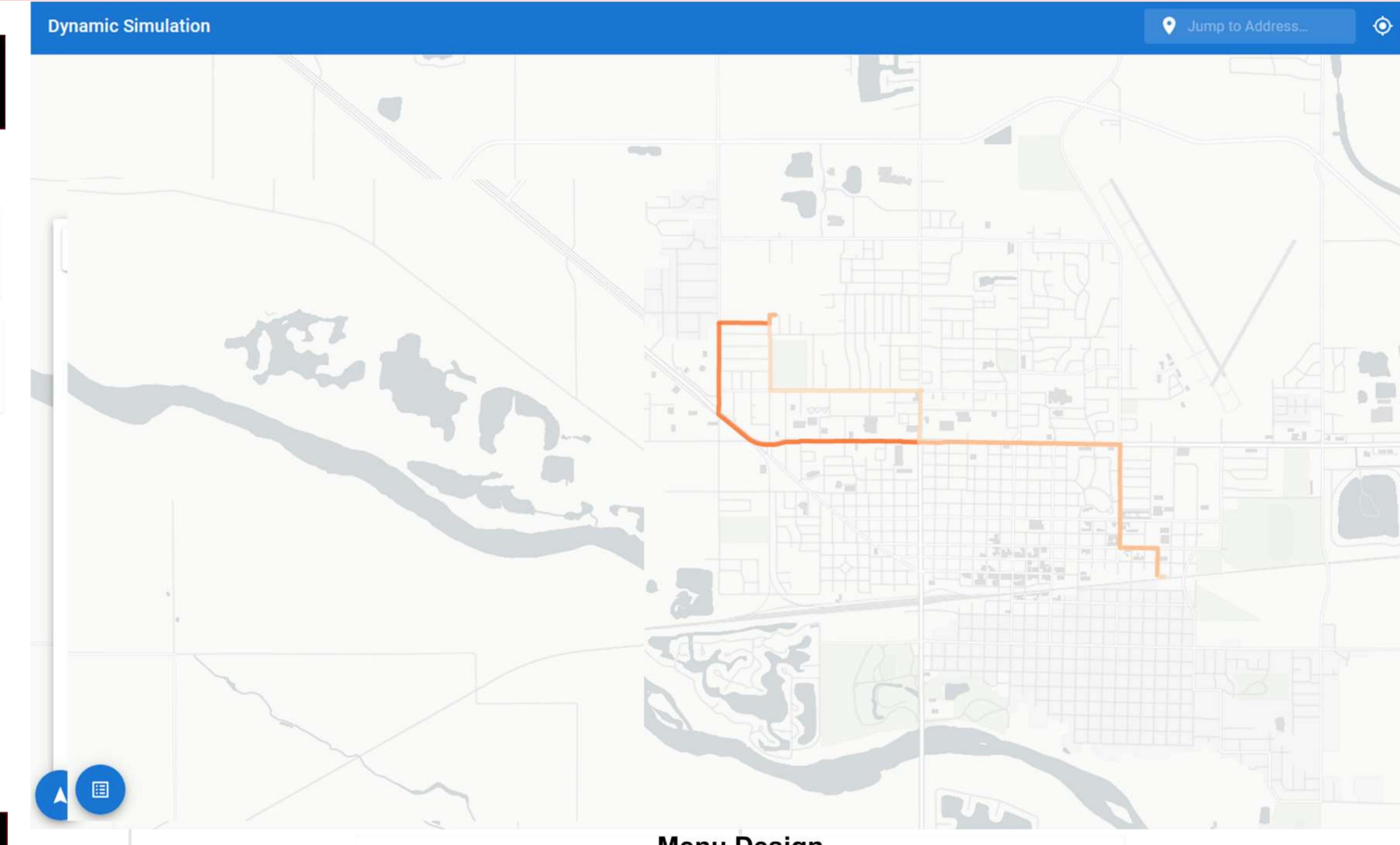
Easy conversion between addresses and coordinates with Nominatim

OSM and NBI Integration

View OSM and NBI data with the help of tags



Upcoming feature to view bridge structural data



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



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



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

Ji Young Lee^a, Bennett Jackson^b, Chungwook Sim^{b,*}, Carrick Detweiler^a

^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

- Transverse cracks observed in concrete bridge elements can accelerate deterioration of bridge health
- Current system exclusively rely on data provided from human inspectors
- Many research 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

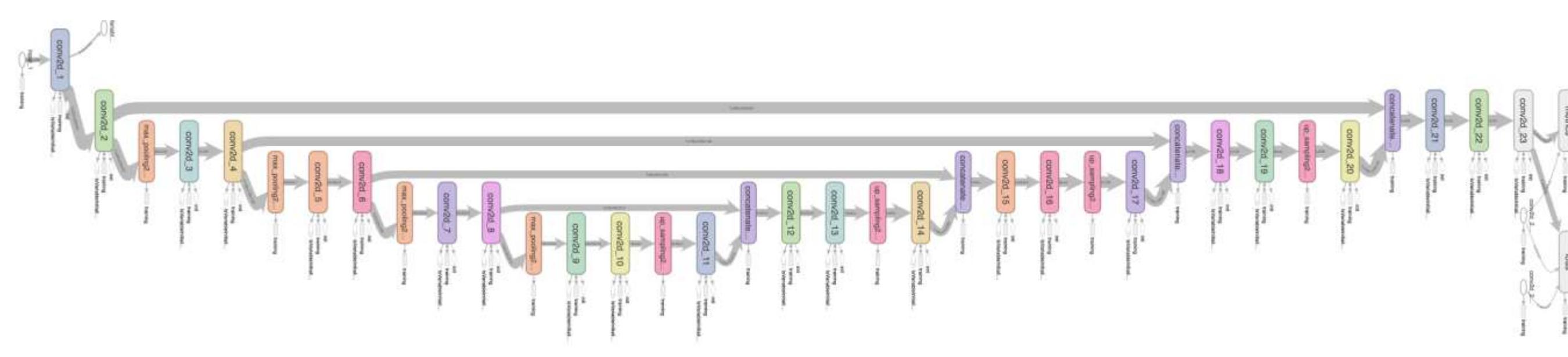
| Title (Location) | Keyword | Location | # of images (raw / augmented) |
|-----------------------|--|-------------|-------------------------------|
| UAV19-1 (Elkhorn, NE) | • concrete overlay • construction marks • patches | Elkhorn, NE | 13 / 3367 |
| UAV19-2 (Elkhorn, NE) | • concrete overlay • tining 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

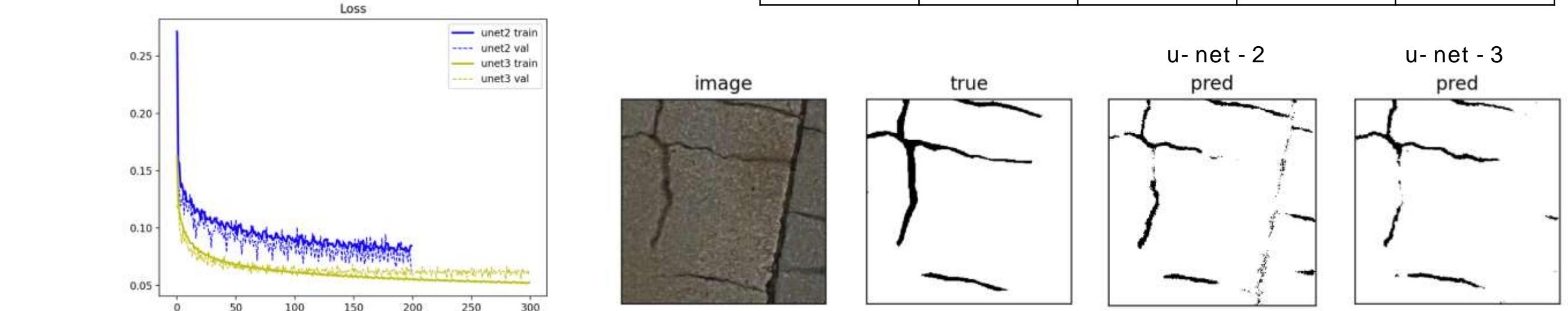


Crack Detection and Width Measurement

Training

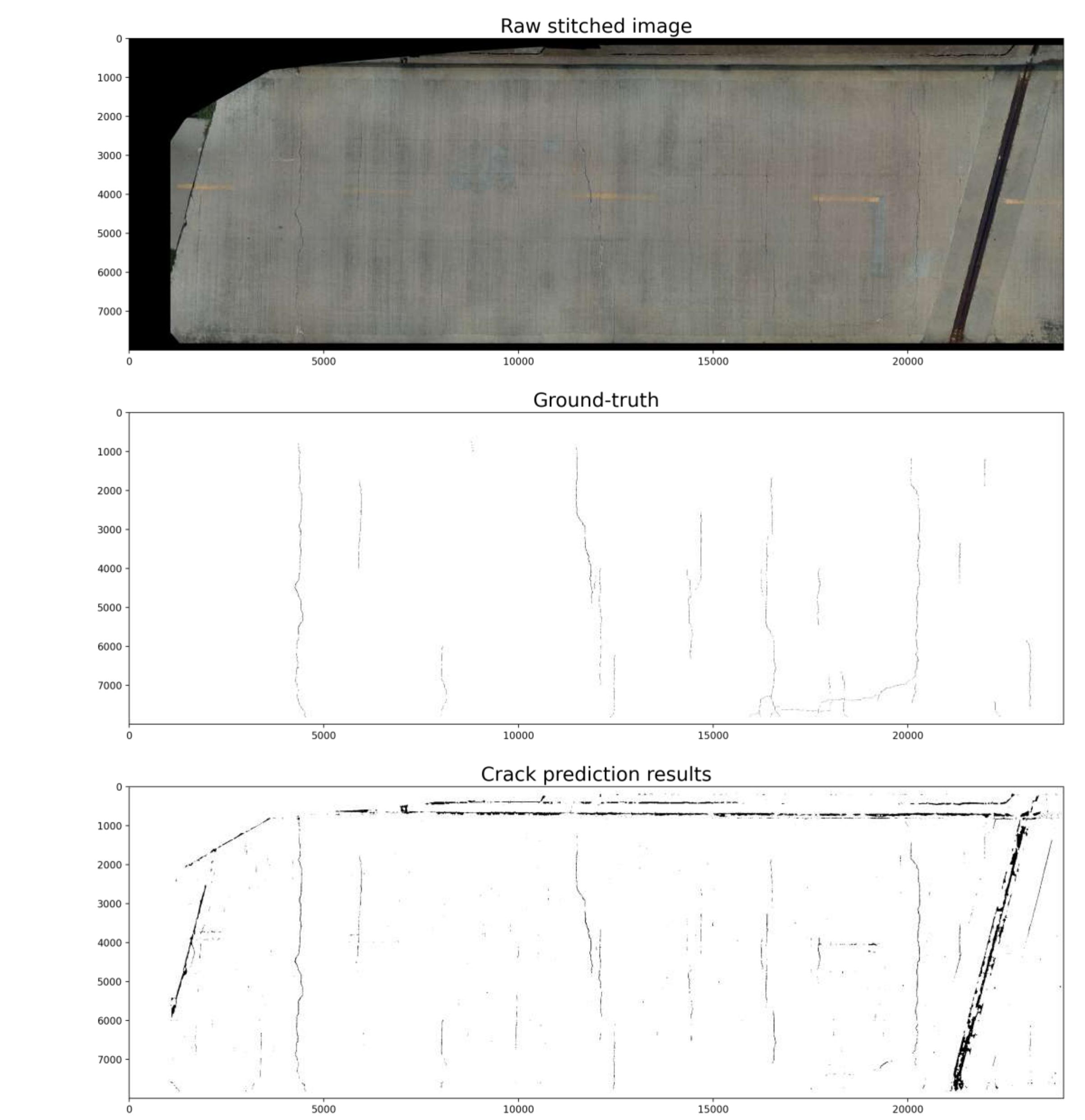
- Model tuning for architectures and hyper-parameters
- Model performed best with 3M params

| | 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 |



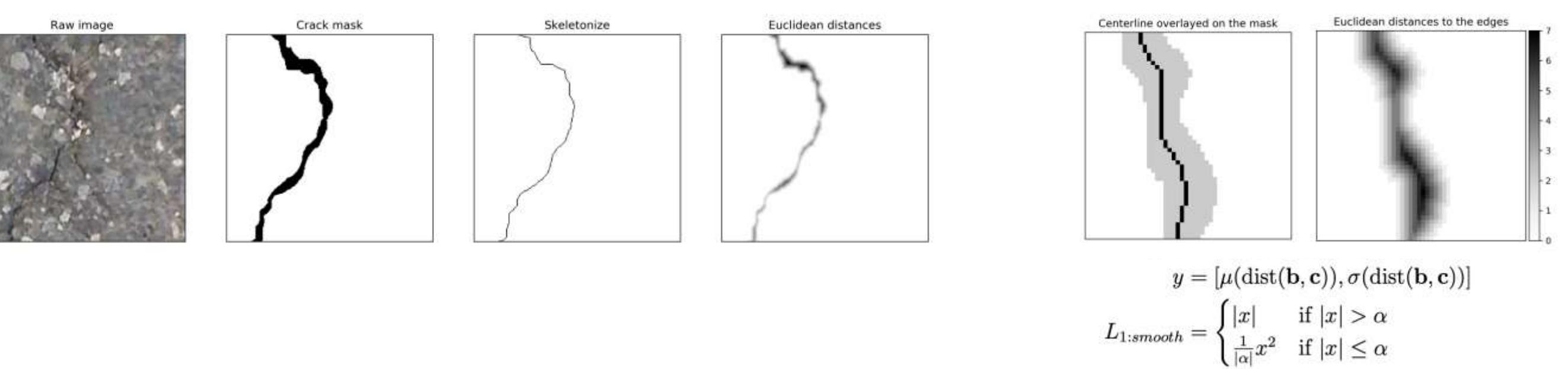
Inference

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



Width Measurement

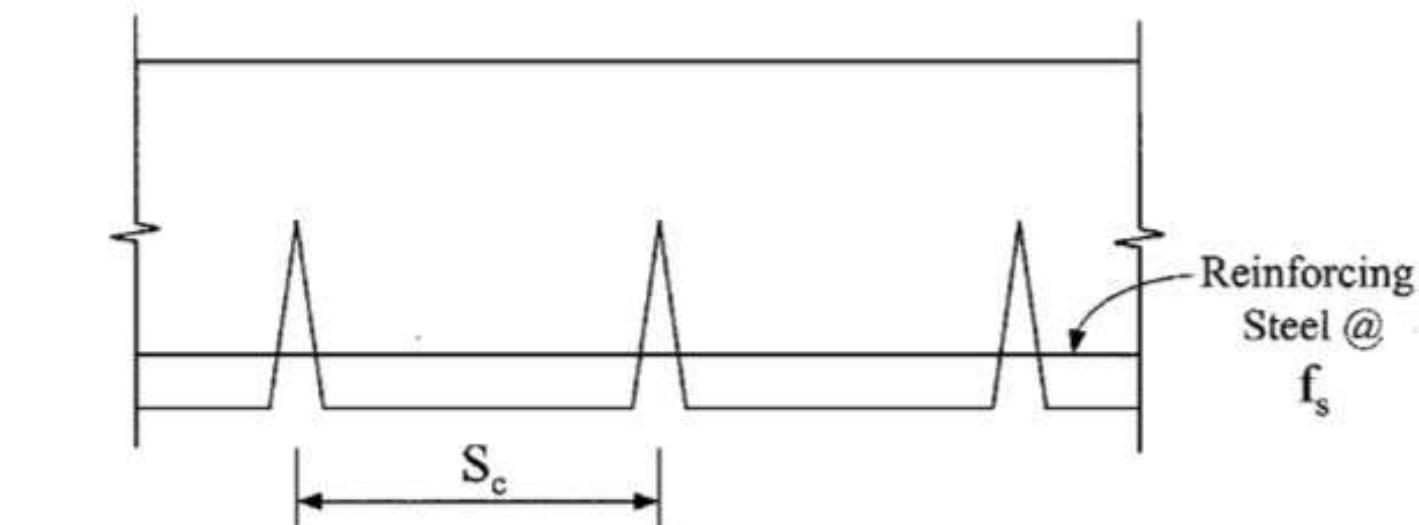
- Extracted Euclidean distances between centerline to boundary pixels



Strain Analysis

Crack Width

- To provide 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



$$w_c = \epsilon_s S_c \quad \beta = \frac{\epsilon_2}{\epsilon_1} = \frac{h-c}{d-c}$$

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.

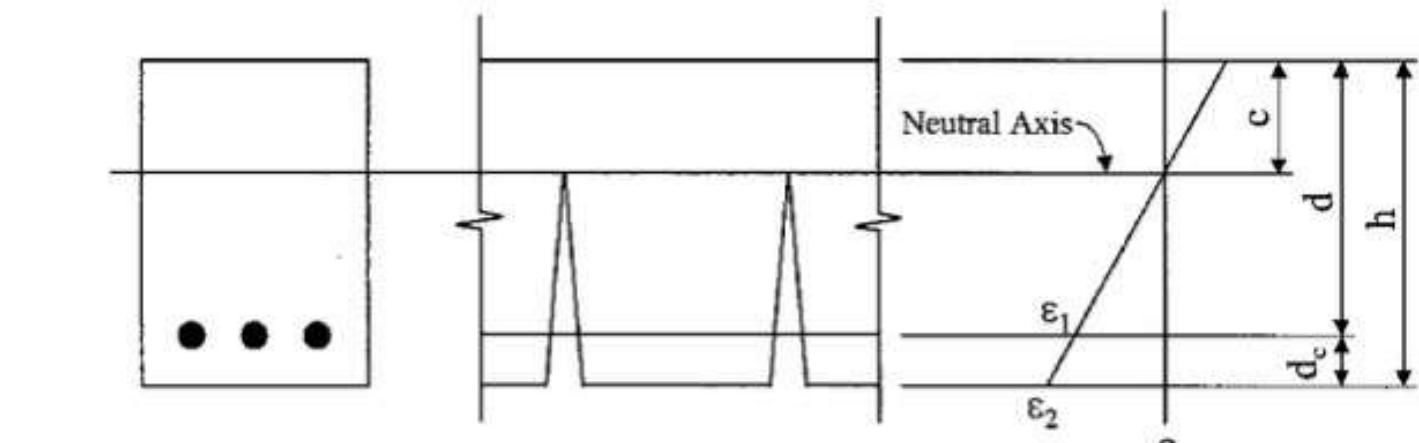


Fig. 2—Cracked section.

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

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 = $1.0 + 0.6d_c$; and
 d_c = bottom cover measured from center of lowest bar, in.

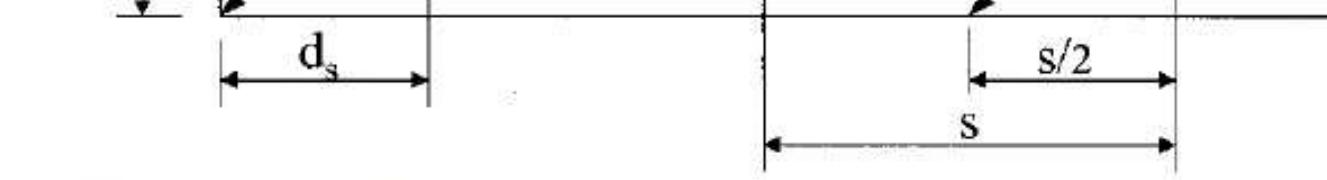


Fig. 4—Controlling cover distance.

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

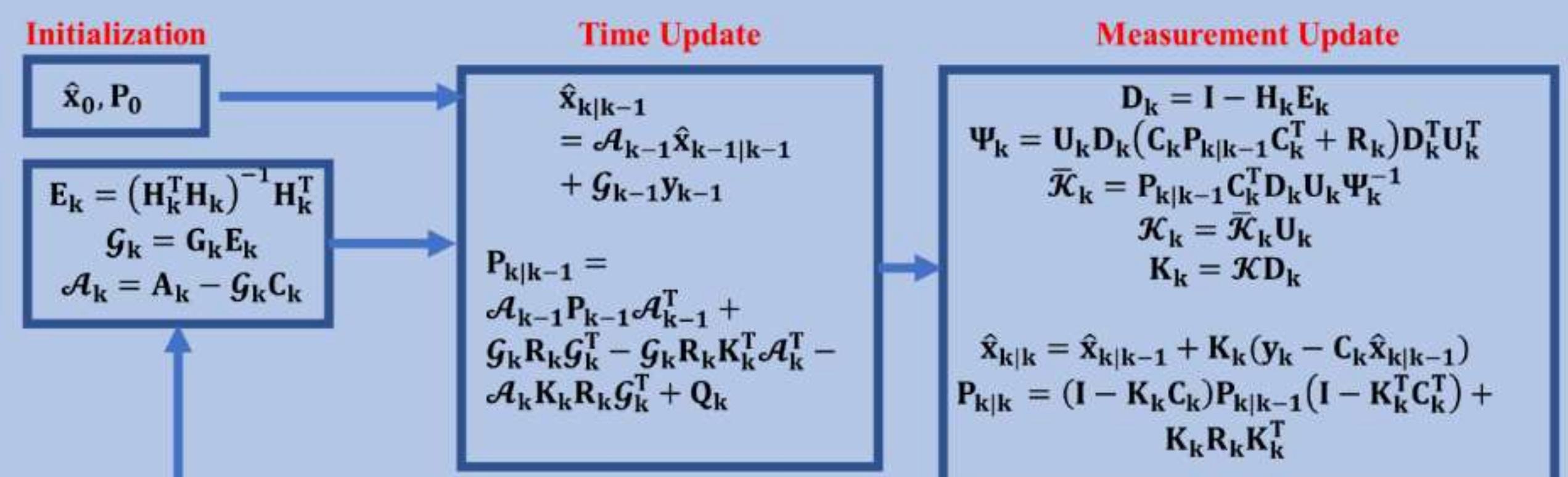
Reference

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

OVERVIEW

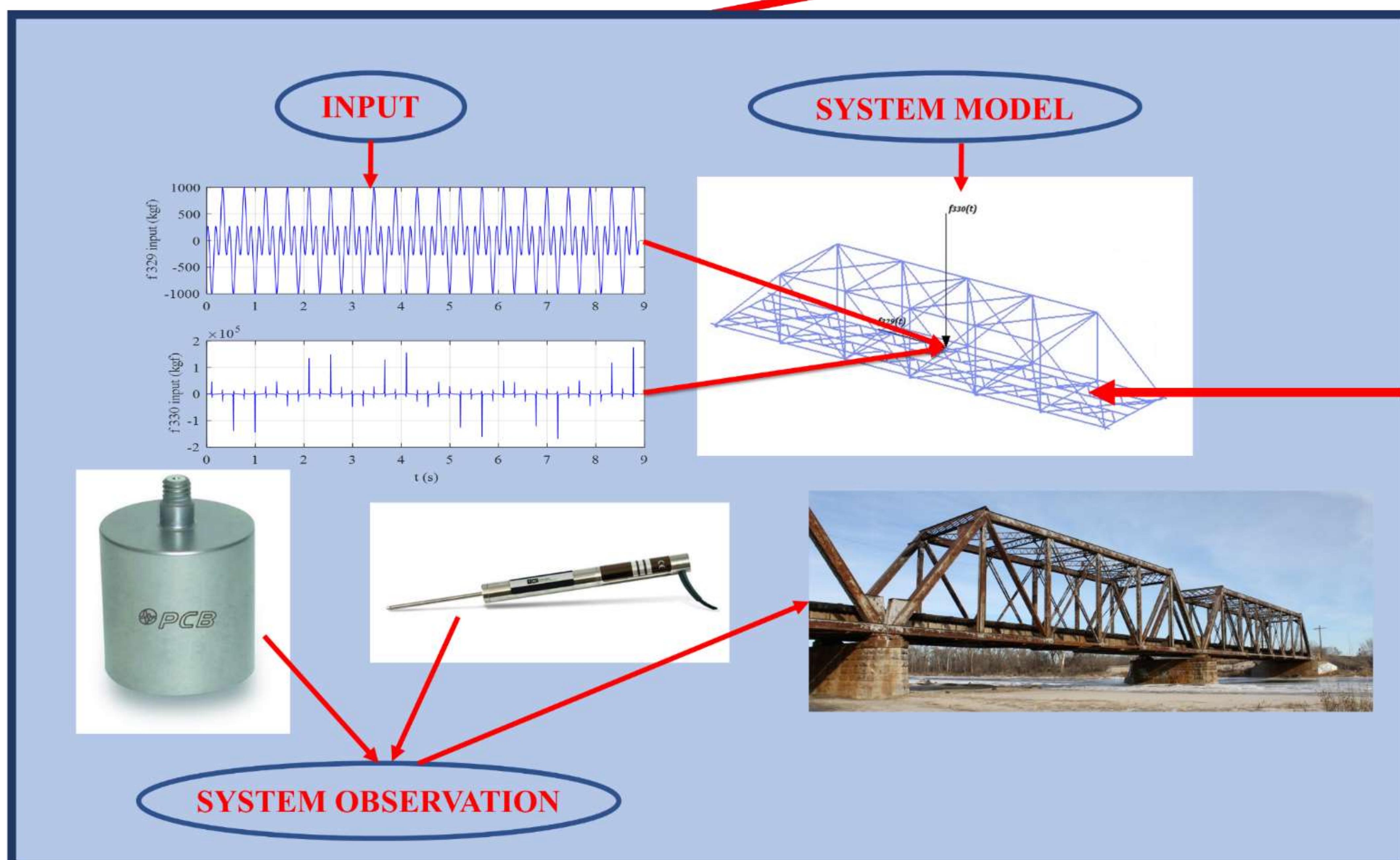
- So, how do we monitor infrastructure if it is, in general, **large scale and with multiple DOFs?**
 - 1st idea is to completely monitor the structure, which is unpractical.
- 2nd idea might be a Virtual sensing technique, through a calibrated model or digital twin.
 - Through Recursive Bayesian Estimation 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

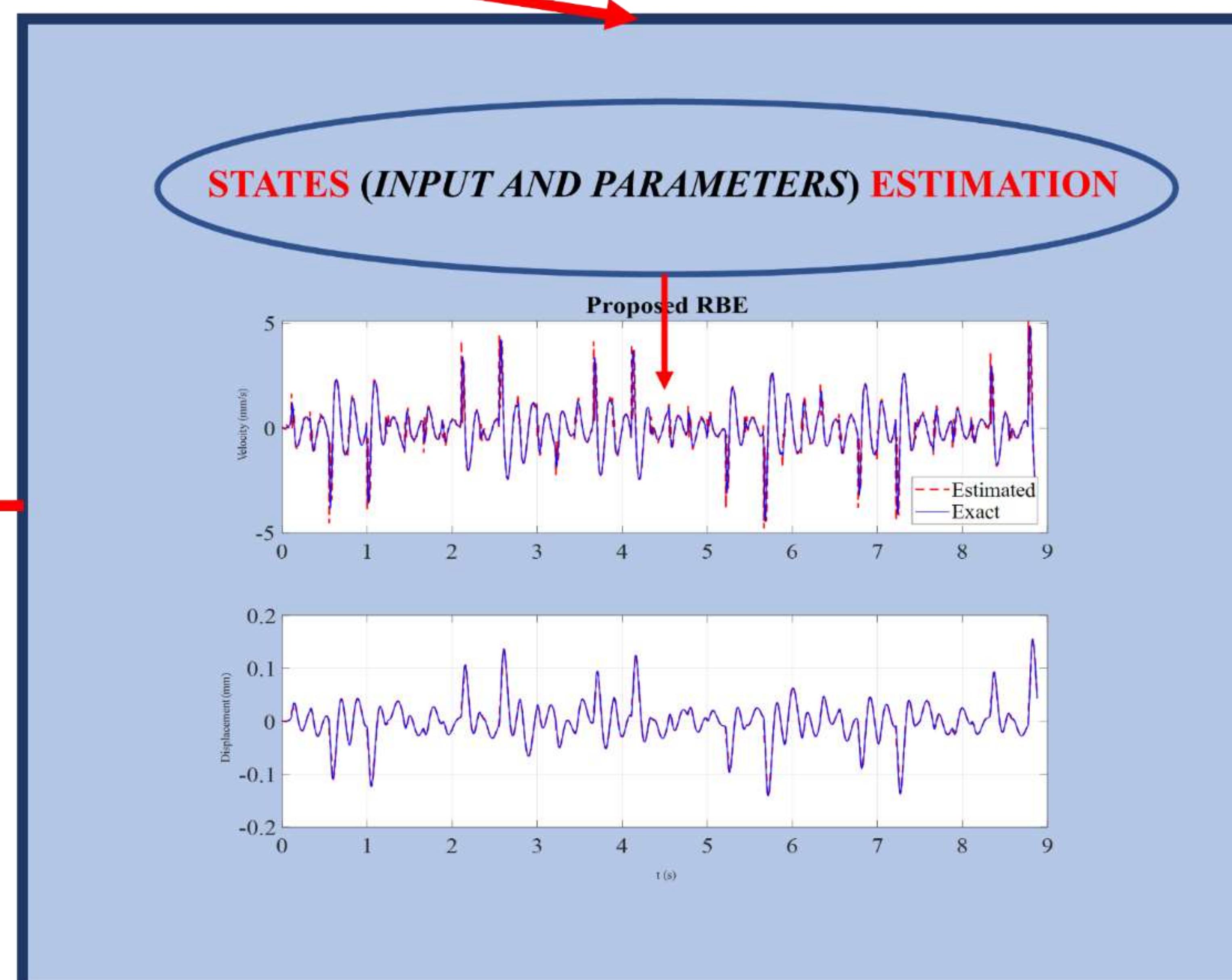


LITERATURE REVIEW

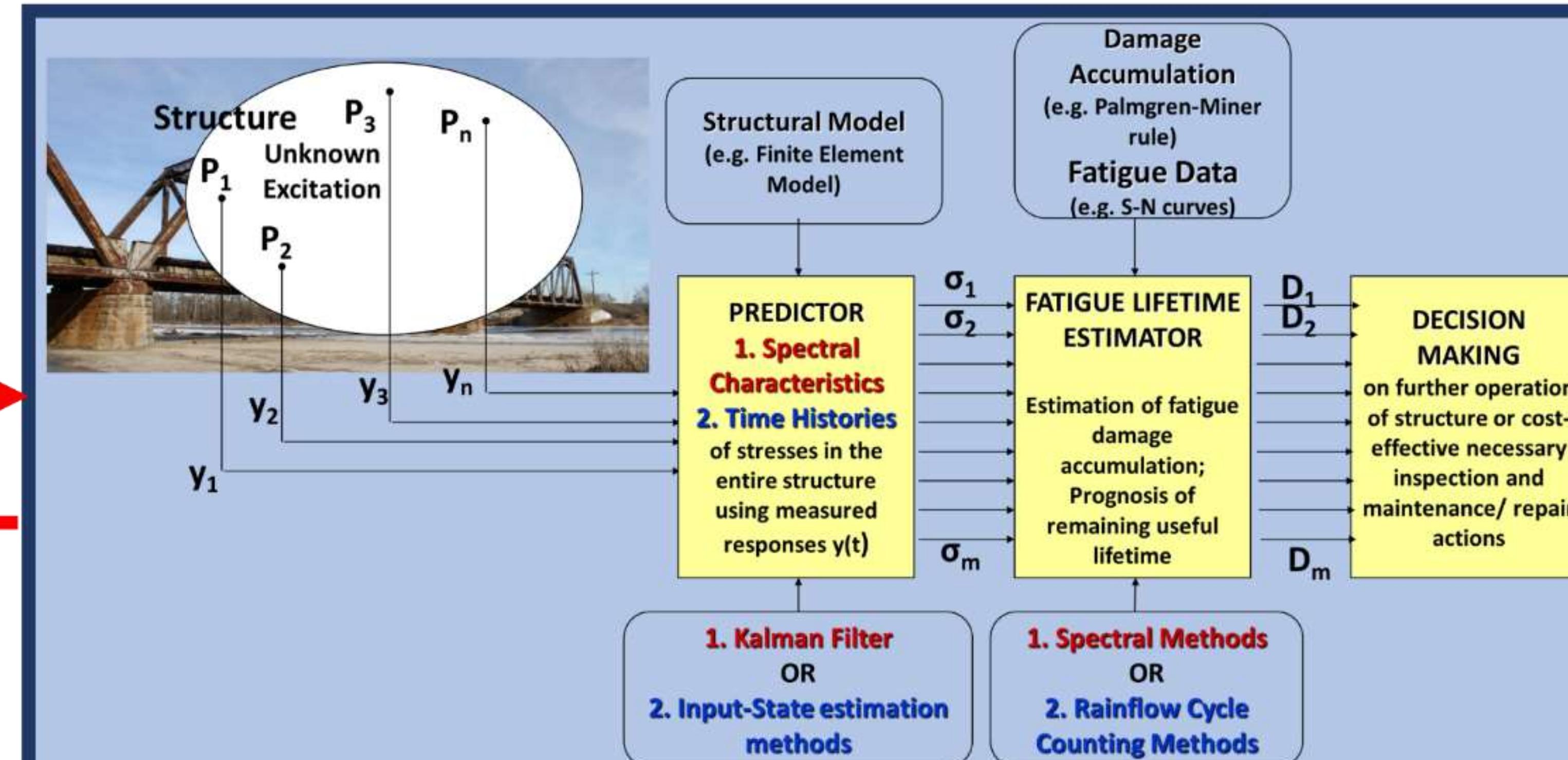
- Kalman Filter (KF) – 1969: needs input f_k
- Augmented Kalman Filter (AKF) – $f_{k+1} = f_k + v_k$
- Dual Kalman Filter (DKF) – 2015: $f_{k+1} = f_k + v_k$
- Gillijns and De Moor (MGDF) – 2012: no assumptions on input, prone to instabilities
- Solution: Eliminate the input
 - M. Hou and R. J. Patton: 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



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.

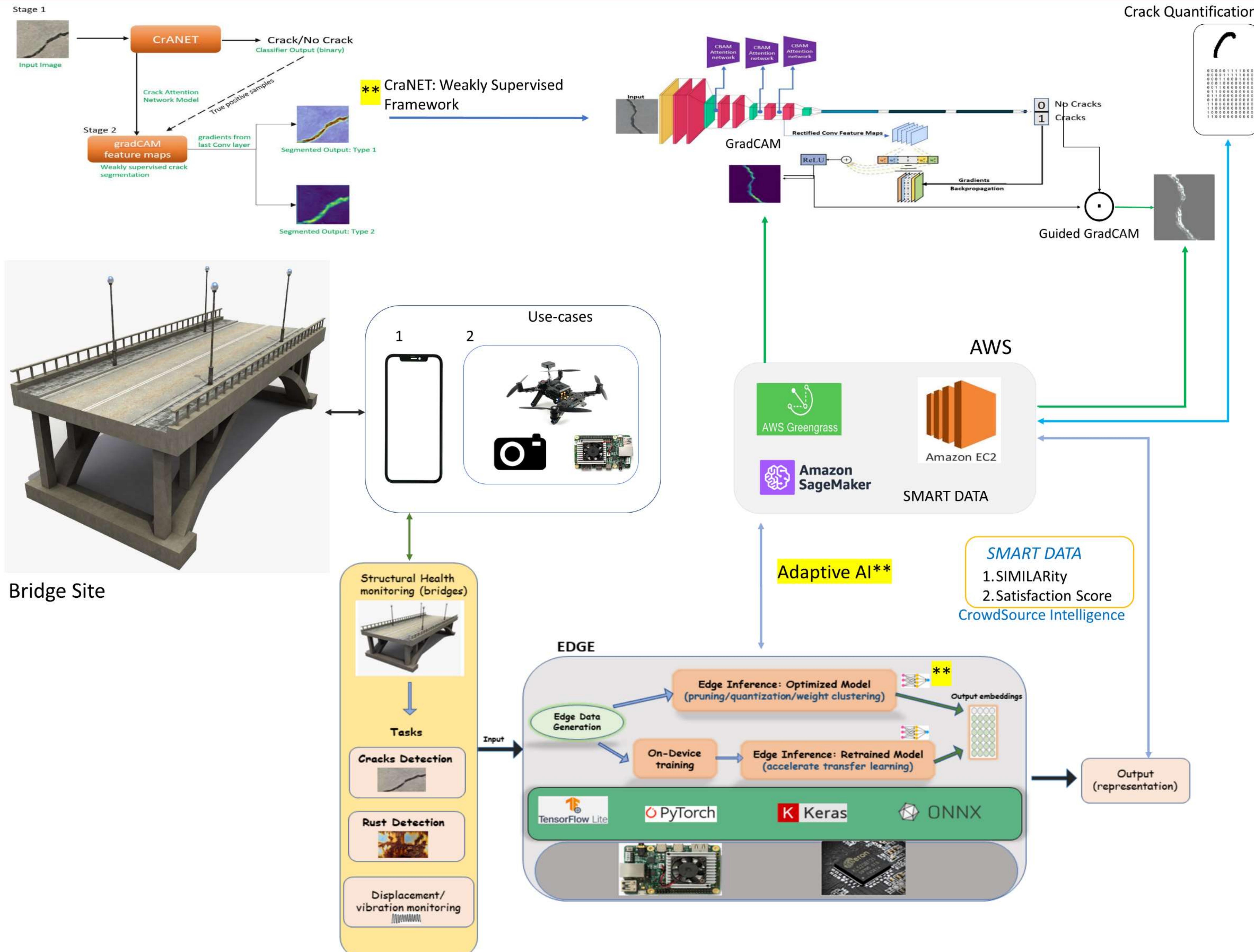


CEAIC: Cloud-Edge Adaptive Intelligence For Concrete Crack Detection and Quantification

University of Nebraska at Omaha, College of IS&T

CONTRIBUTORS:

- Anoop Mishra
- Gopinath Gangisetty
- 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 AI¹

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 knowledge³

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 |

UNIVERSITY OF
Nebraska
Omaha

1. Mishra, A., Gangisetty, G., & Khazanchi, D. (2023). Integrating Edge-AI in Structural Health Monitoring domain. *arXiv preprint arXiv:2304.03718*.

2. Mishra, A., Eftekhari 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*.

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.

Admin Page Snippet

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 | INFRASTRUCTURE | PROVISION | CREATED ON |
|---------------------------|----------------|-----------------|---------------------------|
| Elements | C005512355 | Seismic sensors | May 2, 2023, 8:40 p.m. |
| Infrastructure provisions | C005512355 | Strain Gauge | April 30, 2023, 9:31 p.m. |
| Infrastructures | C007804910 | Strain Gauge | April 30, 2023, 9:31 p.m. |
| Org infrastructures | C002801720 | Strain Gauge | April 30, 2023, 9:30 p.m. |
| Orgs | C002800420P | Strain Gauge | April 30, 2023, 9:28 p.m. |
| Provisions | | | |

Architectural Diagram

```

graph TD
    subgraph "Heroku Application Server"
        direction TB
        V[VueJS] --- R[Router]
        R --- C[Components]
        C --- S[Service]
        S --- DF[Rest Framework]
        DF --- P[Axios]
        P --- M[Model]
    end
    DA[Django API]
    PSQL[PostgreSQL]
    S3[AWS S3]
    S3 --> DA
    DA --> PSQL
    subgraph "Scheduled Data load"
        direction TB
        S[Python Automatic Data load process] --> S3
    end
    S3 --> PSQL
  
```

Flowchart of Data Pipeline

```

graph TD
    Start([Start]) --> FHWA[FHWA Website]
    FHWA --> Download{Download XML/Zip files}
    Download --> Validation{Validation}
    Validation --> LogServer[Log on server]
    LogServer --> End([End])
    Validation --> LogDB[Log to DB table]
    LogDB --> Convert[Convert to csv]
    Convert --> UploadAWS[Upload to AWS S3]
    UploadAWS --> PSQL((PostgreSQL))
  
```

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 condition¹
- 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

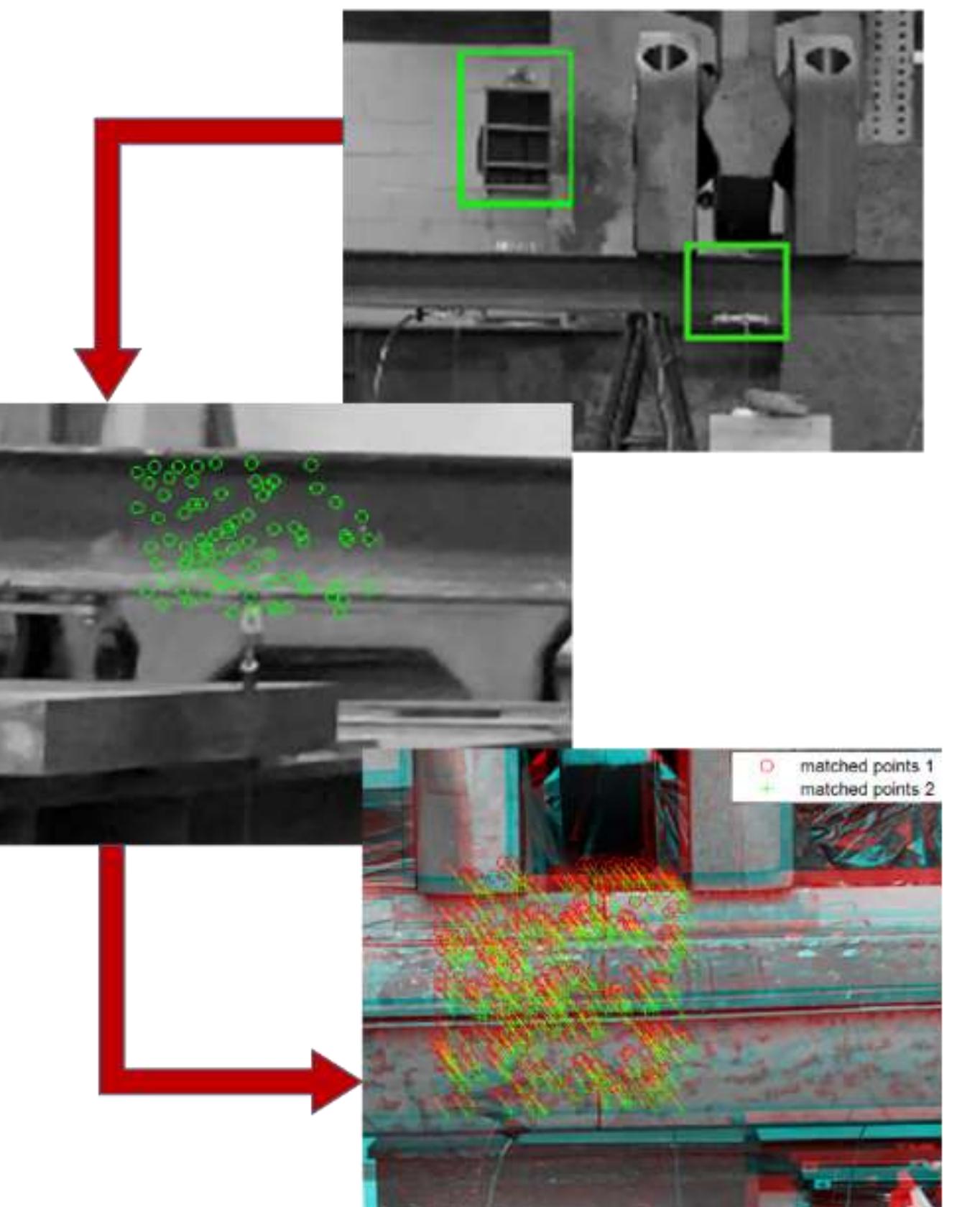
Computer Vision for Motion Tracking

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

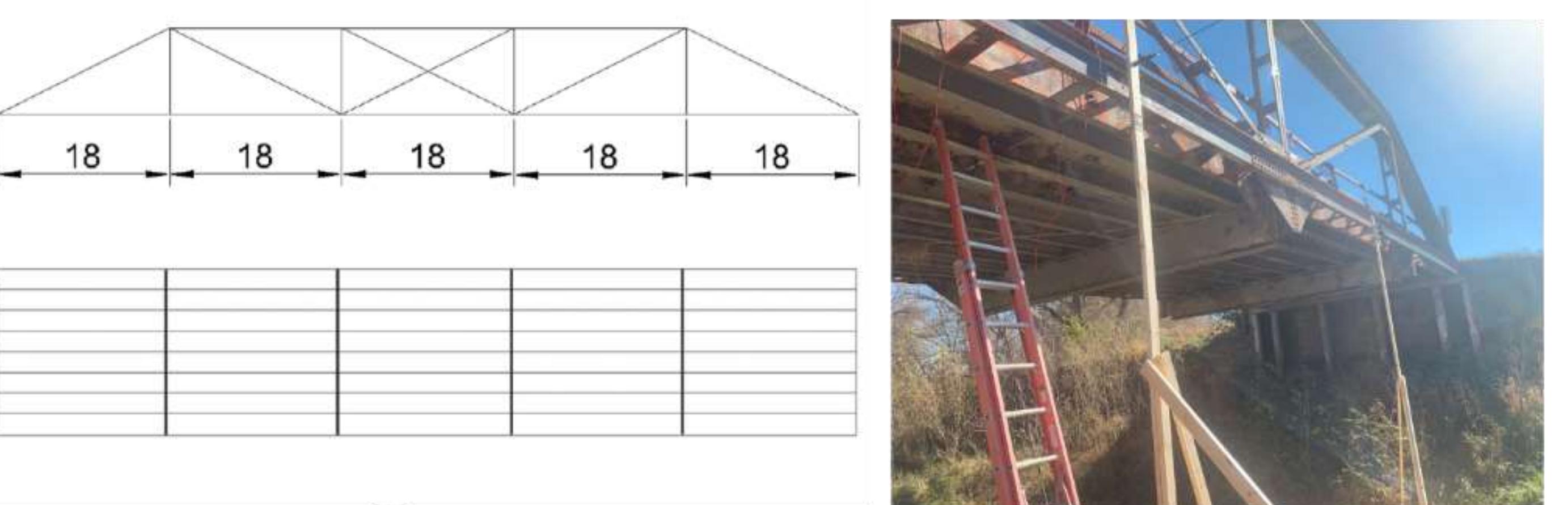
- Identify regions of interests
- Detect feature points
- Track motion by matching feature points across frames
- Convert measurements to world coordinates



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



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

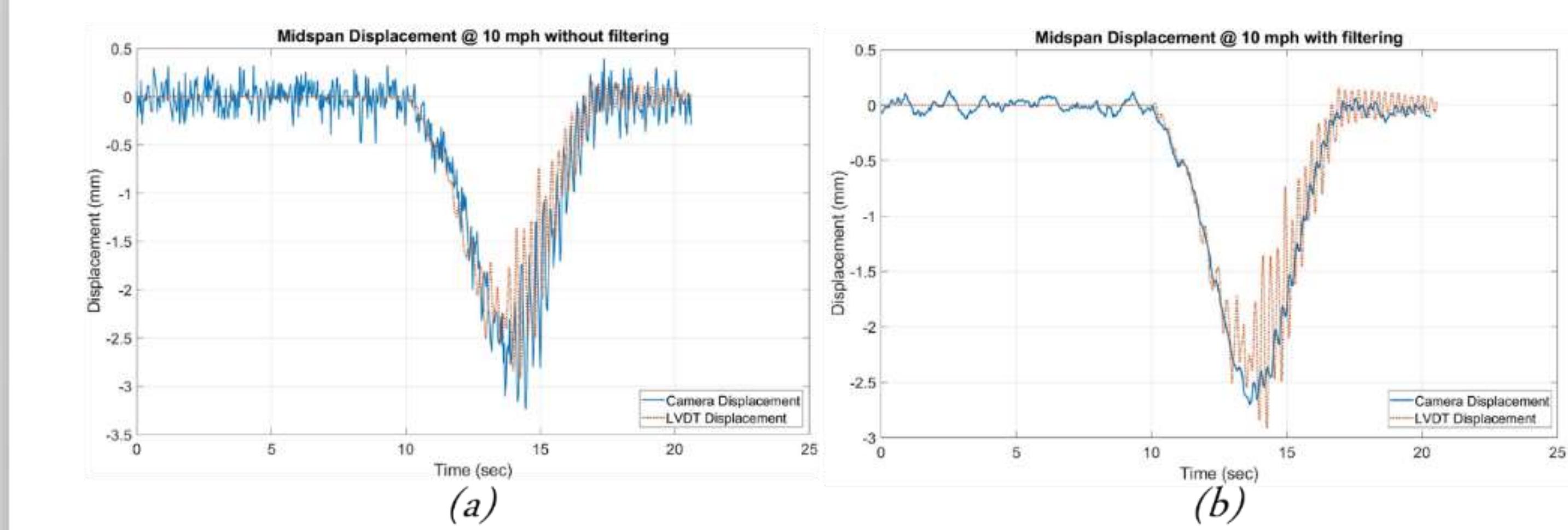


Bridge instrumentation and experiment

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:

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



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

Acknowledgement

- This project is funded by the Department of Defense Army Corps of Engineers. The authors would like to take the opportunity to thank to Qusai Alomari, Rola El-Nimri, Peter Hilsabeck, Riley Einspahr for their help in field experiments and data arrangement. Here also, authors thank Nebraska county for providing access to the bridge site to conduct experiments.

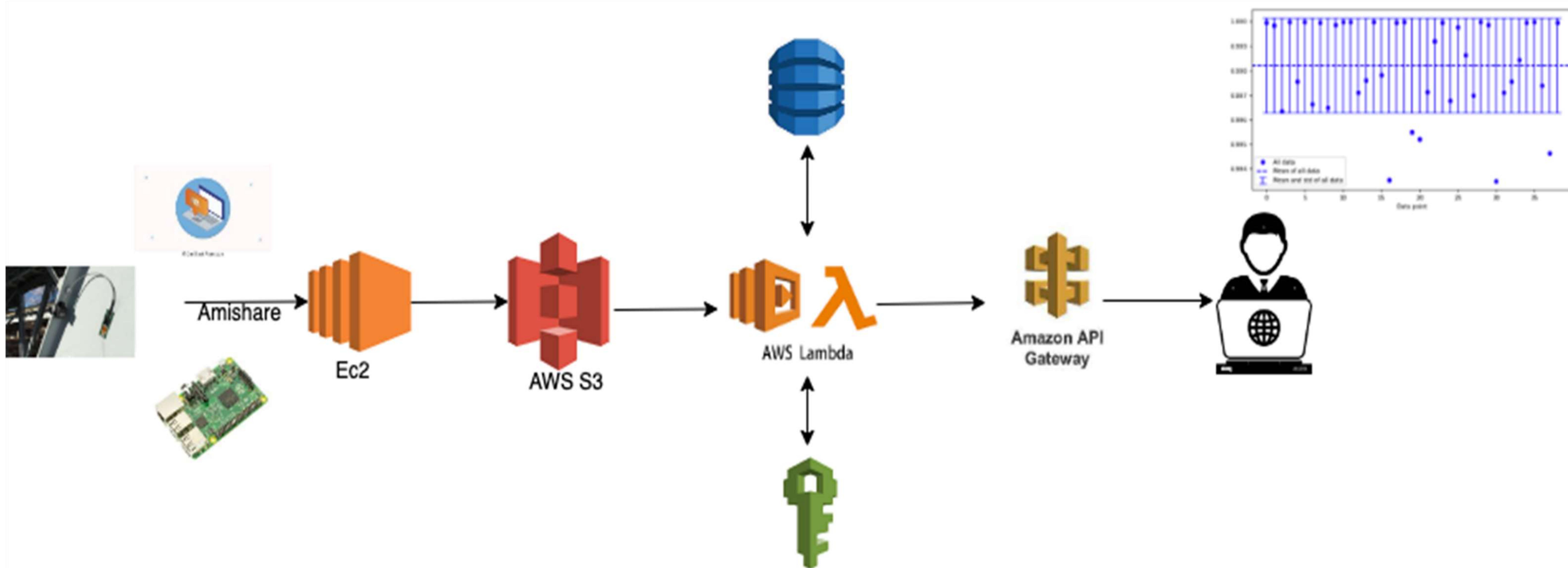
Bridging Big Data Convoys: Calculation and Visualization of Novelty Index in AWS

Nethakani Rahul Kumar

University of Nebraska at Omaha: Dr. Robin Gandhi, Dr. Deepak Khazanchi, Dr. Brian Ricks, Dr. George Grispos, Dr. Sachin Pawaskar

University of Nebraska – Lincoln: Dr. Daniel Linzell, Dr. Chungwook Sim, Dr. Jinying Zhu, Dr. Carrick Detweiler

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



- Generates TDMS File from sensor data.
- Store data in Raspberry-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:

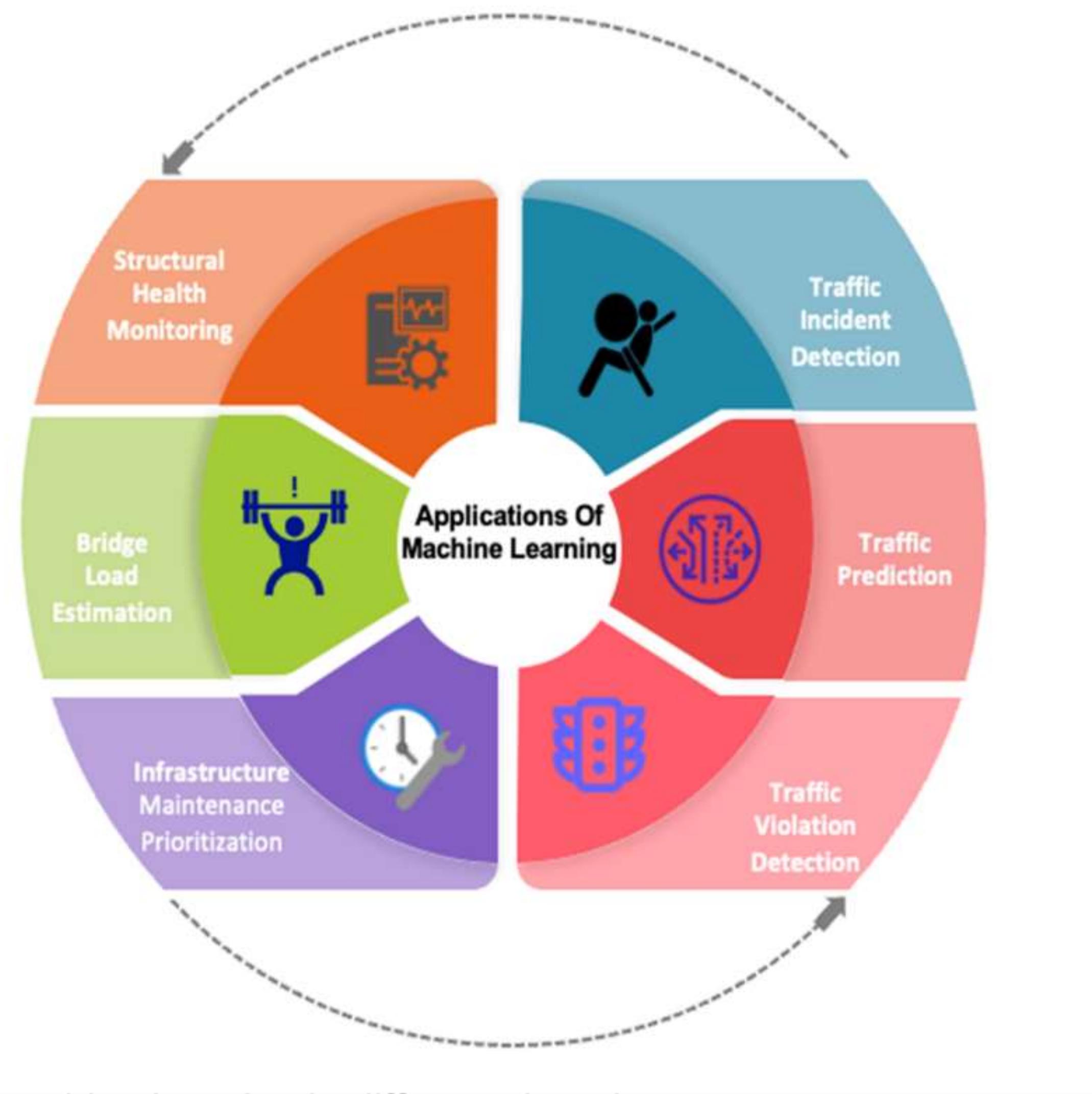
Model Training, selection, and deployment with Explainability

University of Nebraska at Omaha, School of Interdisciplinary Informatics

Presented by:
Vudit Singh
Supervisor:
Dr. Robin Gandhi
Dr. Brian Ricks
Dr. Yonas Kassa

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.



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

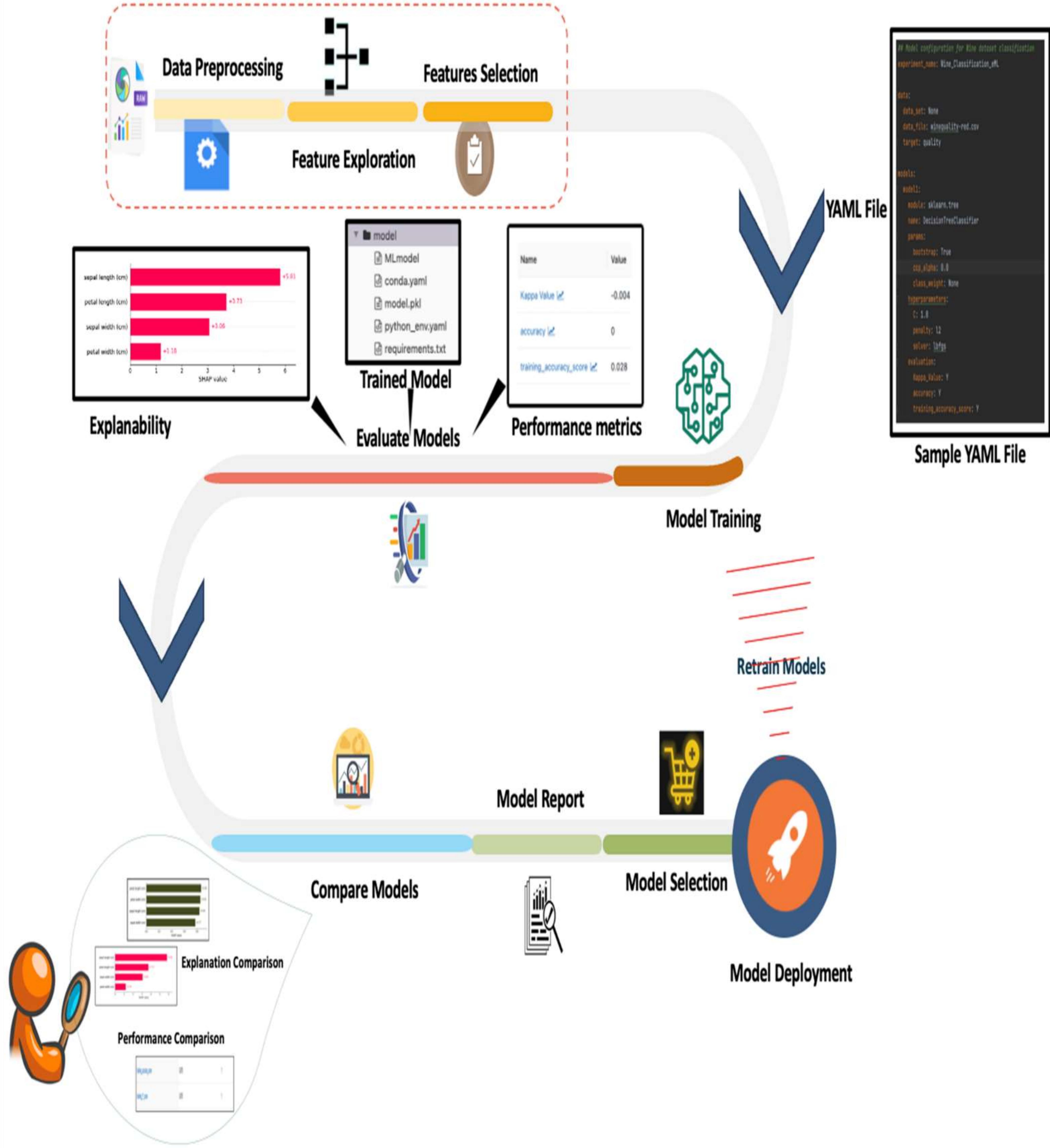


5/24/2023

Machine Learning Lifecycle

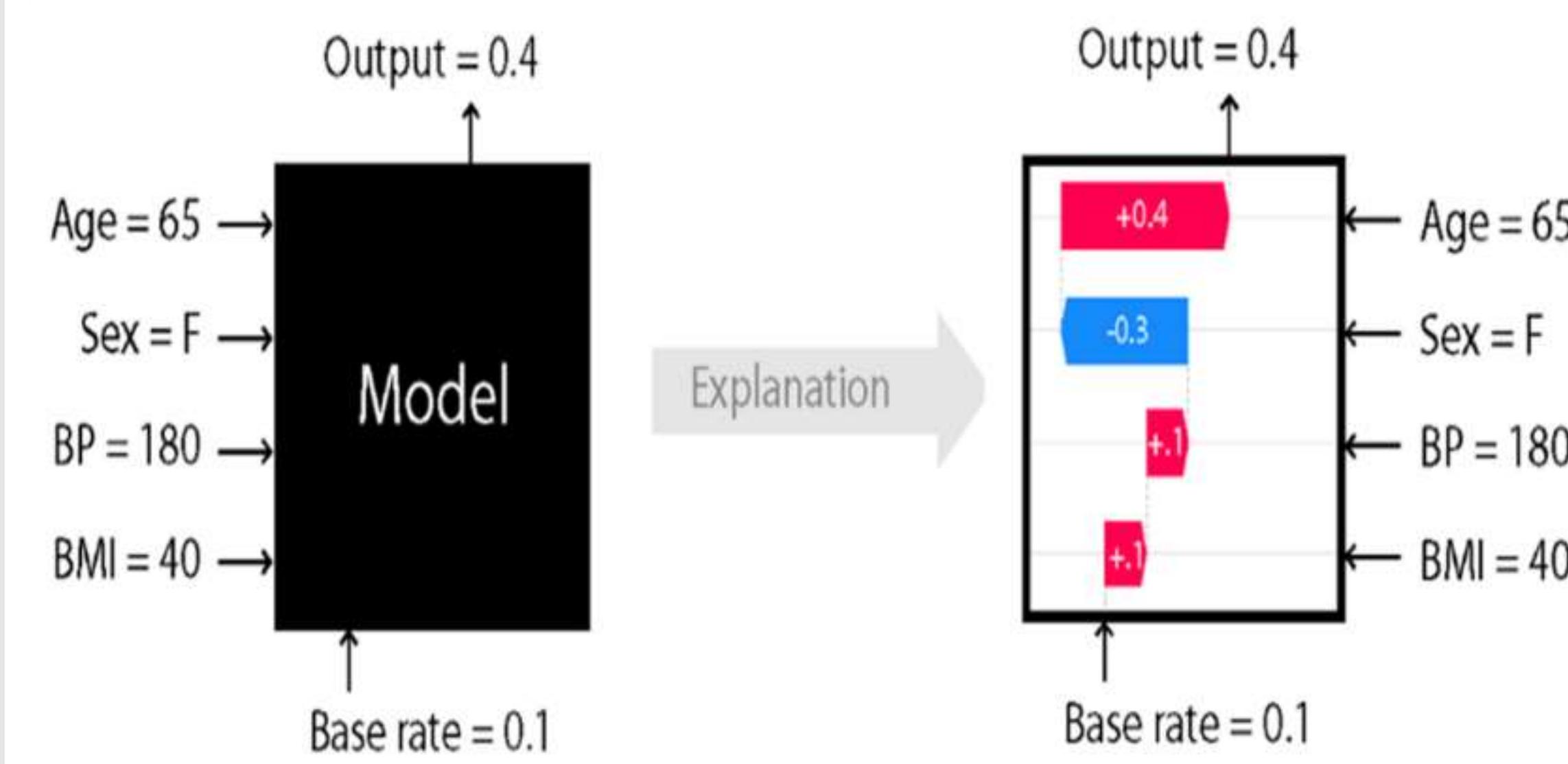
A set of interrelated stages for training and deploying machine learning models. It is divided into phases, each with its own set of activities and needs. It needs an important component – Explainability.

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

This work is partially supported by contracts W912HZ21C0060 and W912HZ23C0005, US Army Engineering Research and Development Center (ERDC), and Award Number 1762034 from the National Science Foundation.

References

- [1] Zaharia, Matei, et al. "Accelerating the machine learning lifecycle with MLflow." *IEEE Data Eng. Bull.* 41.4 (2018): 39-45.
 - [2] Salvucci (2021). *Mlops-standardizing the machine learning workflow* (Doctoral dissertation, University of Bologna)
 - [3] Shap documentation, Retrieved May 5,2023,from <https://shap.readthedocs.io/en/latest/index.html>



Progress in a New Visualization Strategy for ML Models

A Mid-Project Summary of Design and Ongoing Problems

University of Nebraska at Omaha, College of IS&T

CONTRIBUTORS:

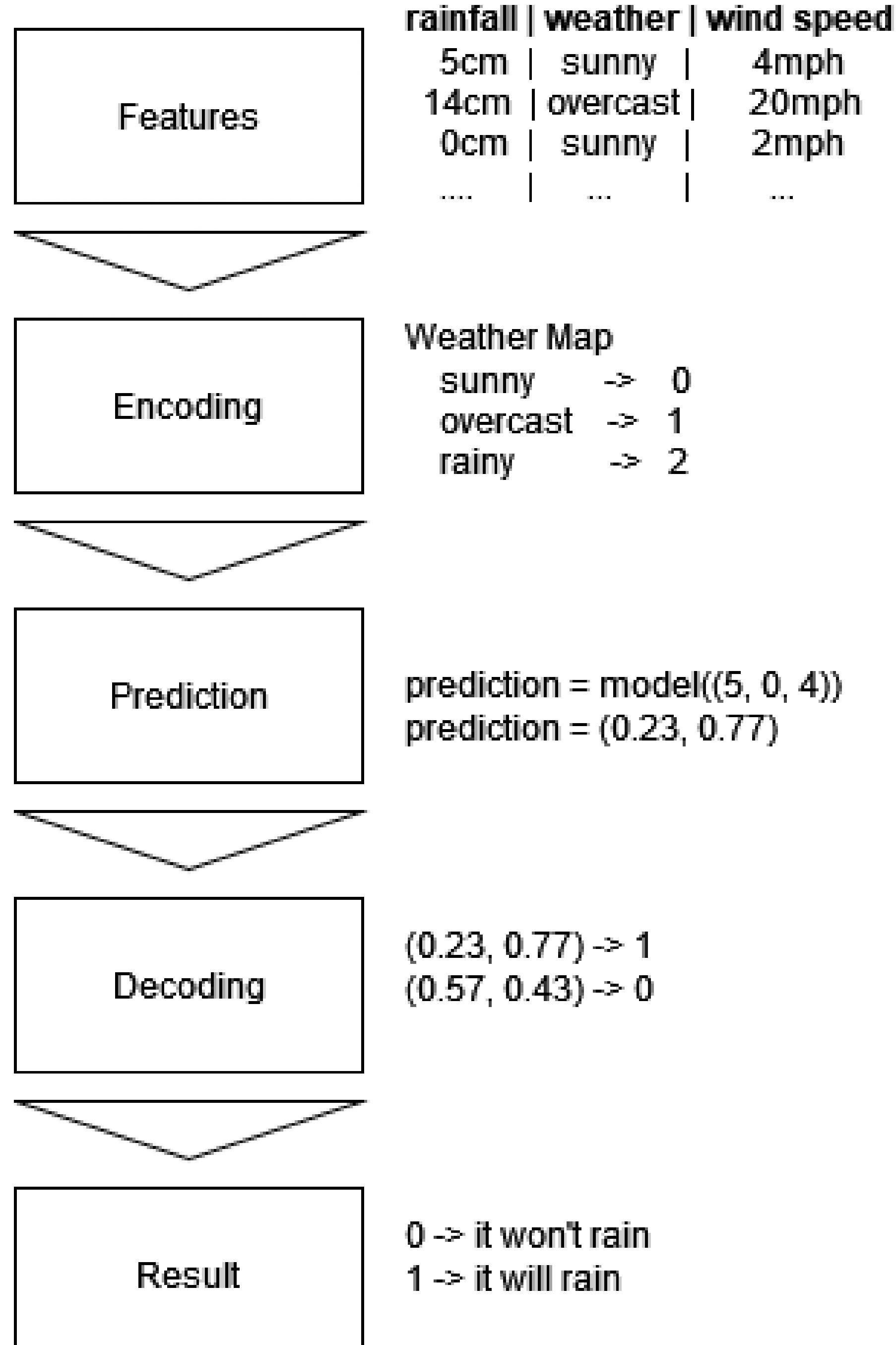
- Alex Wissing
- Dr. Brian Ricks
- Dr. Robin Gandhi
- Dr. Yonas Kassa
- Akshay Kale

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.

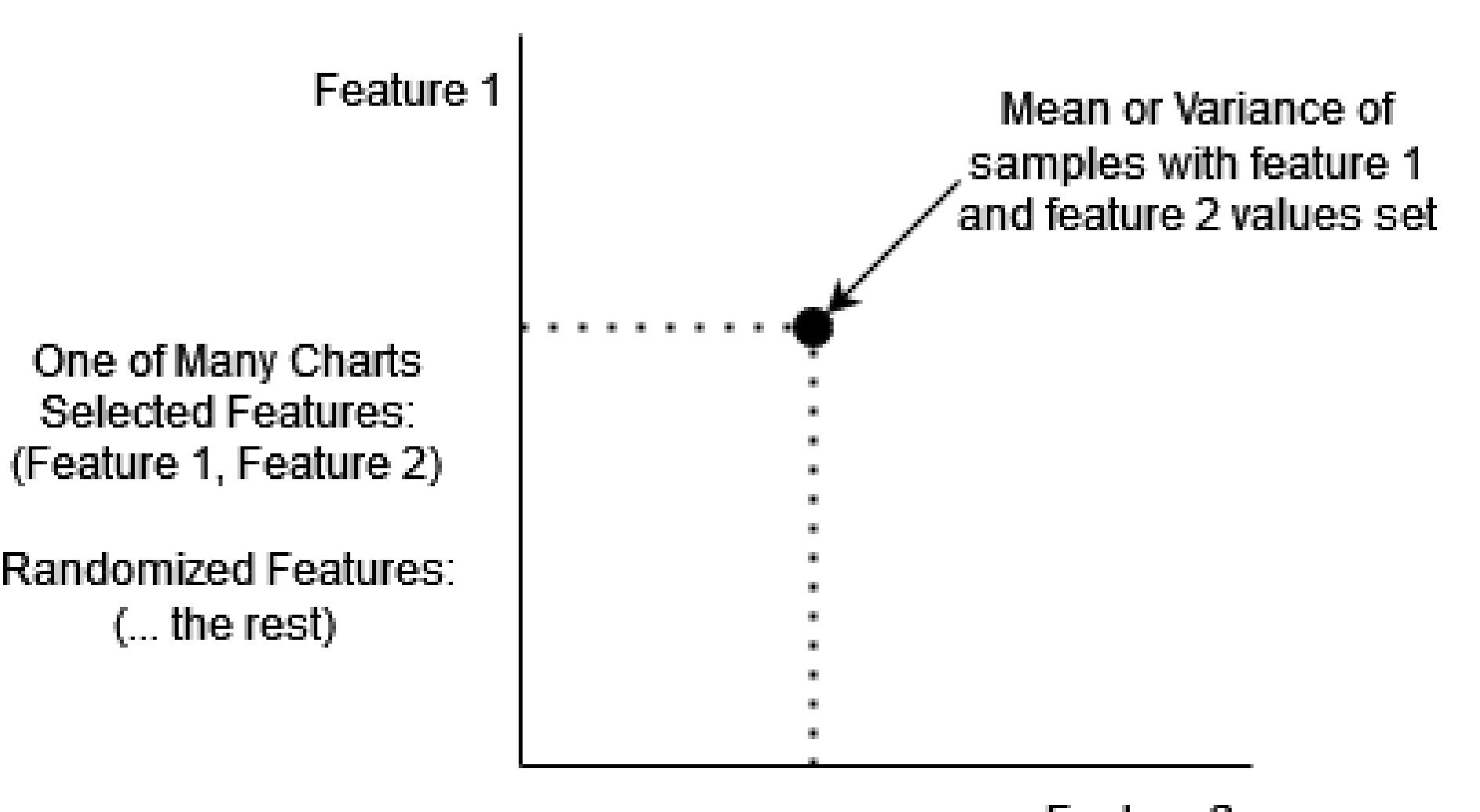
Visualization

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.

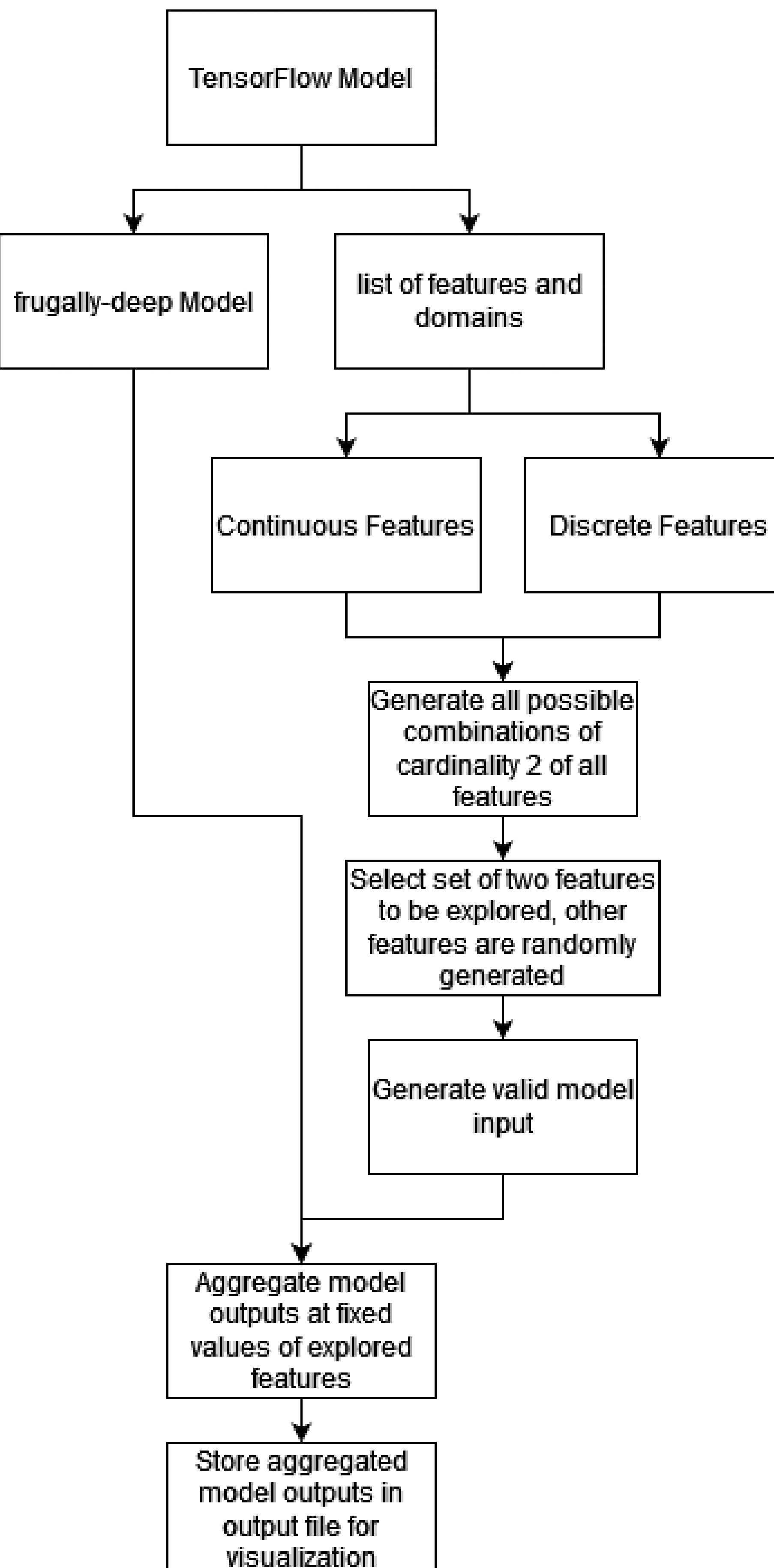


Usefulness of Visualization

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

Acknowledgements

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 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