IncidentNet

Traffic Incident Detection, Localization and Severity Estimation with Sparse Sensing

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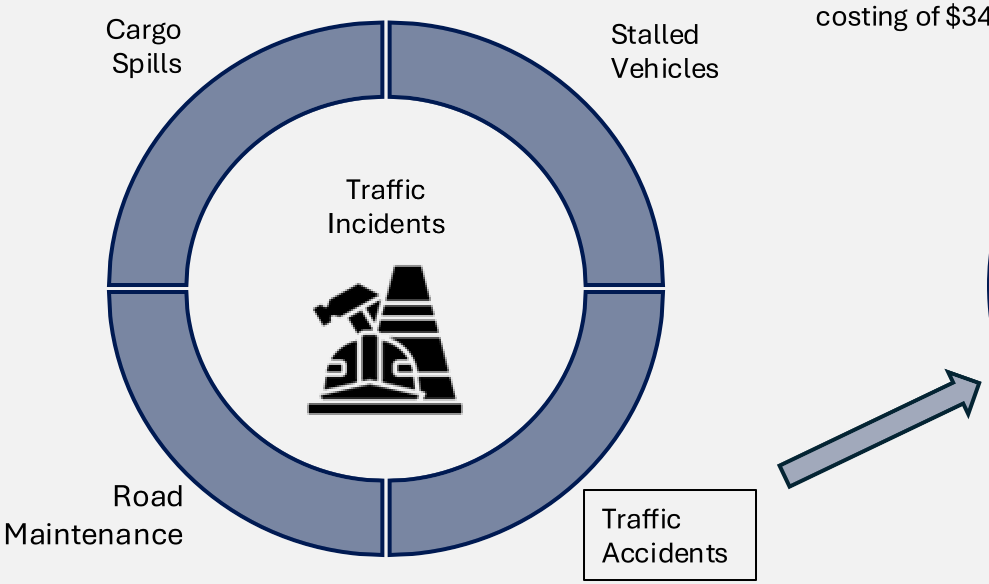
Motivation for Incident Detection

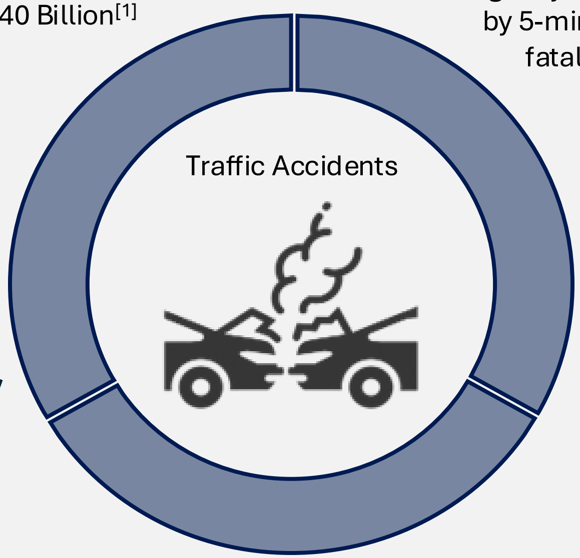
Traffic Incident Categories



Impact of Traffic Accident

28 million incidents, costing of $340 Billion[1]

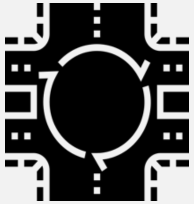
Emergency response delayed by 5-minutes, increasing fatality rate by 46% [2]



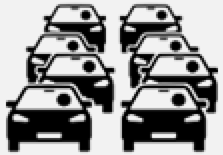
Emergency response under 7-minutes, decreasing fatality rate by 58% [2]

Broader Issues of Traffic Incidents

Delayed emergency services



Commuter’s safety



Traffic congestion

[1] Lawrence Blincoe et al. The economic and societal impact of motor vehicle crashes, 2019. Technical report, 2022.
[2] James P Byrne et al. Association between emergency medical service response time and motor vehicle crash mortality in the United States. JAMA Surgery, 154:286–293, 2019.

Existing Incident Detection Works

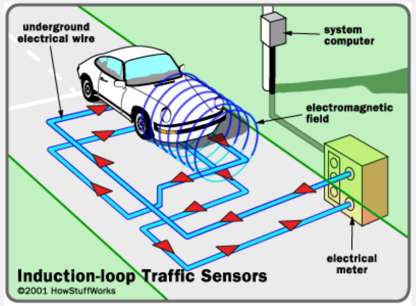
Previous Works	Region	Dataset	Sensor Modality	Model	Approach	Limitations
Chen *et al.*[1]	Highway	Macroscopic	Inductive Loop Detectors	XGBoost	Trained on data from upstream and downstream traffic detectors	Requires data from consecutive detectors
Bao *et al.*[2]	Highway	Microscopic	Traffic Cameras	YOLOv3	Detects incidents based on vehicle speed by tracking vehicles in the camera's field of view	Can detect incidents only in field-of-view
Han *et al.*[3]	Urban	Microscopic	GPS probes	Clustering	Detects incidents by matching real-time GPS speed vectors with historical incident patterns	Affected by noise and interference and mandates the installation of a GPS probe in every vehicle
Yang *et al.*[4]	Urban	Macroscopic	Inductive Loop Detectors	Deep Learning	Detects incidents using deep-learning network to detect incidents	Uses Simplistic simulation which does not model real city traffic
Zhu *et al.*[5]	Urban	Macroscopic	Inductive Loop Detectors	Custom CNN	Detects incidents based on constructed a connectivity matrix of sensors	Uses only traffic counts for detecting incidents
IncidentNet	Urban Highways	Microscopic	Traffic Cameras	XGBoost TabNet	Used Tabular ML models to detect incidents from data derived from microscopic traffic data	-

[1] Chen et al. More robust and better: Automatic traffic incident detection based on XGBoost (ATTCA 2023)
[2] Bao et al. Research on Highway Traffic Event Detection Method Based on Image Processing (IOP EES 2021)
[3] Han et al. Traffic incident detection: A trajectory-based approach, (ICDE 2020)
[4] Yang et al. Traffic Incident Generation And Supervised Learning-Based Detection Via A Microscopic Simulation Platform (ITSC 2023)
[5] Zhu et al. Deep learning approach for traffic incident detection in urban networks, (ITSC 2018)

Existing Incident Detection Works (continued...)

Macroscopic dataset

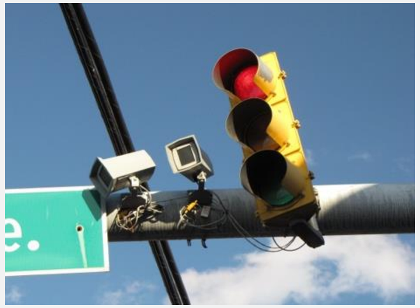
- Features: average traffic flow, count, and density calculated over time.
- Sensors: Inductive Loop Detectors.
- Examples: datasets PEMS Bay, METR-LA, SFO I-880



Time	Average Speed	Traffic Count	Average traffic occupancy
5	67.04	48	0.20
10	70	45	0.18
15	71	59	0.15

Microscopic dataset

- Features: individual vehicle speed, timestamps, vehicle unique identifiers
- Sensors: Cameras, Bluetooth Sensors, GPS.
- Example datasets: Highway 99-W, NYC taxi data.



Timestamp	Vehicle Identifier	Speed	Lane Number
10:00:23	Purple Sedan	72	3
10:02:11	Blue SUV	40	1
10:07:00	Black Sedan	65	3

Challenges for Accurate Incident Detection

Our Contributions

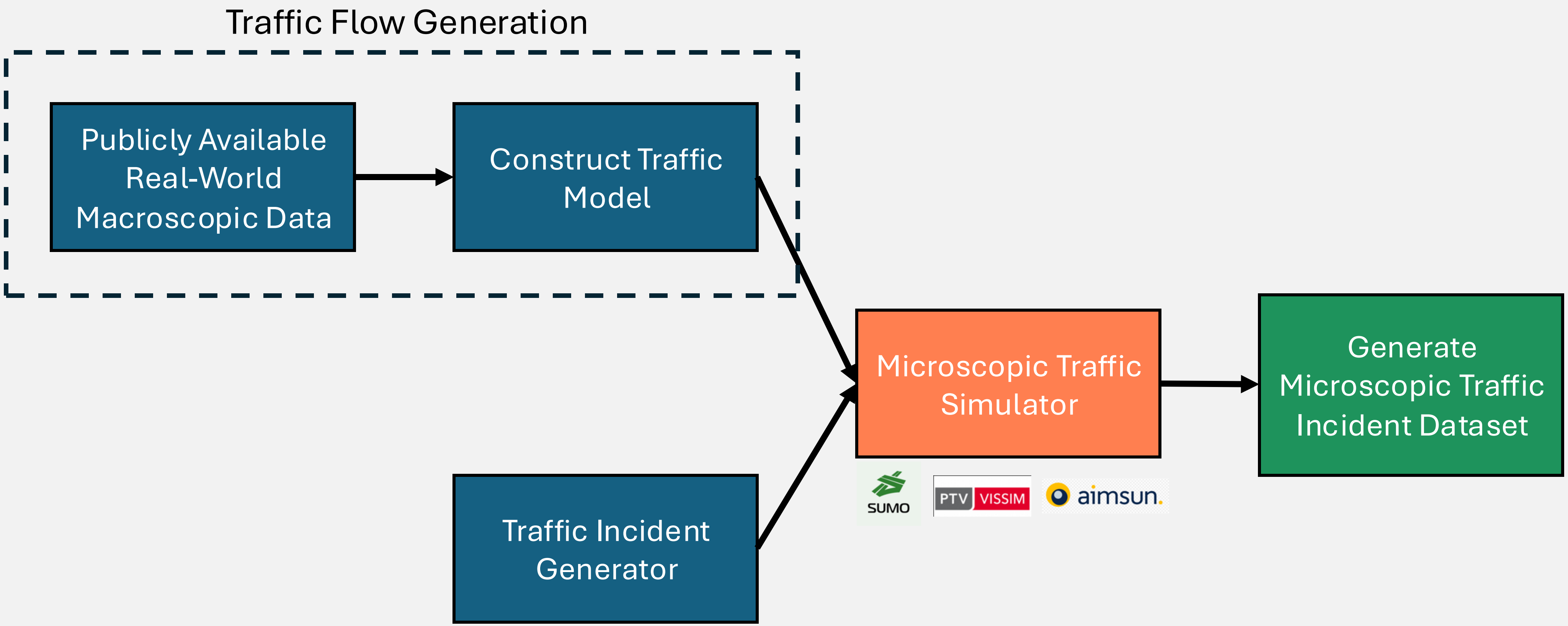
Lack of microscopic datasets → A generic approach for generating realistic microscopic datasets using real-world captured macroscopic data

Algorithm to detect, locate, and estimate severity of incidents in urban regions → A deep-learning-based algorithm that can detect, localize and estimate severity on microscopic datasets for both urban regions and highways

Our Approach

Workflow of Microscopic Traffic Dataset Generation | Generalized Approach for Traffic Incident Detection, Localization and Severity Estimation

Workflow of Microscopic Traffic Dataset Generation

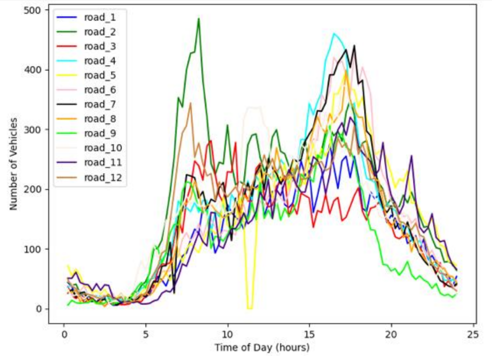


Traffic Flow Simulation

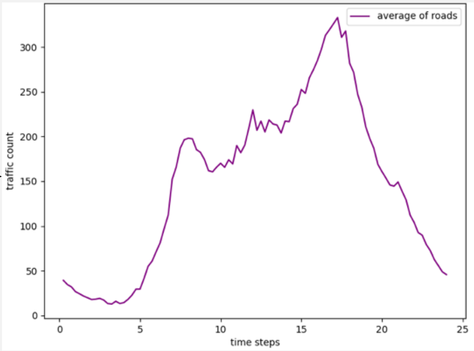
Target map region

Tempe DOT vehicle count data

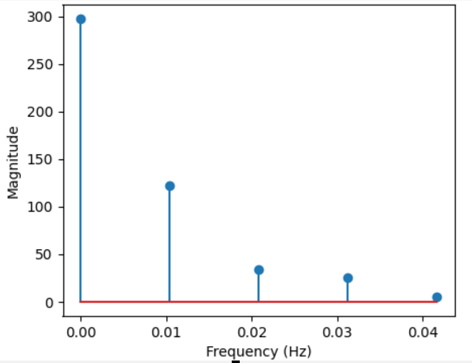
Plot of Traffic Counts vs Timestep



Plot of Average Traffic count vs Timestep

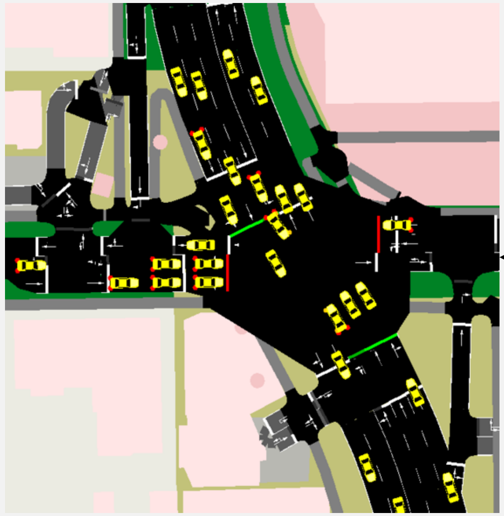


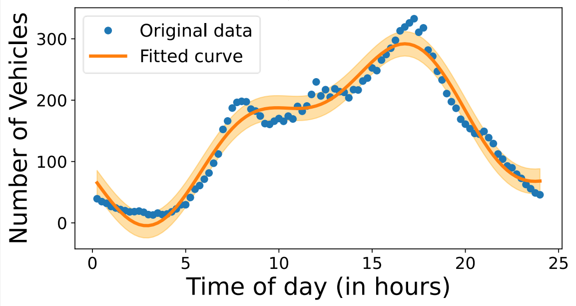
FFT spectrum of average traffic data



$$f(t) = A_1 \sin(B_1 t + C_1) + A_1 \sin(B_1 t + C_1) + D + \alpha$$

$$\delta = \frac{J^T[y - f(t)]}{J^T \cdot J + \lambda I}$$





Traffic Incident Simulation

Probability of incident per vehicle

Total number of vehicles in simulation

Incident occurrence decision function

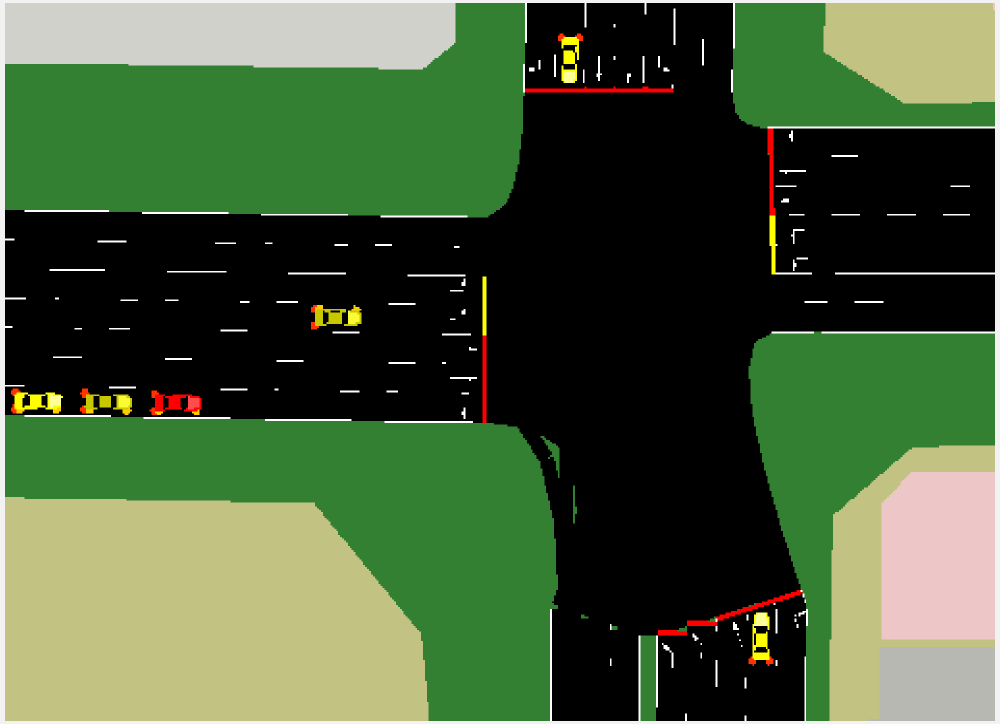
YES

Randomly select Incident severity

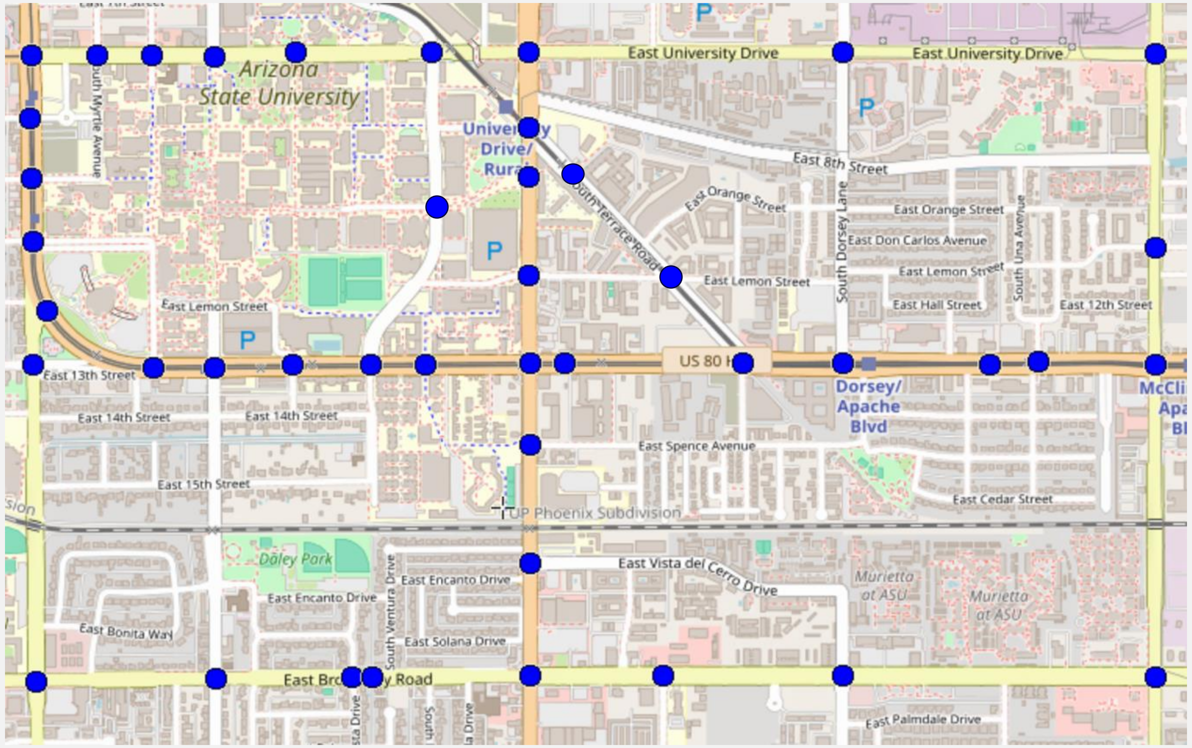
Randomly select Incident clearance time

Slow down cars within a radius of incident

NO



Dataset Generation from Microscopic Traffic Simulators



43 traffic signals are marked as blue dots, indicating potential locations for placing traffic cameras to collect data

Traffic Cameras placed at traffic signals collect Data

Raw Features
Individual Vehicle Identifiers
Vehicle Speed
Intersection ID
Timestamp
Traffic Count
Traffic Occupancy

Labels
Incident Occurrence
Incident Severity
Incident Localization

Data Pre-processing and Feature Extraction

Timestamp	Vehicle Identifier	Junction Identified	Vehicle Speed
7:02:10	Red SUV	1	32
7:04:40	Blue SUV	1	25
7:08:00	Red SUV	2	20

Travel Time for junction 1 to 2

Travel Times across all Junction combinations

+

Traffic metrics from raw data

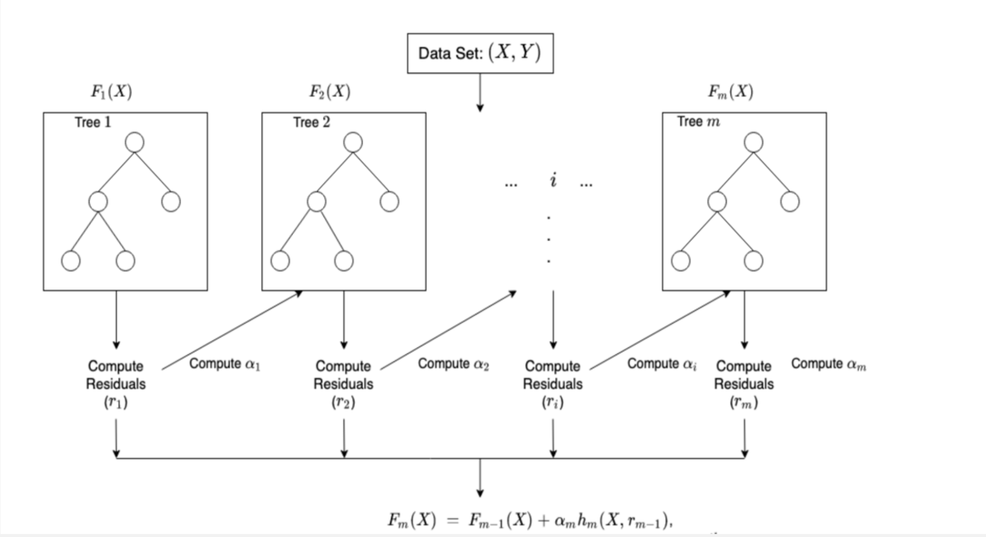
Rolling Window

Averages

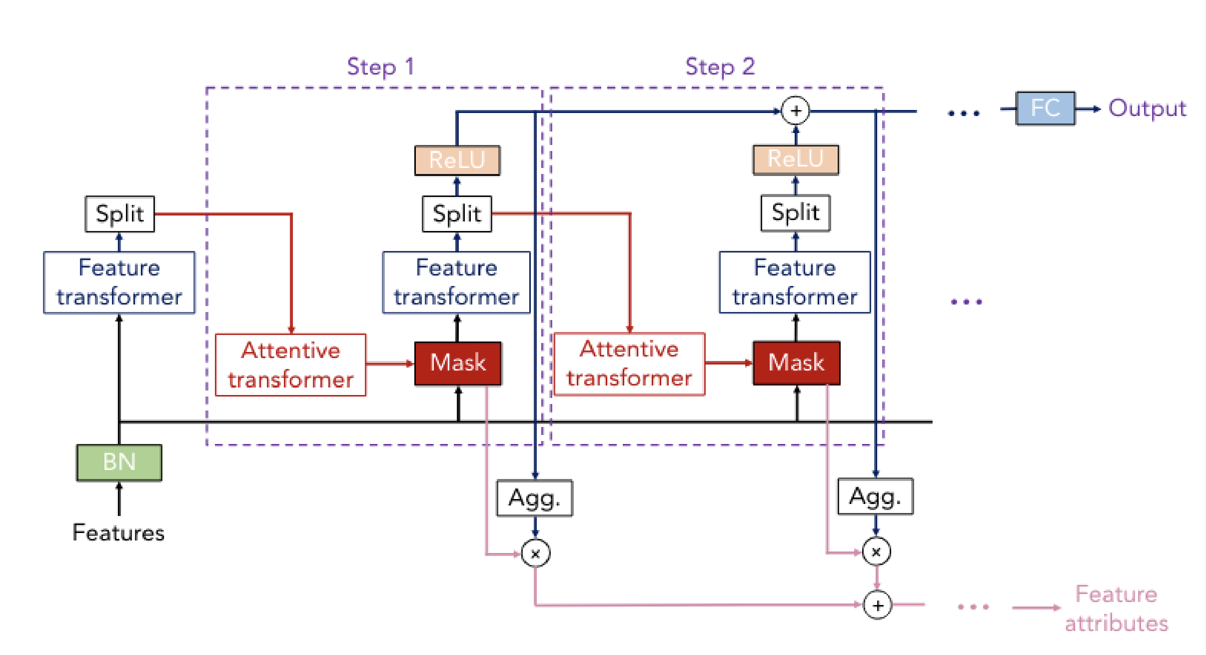
Processed Dataset

Model Selection and Architecture

			Incident Label	Incident Location	Incident Severity
Processed Tabular Data			FALSE	None	None
			FALSE	None	None
			TRUE	Road 4	High
			TRUE	Road 2	Low
			TRUE	Road 1	Low

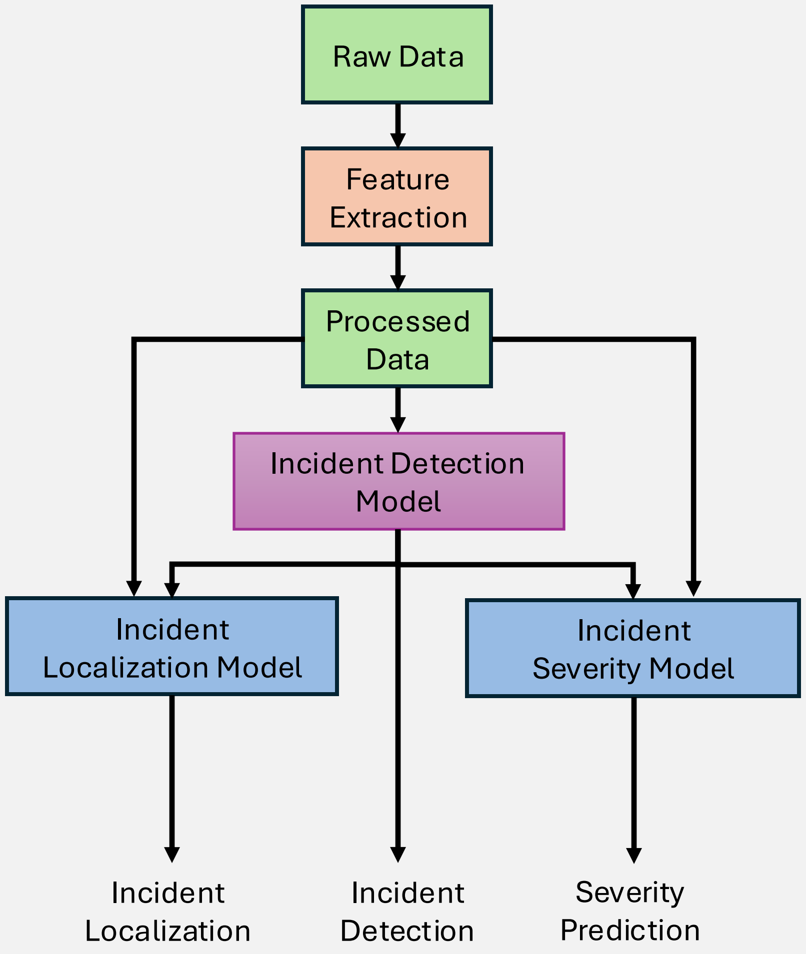


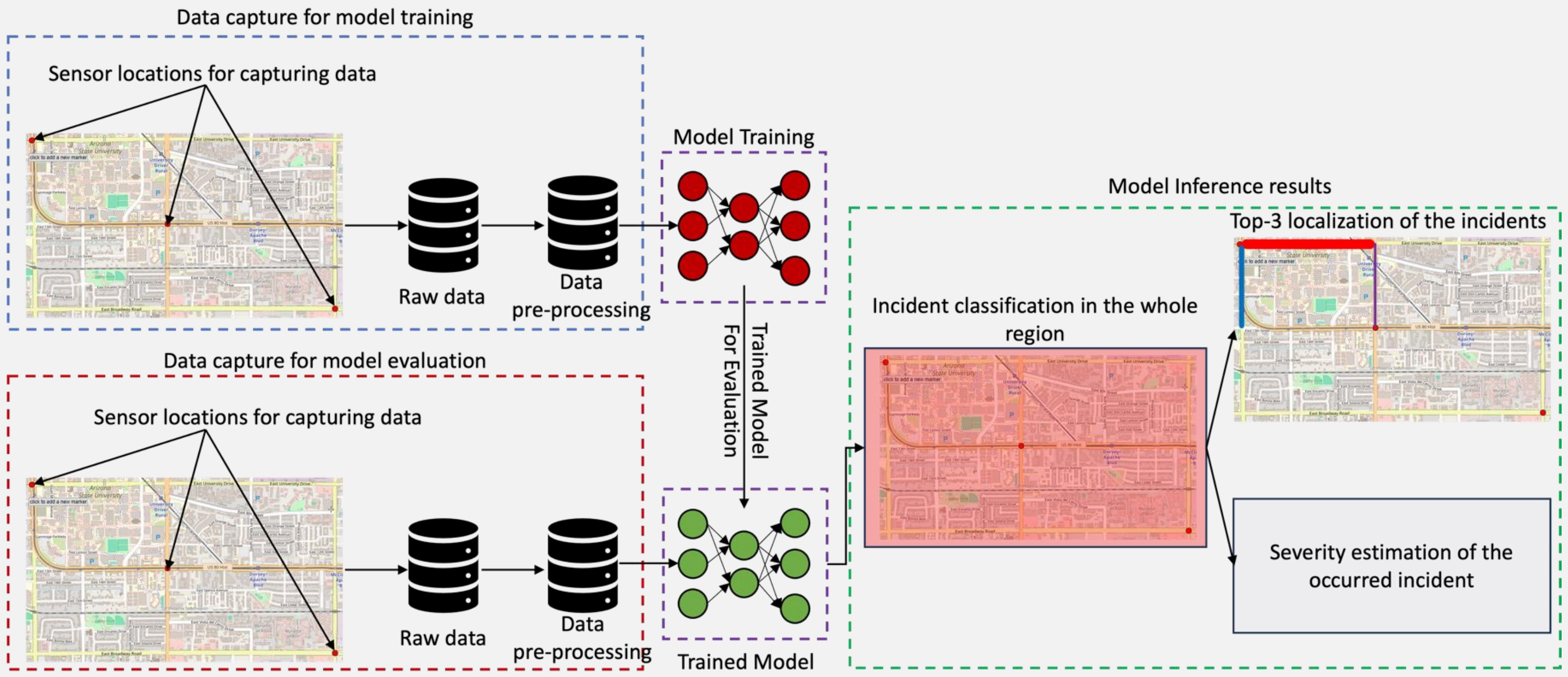
XGBoost Architecture



TabNet Architecture

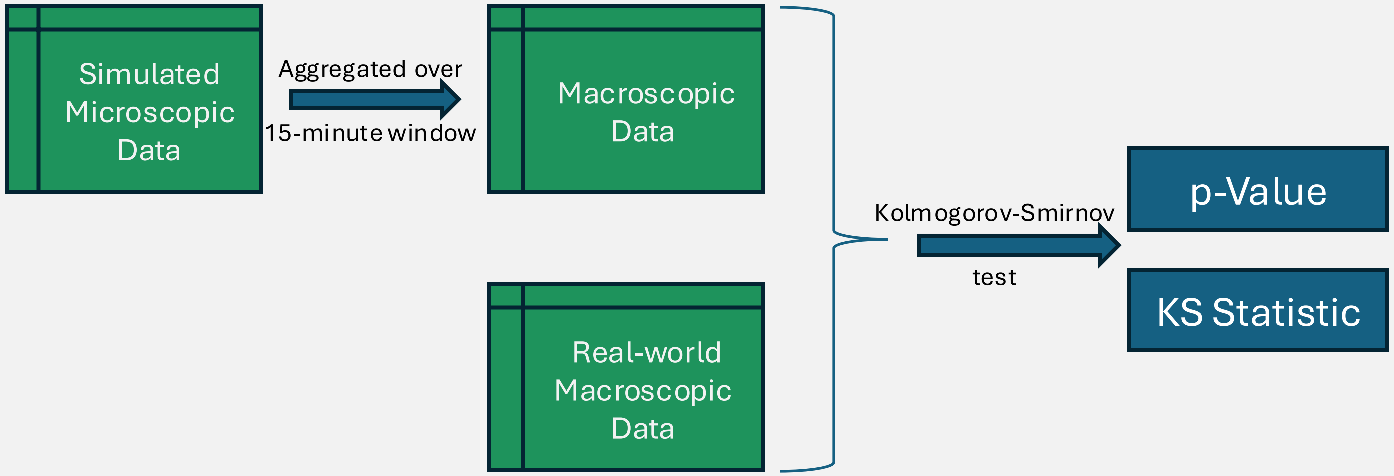
Model Selection and Architecture (continued…)



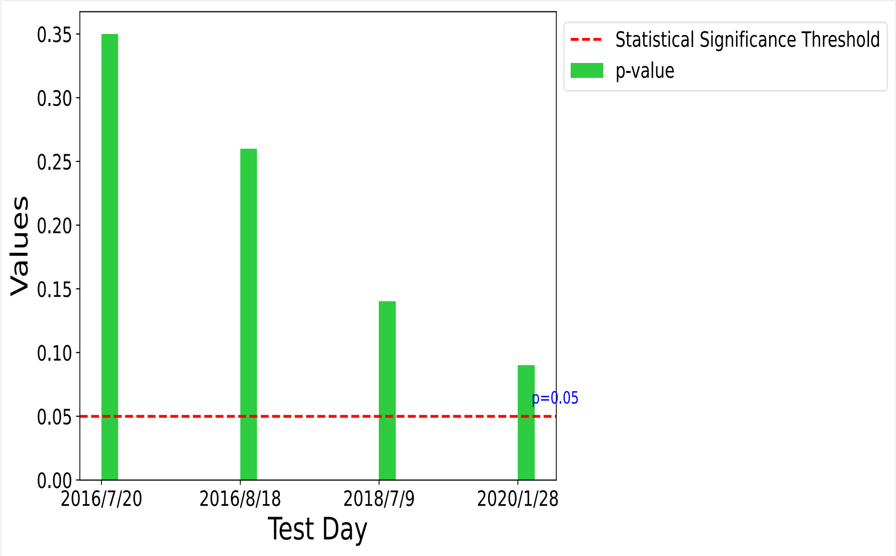


Experiments and Results

Our Microscopic Data Matches with Real-World Macroscopic Data



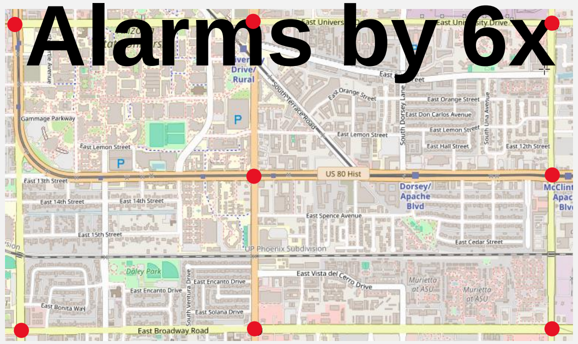
Evaluation Metrics



Two similar distributions will have the same cumulative probability distribution function (CDF)
CDF : F(x) = P(X <= x))

Null Hypothesis: The two samples come from same continuous distribution

IncidentNet Detects 2x More Incidents with 2.5x Faster Mean-Time-To-Detect while Reducing False Alarms by 6x



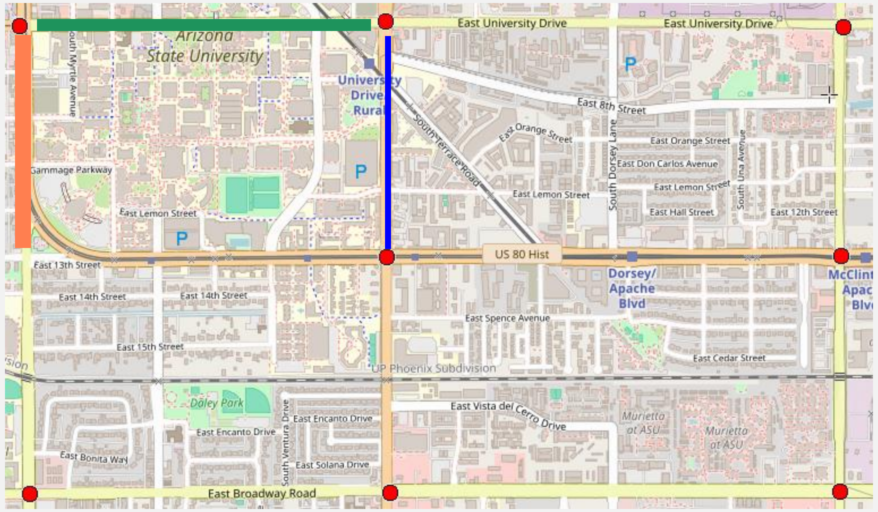
8 sensor placement for incident detection evaluation

Evaluation Metrics

Algorithm	DR	MTTD	FAR	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Specificity
IncidentNet (XG Boost)	96%	94 secs	11%	92%	93%	90%	87%	91%	95%
IncidentNet (TabNet)	98%	197 secs	6%	93%	94%	91%	92%	93%	95%
Zhu *et al.* (CNN)	51%	471 secs	35%	60%	40%	50%	44%	51%	64%

DR: Detection Rate
MTTD: Mean-Time-To-Detect
FAR: False Alarm Rate

IncidentNet can also Localize and Estimate Severity of Incidents

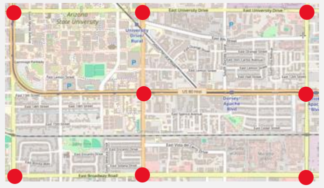


Evaluation Metrics

Algorithm	Severity	Localization - Top 1	Localization - Top 2	Localization - Top 3
IncidentNet (XGBoost)	77%	68%	75%	80%
IncidentNet (TabNet)	82%	70%	80%	85%

IncidentNet can Accurately Detect, Localize and Estimate Severity with Few (8/43 to 3/43) Sensors

Evaluating IncidentNet up to 8 out of 43 sensors



8 junctions

5 junctions

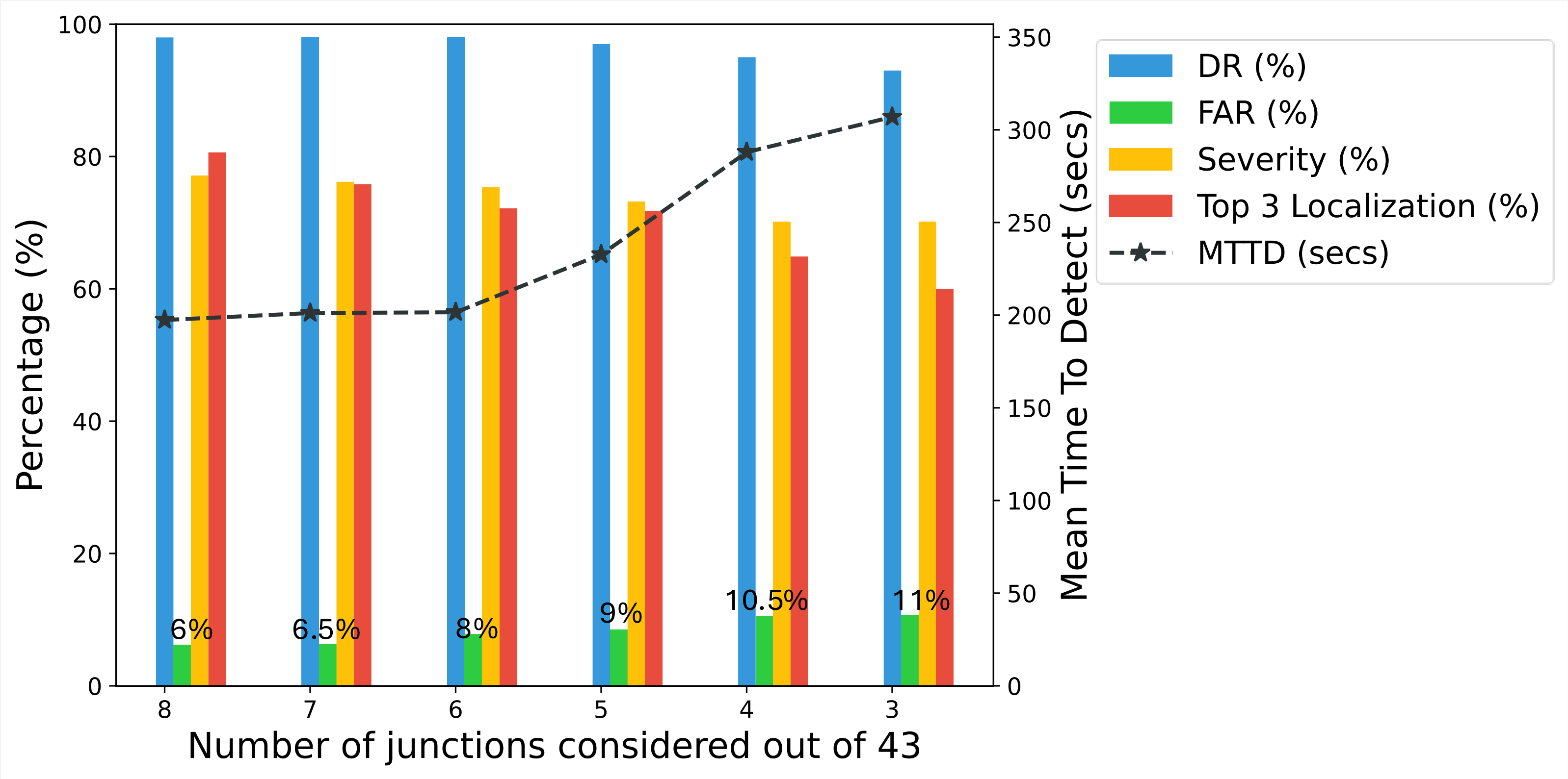
7 junctions

4 junctions

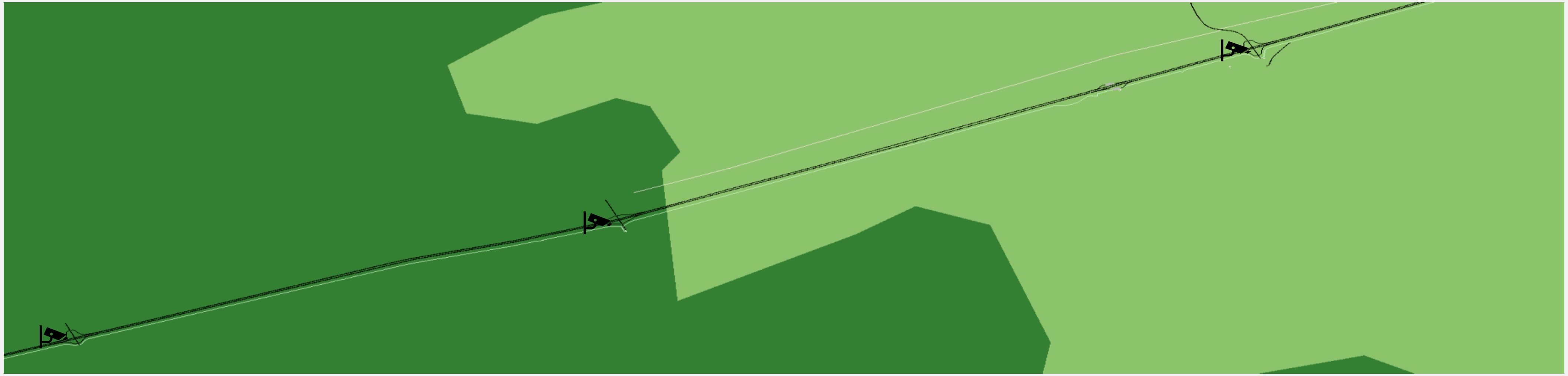
6 junctions

3 junctions

Evaluation Metrics



IncidentNet can also Accurately Detect Incidents on Highways



Evaluation Metrics

Algorithm	DR	MTTD	FAR
IncidentNet (XGBoost)	98%	45 secs	6.02%
IncidentNet (TabNet)	99%	70 secs	4.17%

Importance of Sensor Placement (Future Direction)

<u>Randomly selected 3 sensor placements out of 12341 possibilities</u>

Placement 1

Placement 2

Placement 3

Evaluation Metrics

Sensor Placement	Accuracy (%)	F1 score (%)
Placement 1	88.22	86.17
Placement 2	95.73	94.96
Placement 3	97.85	97.46

~10%⬆

For 3 sensor placement : We have $^{43}C_3$= 12341 combinations!!

Conclusion

<u>Validation</u>

Simulation-based generated traffic data was similar to real-world macroscopic data

<u>Generalization</u>

IncidentNet can detect incidents for landscapes such as for urban regions and highways

<u>Efficiency</u>

IncidentNet can detect more incidents with minimal false alarms while being faster

<u>Insightful</u>

IncidentNet can also localize the incident and estimate its severity.