



Condition Assessment of Bridges using Physics-based and Data-driven Methods

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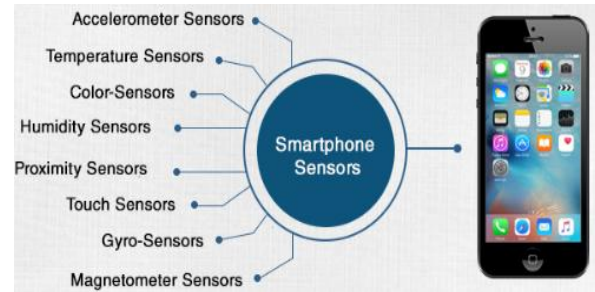
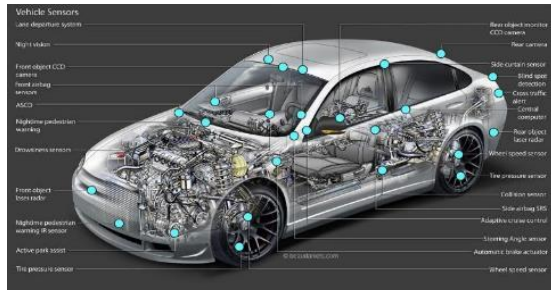


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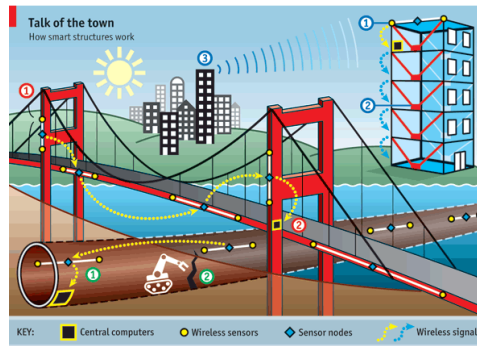
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- 2 Vehicle weight limit determination
- 3 Condition rating using NLP-based method
- 4 SVM-based train classification
- 5 Data-driven fatigue damage prediction
- 6 Automated bridge defect inspection
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1 Background

In modern society, we are surrounded by sensors, which provides a large amount of data.

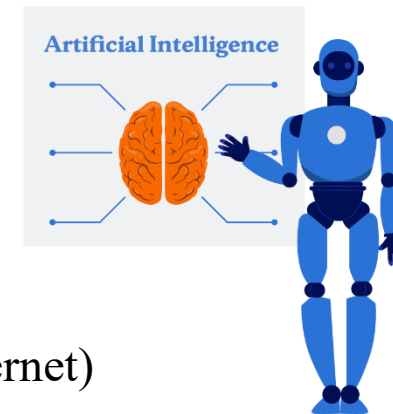


‘The Economist’,
2010



“If a car can be made smart enough to spot when the oil is low or a brake light has failed, why not do the same for bridges, tunnels and buildings?”

Artificial Intelligence (AI)



Machine Learning (ML)

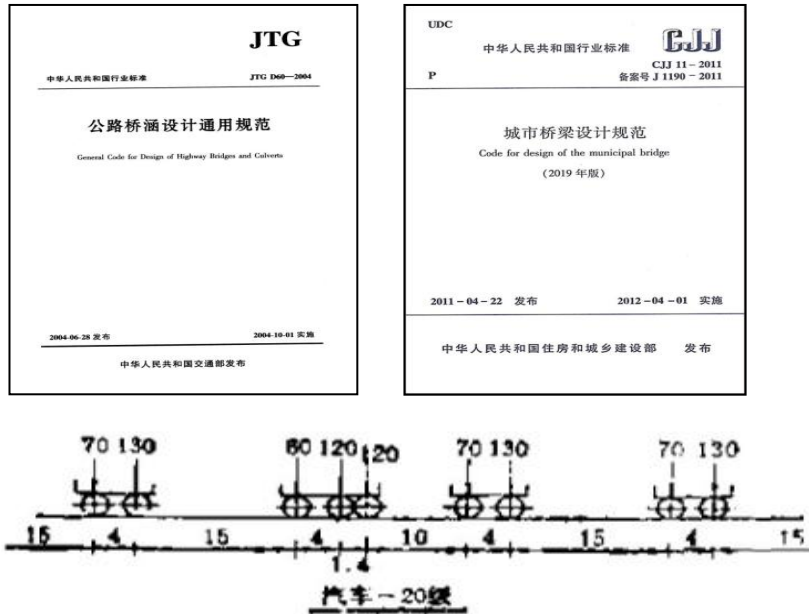


(Images from internet)

Physics-based and data-driven methods
comprehensively utilized for health monitoring and condition assessment of bridges

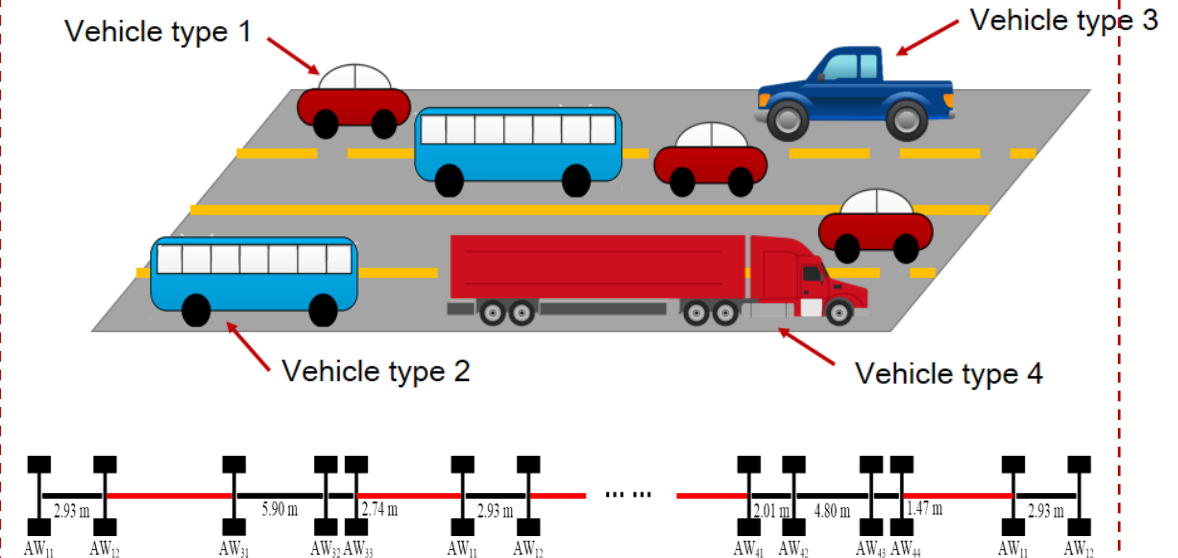
2 Vehicle weight limit determination

Vehicle load model



- Static, fixed load
- Single vehicle type
- Varying codes

Stochastic traffic load model



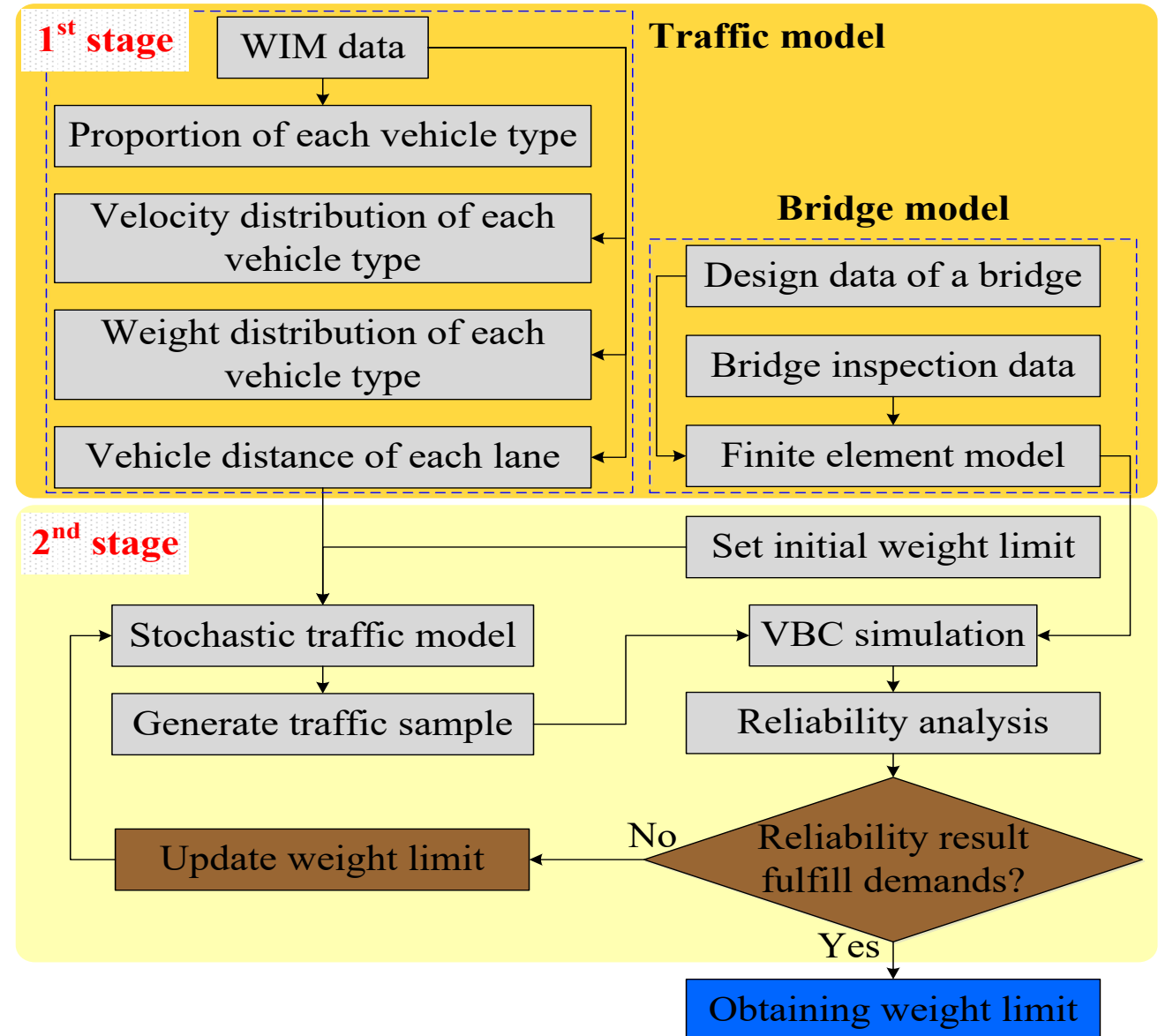
- Vehicle types
- Total and axle weight, speed
- Vehicle distance
- Lane distribution

2 Vehicle weight limit determination

A reliability-based method for vehicle weight limit determination

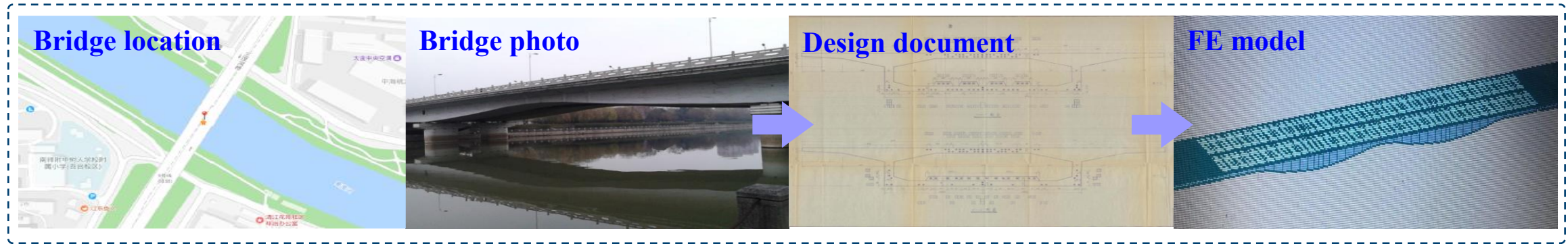
Stochastic traffic model
using site-specific WIM data

Determine the vehicle
weight limit.

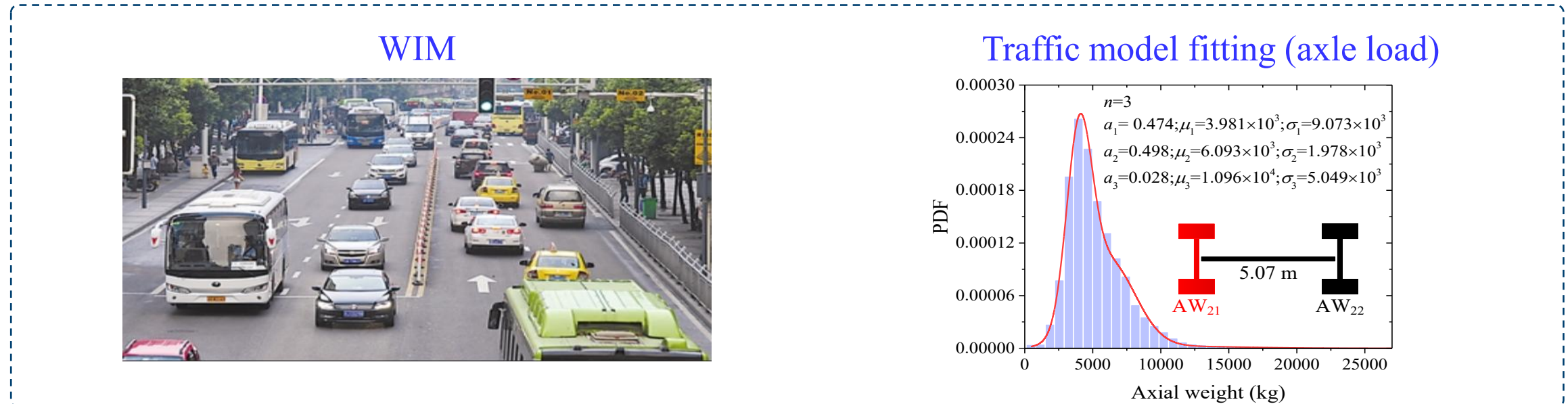


2 Vehicle weight limit determination

Example: Sancha River Bridge



Step1: WIM Data collection



2 Vehicle weight limit determination

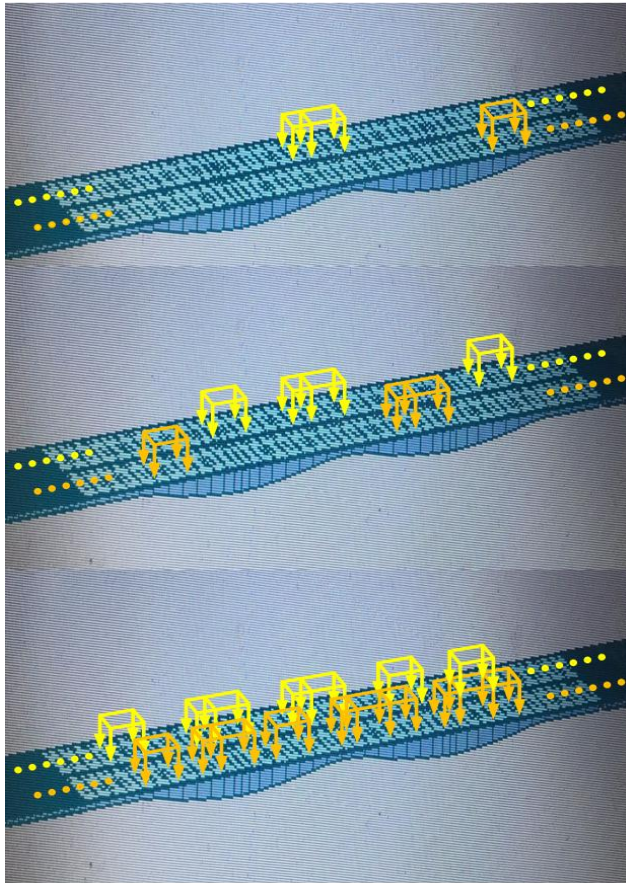
Step2: FEM analysis

Traffic scenarios

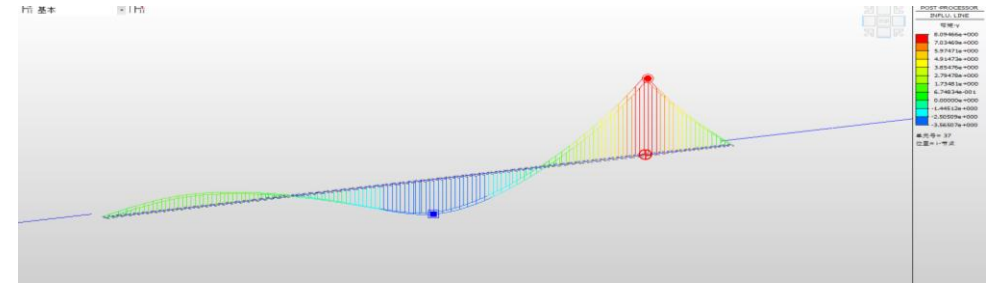
Low traffic volume

Normal traffic volume

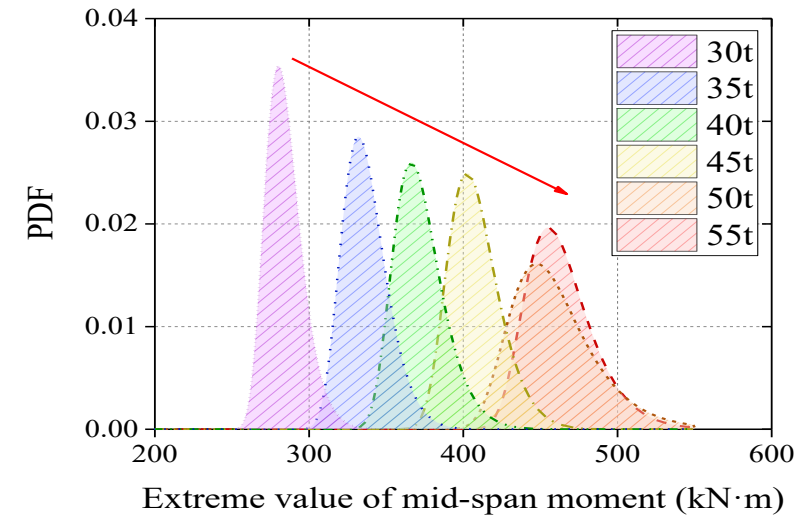
High traffic volume



Calculation of mid-span moment



Extreme value distribution under various weight limits



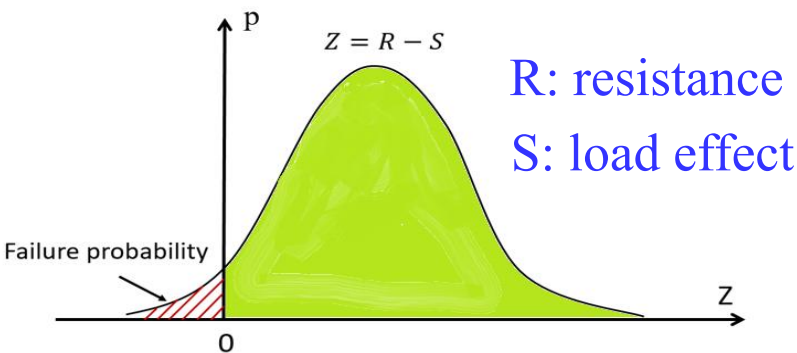
2 Vehicle weight limit determination

Step3: Vehicle weight limit determination

Reliability index calculation

Failure probability $p_f = \Pr(Z < 0)$

Reliability index $\beta = -\Phi^{-1}(p_f)$



Reliability index	Safety importance level		
	A	B	C
β	4.7	4.2	3.7

Sancha River Bridge is in safety level B

Vehicle weight limit		Mid-span moment			
		30 t	36 t	40 t	50 t
Reliability	Traffic model 1	8.23	6.29	5.00	3.24
index β	Traffic model 2	8.86	6.77	5.38	3.42

Vehicle weight limit determined as 40 t

3 Condition rating using NLP-based method



Condition rating

Based on textual description on damages of the bridge members such as girders, bearings, expansion joints, and piers.

Member weighting
coefficient

1%~24%



Member
rating

1~5 levels

Bridge
rating

1~5 levels

3 Condition rating using NLP-based method

$$D_r = 100 - \sum_{i=1}^n R_i W_i / 5$$

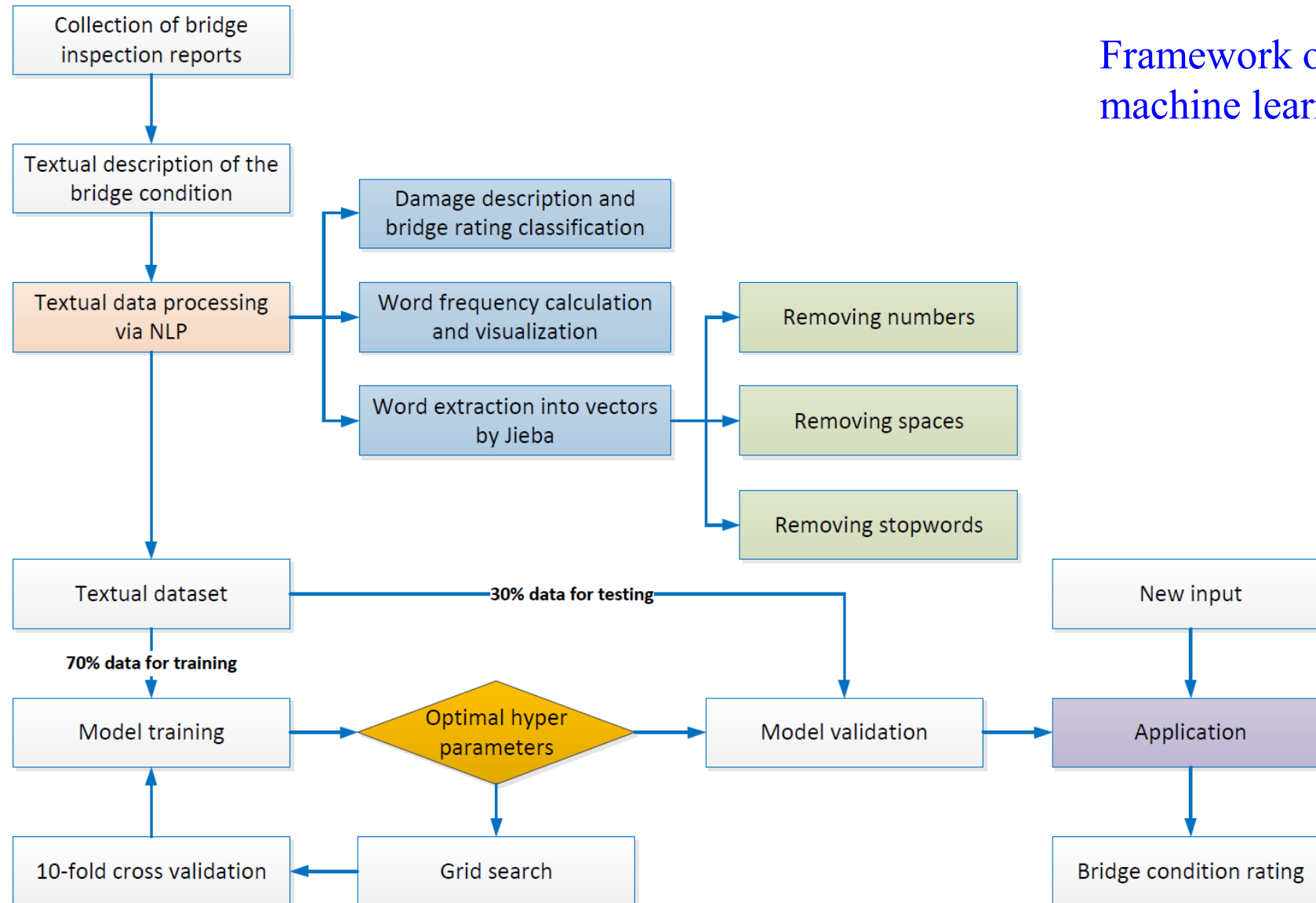
In which, R_i is the rating of each member ranging from 0~5;
 W_i is the weighting coefficient of each member, and $\sum W_i=100$;
 D_r is the score of condition rating for the bridge.
According to the score, the condition rating is classified into four levels.

$D_r \geq 88$	Level 1;
$88 > D_r \geq 60$	Level 2;
$60 > D_r \geq 40$	Level 3;
$40 > D_r$	Level 4 or 5.

Defect status and scale		Combined rating				
		Small → Big				
		Few → Many				
		Light → Severe				
		Scale	0	1	2	
Effect on the structural function	No, Unimportant	0		0	1	2
	Small, Secondary	+1		1	2	3
	Big, Important	+2		2	3	4
Combination of the above two evaluations		-	0	1	2	3 4
Modification on the defect development	Stable	-1	-	0	1	2 3
	Develop slowly	0	0	1	2	3 4
	Develop faster	+1	1	2	3	4 5
Final condition rating result			1	2	3	4 5

Time-consuming and labor-intensive

3 Condition rating using NLP-based method



Framework of NLP-based machine learning method

3 Condition rating using NLP-based method

A total of 263 inspection reports of concrete bridges in different health conditions are collected

The condition of bridges in the four rating levels

Level	Overall condition	Key members condition	Secondary members condition
A	Perfect	Good functionality and good material property	Good functionality, minor damage in material (less than 3%)
B	Good	Good functionality, minor damage in material (less than 3%), crack less than threshold	Some members with moderate damage in material (less than 10%)
C	Fairly poor	Some members with moderate damage in material (less than 10%), crack greater than threshold, minor functional damage	Many members with severe damage (10 to 20%), degradation in function
D	Poor	Many members with severe damage in material (10 to 20%), crack greater than threshold, severe weathering, peeling, spalling and corrosion, moderate functional damage.	More than 20% members with severe damage, loss of function

3 Condition rating using NLP-based method

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6.4.1 The expansion joint rubber strip damage and section steel rupture

During the inspection, it was found that the rubber strips of the expansion joints of the xxxx Bridge were damaged, and the section steel was ruptured.

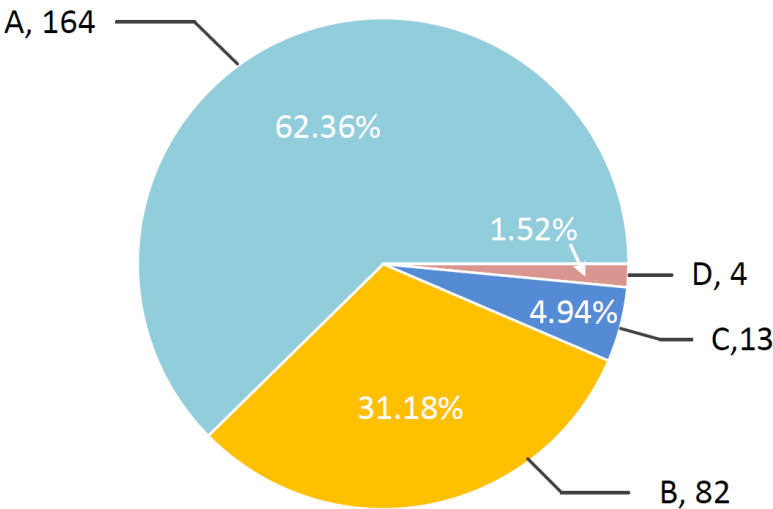
Cause analysis: 1) The rubber strips between the expansion joints are aging, deformed, and defective; 2) The expansion joints have abnormal expansion and contraction under vehicle and environmental loads, causing the rubber strips to fall off and damage; 3) The anchoring connection of the expansion joints is damaged under the repetitive impact of the vehicles.

Suggestions: 1) Replace the rubber strip; 2) Replace the expansion joint section steel, and re-weld.

3 Condition rating using NLP-based method



Bridge locations



Condition rating levels

Word cloud of term frequency (TF)



3 Condition rating using NLP-based method

Word frequency and TF, TF-IDF values for top 10 words

A

Words	Frequency	TF	Words	TF-IDF
Deck	237	1.45	Inspection	0.426
Superstructure	163	0.99	Deck	0.413
Substructure	163	0.99	Found	0.378
Crack	160	0.98	Substructure	0.365
Cracking	158	0.96	Expansion joints	0.307
Damage	148	0.90	Cracking	0.255
Expansion joints	143	0.87	Damage	0.245
Deck bottom plate	113	0.69	Crack	0.244
Longitudinal	111	0.68	Superstructure	0.231
Lateral	108	0.66	Deck bottom plate	0.203

B

Words	Frequency	TF	Words	TF-IDF
Crack	250	3.05	Rebar rusting	0.427
Damage	232	2.83	Damage	0.413
Rebar rusting	207	2.52	Crack	0.409
Concrete	167	2.04	Exposed rebar	0.351
Cracking	159	1.94	Cracking	0.276
Exposed rebar	152	1.85	Concrete	0.258
Deck	128	1.56	Deck	0.240
Lateral	111	1.35	Vertical	0.239
Vertical	104	1.27	Found	0.214
Longitudinal	90	1.10	Expansion joints	0.201

C

Words	Frequency	TF	Words	TF-IDF
Damage	40	3.08	Damage	0.421
Crack	37	2.85	Crack	0.358
Deck bottom plate	31	2.38	Slab bridge	0.354
Slab bridge	26	2.00	Deck bottom plate	0.354
Cracking	25	1.92	Cast-in-place	0.299
Deck	24	1.85	Exposed rebar	0.272
Lateral	23	1.77	Deck	0.265
Cast-in-place	21	1.62	Cracking	0.256
Concrete	20	1.54	Expansion joints	0.231
Exposed rebar	20	1.54	Lateral	0.212

D

Words	Frequency	TF	Words	TF-IDF
Cracking	35	8.75	Cracking	0.567
Crack	32	8.00	Rebar rusting	0.498
Rebar rusting	26	6.50	Crack	0.487
Damage	23	5.75	Exposed rebar	0.428
Exposed rebar	20	5.00	Vertical	0.386
Vertical	18	4.50	Damage	0.381
Efflorescence	16	4.00	Efflorescence	0.342
Lateral	15	3.75	Lateral	0.218
Longitudinal	9	2.25	Box girder	0.171
Spalling	8	2.00	Longitudinal	0.137

3 Condition rating using NLP-based method

DT, SVM, GBRT models are used for the classification, and precision, recall and accuracy are calculated.

		Predicted condition				
		A	B	C	D	Recall
Actual condition	A	108 (42%)	7 (2%)	2 (1%)	0 (0%)	92%
	B	7 (2%)	49 (19%)	0 (0%)	0 (0%)	88%
	C	3 (1%)	0 (0%)	6 (2%)	0 (0%)	67%
	D	0 (0%)	2 (1%)	0 (0%)	0 (0%)	0%
Precision		92%	84%	75%	N/A	88%

Accuracy

		Predicted condition				
		A	B	C	D	Recall
Actual condition	A	41 (15%)	5 (2%)	1 (1%)	0 (0%)	87%
	B	5 (2%)	51 (19%)	0 (0%)	0 (0%)	91%
	C	3 (1%)	0 (0%)	6 (2%)	0 (0%)	67%
	D	0 (0%)	2 (1%)	0 (0%)	0 (0%)	0%
Precision		94%	94%	100%	N/A	94%

Accuracy

		Predicted condition				
		A	B	C	D	Recall
Actual condition	A	44 (16%)	3 (1%)	0 (0%)	0 (0%)	94%
	B	6 (2%)	20 (8%)	0 (0%)	0 (0%)	91%
	C	2 (1%)	0 (0%)	2 (1%)	0 (0%)	67%
	D	0 (0%)	2 (1%)	0 (0%)	0 (0%)	0%
Precision		85%	80%	100%	N/A	94%

Accuracy

		Predicted condition				
		A	B	C	D	Recall
Actual condition	A	47 (17%)	0 (0%)	0 (0%)	0 (0%)	100%
	B	4 (2%)	22 (8%)	0 (0%)	0 (0%)	85%
	C	3 (1%)	0 (0%)	1 (1%)	0 (0%)	25%
	D	0 (0%)	2 (1%)	0 (0%)	0 (0%)	0%
Precision		87%	92%	100%	N/A	89%

Accuracy

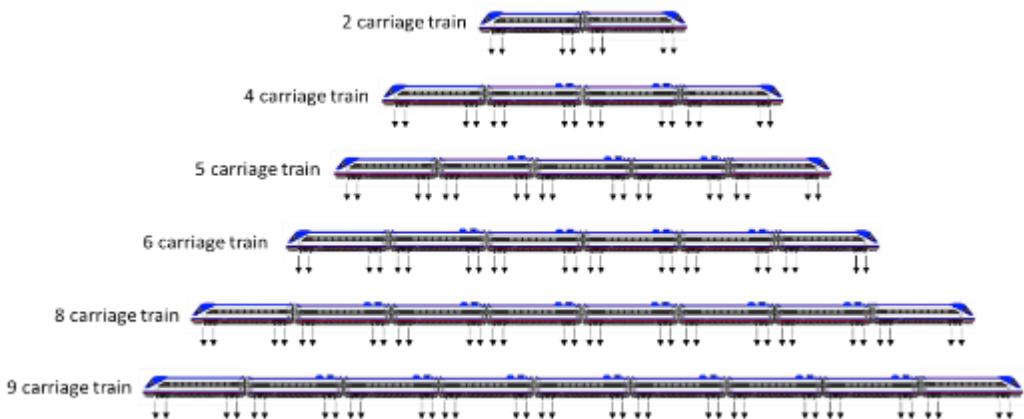
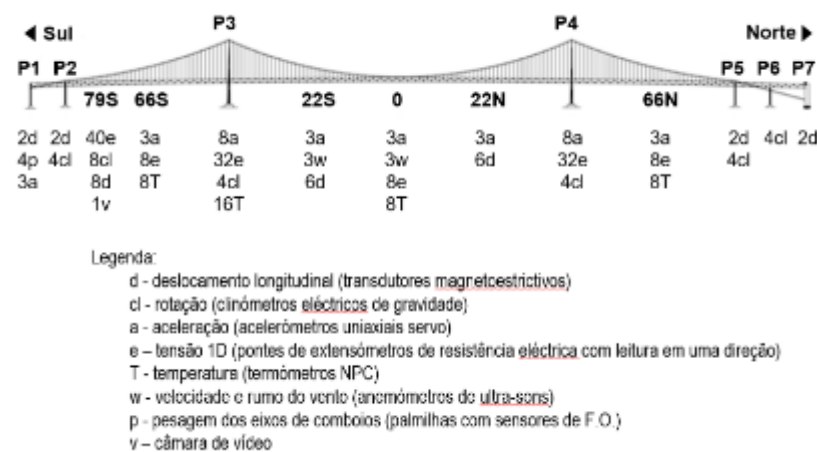
- Textual data of component-level exploited to realize bridge-level assessment.
- Condition ratings automated with an accuracy of 89%.

4 SVM-based train classification

Trainloads are important, quantifying the number and category of trains necessary.

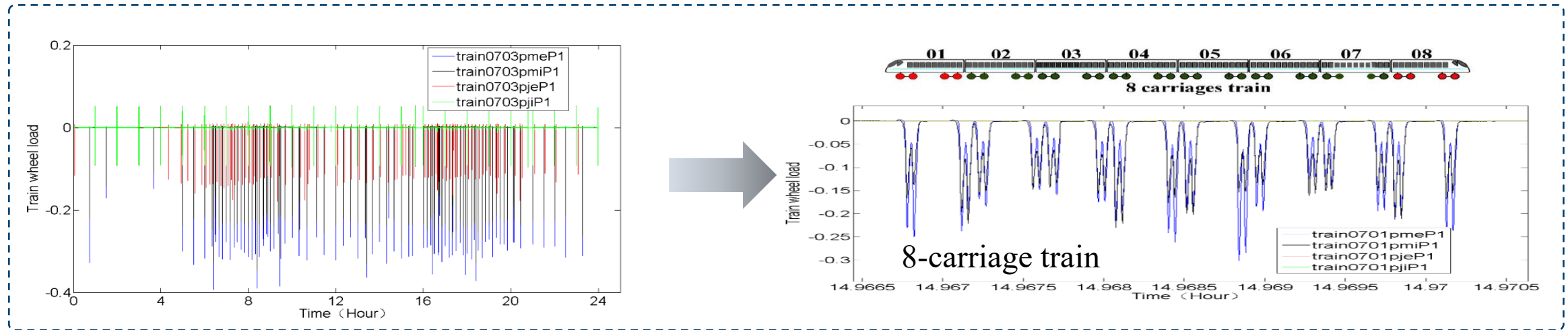


SHM of April 25th suspension Bridge

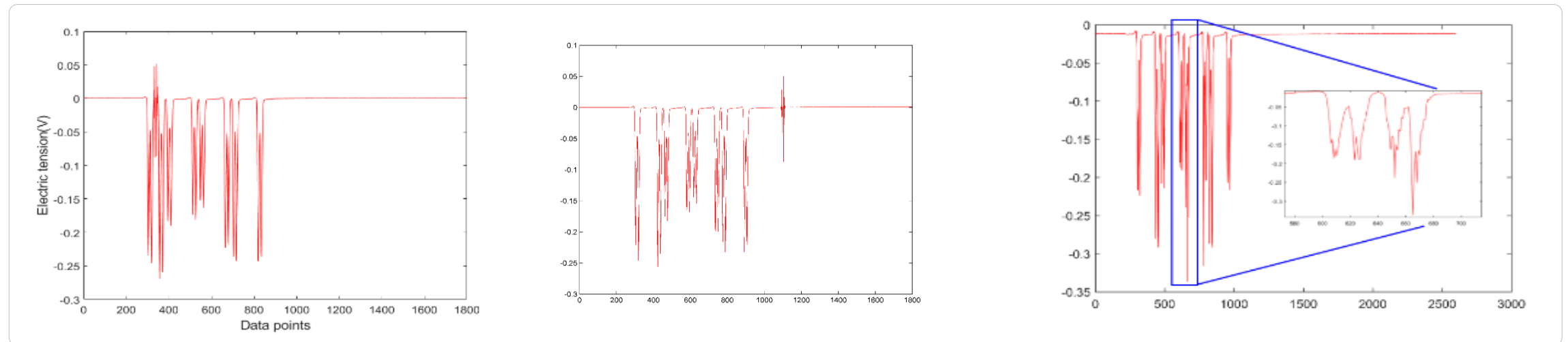


4 SVM-based train classification

Peak-picking method

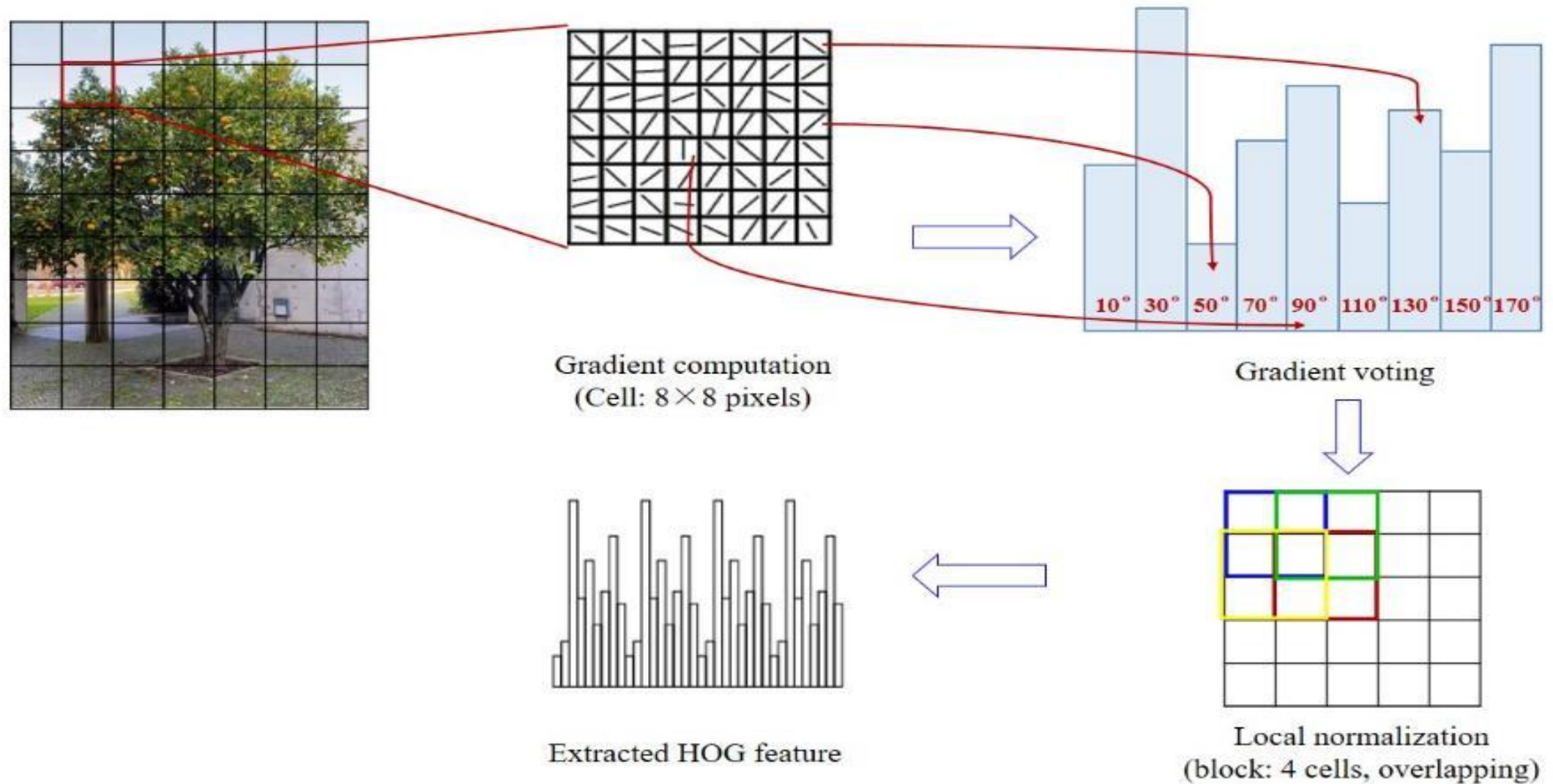


Facing difficulty when there is noise



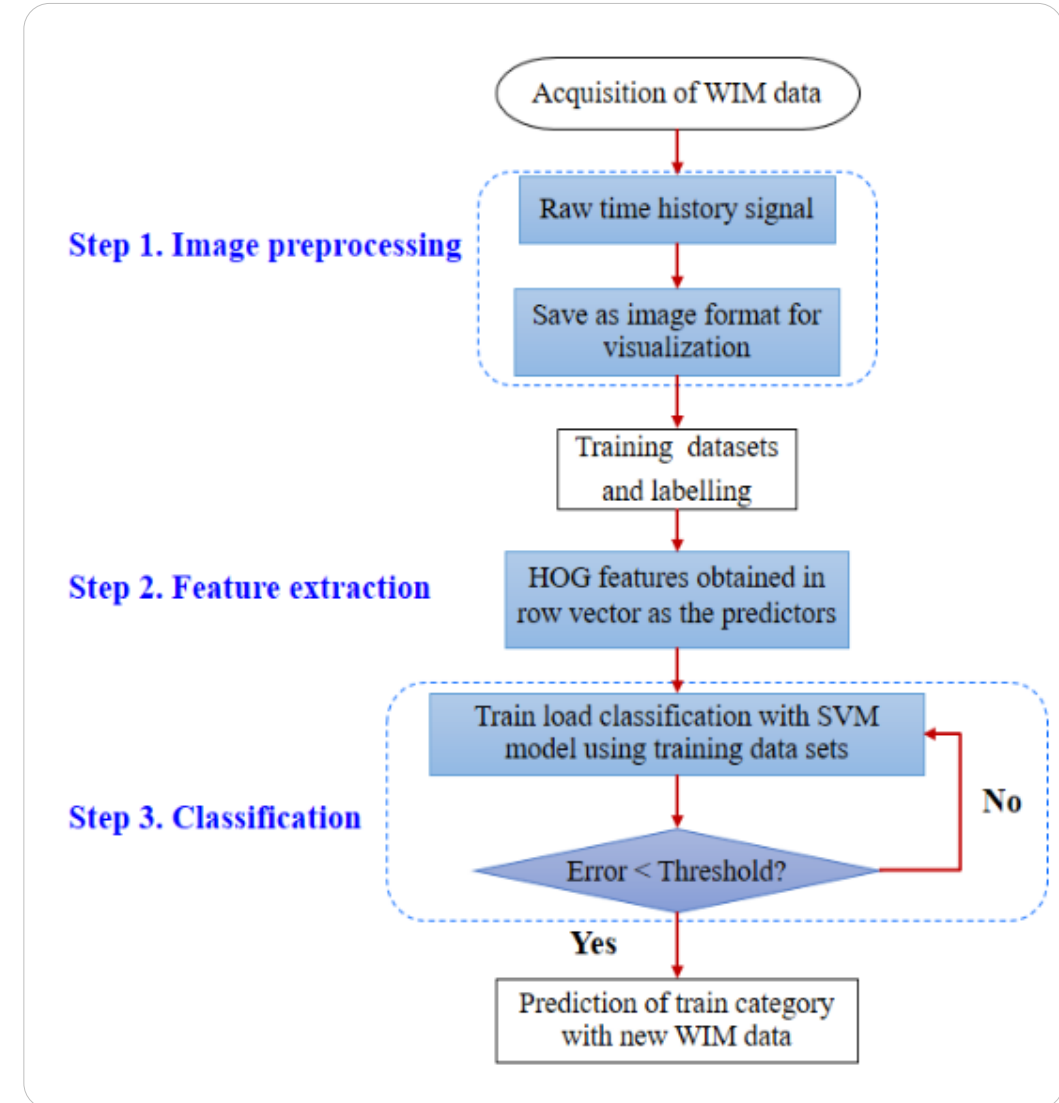
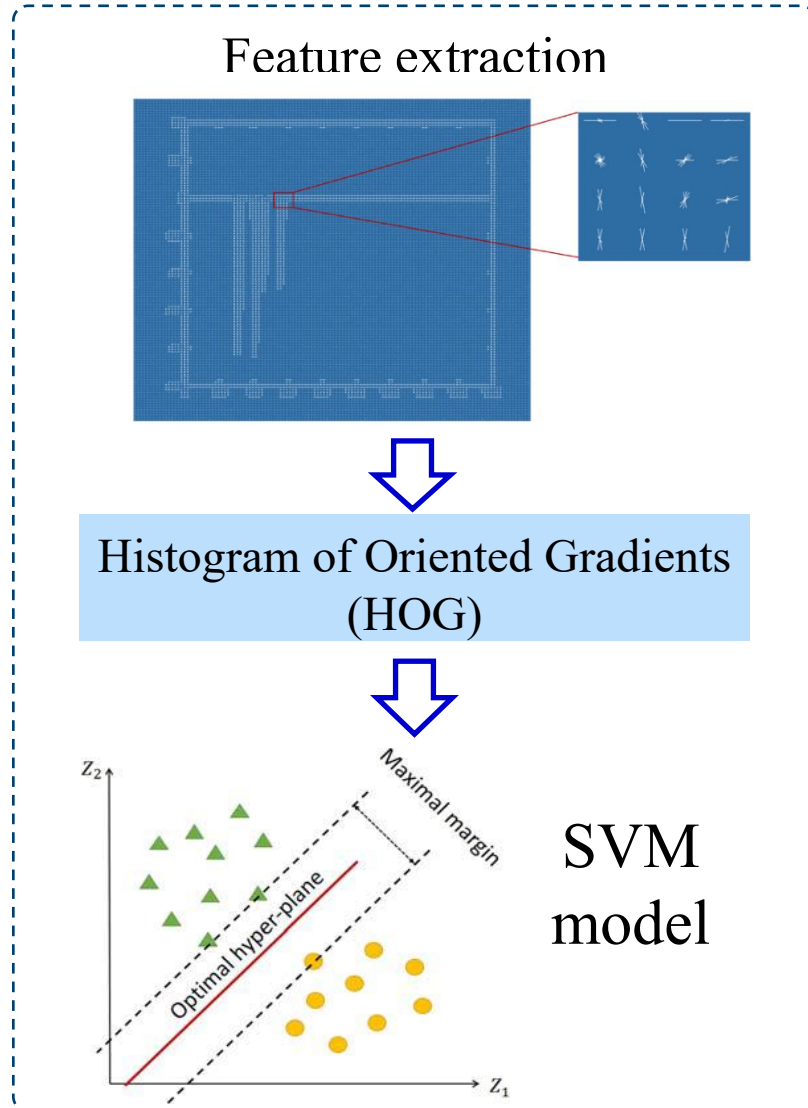
4 SVM-based train classification

Histogram of gradients (HOG)



4 SVM-based train classification

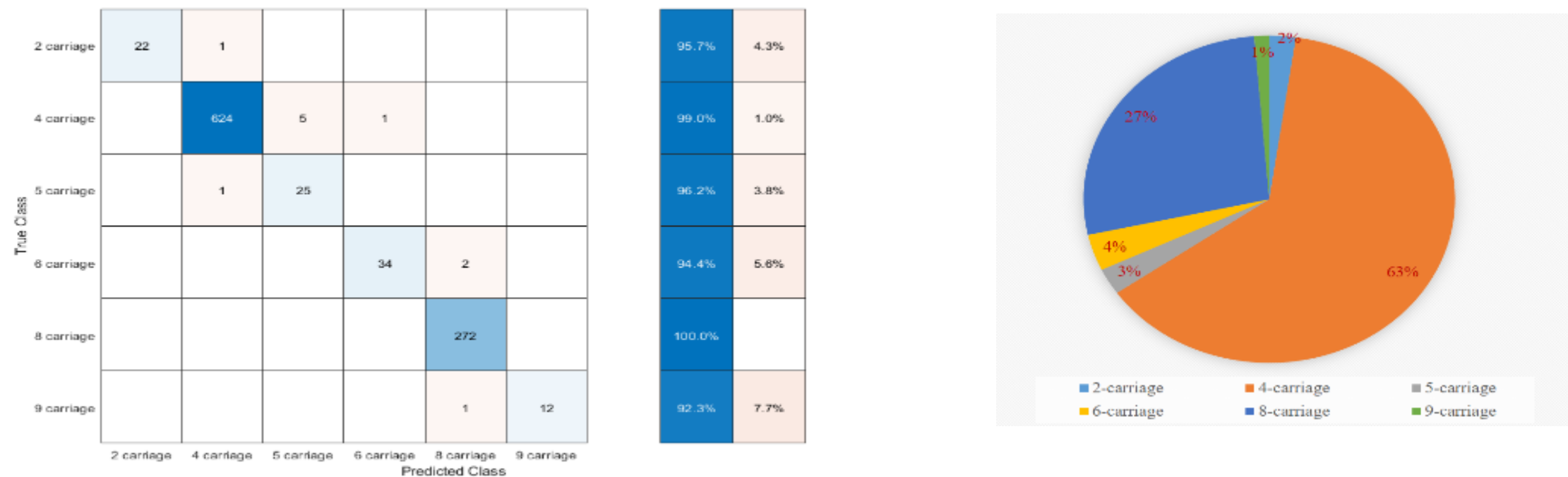
Vision and Support Vector Machine based train classification



4 SVM-based train classification

Classification results

After training the SVM model with 500 images, 1000 images are chosen for the classification, **accuracy of 98.9%** is achieved.



High prediction **accuracy** and computation **efficiency**. **Robust for noise**.

5 Data-driven fatigue damage prediction

For a suspension bridge with stiffening truss girder, fatigue is an essential issue which concerns the bridge operator.



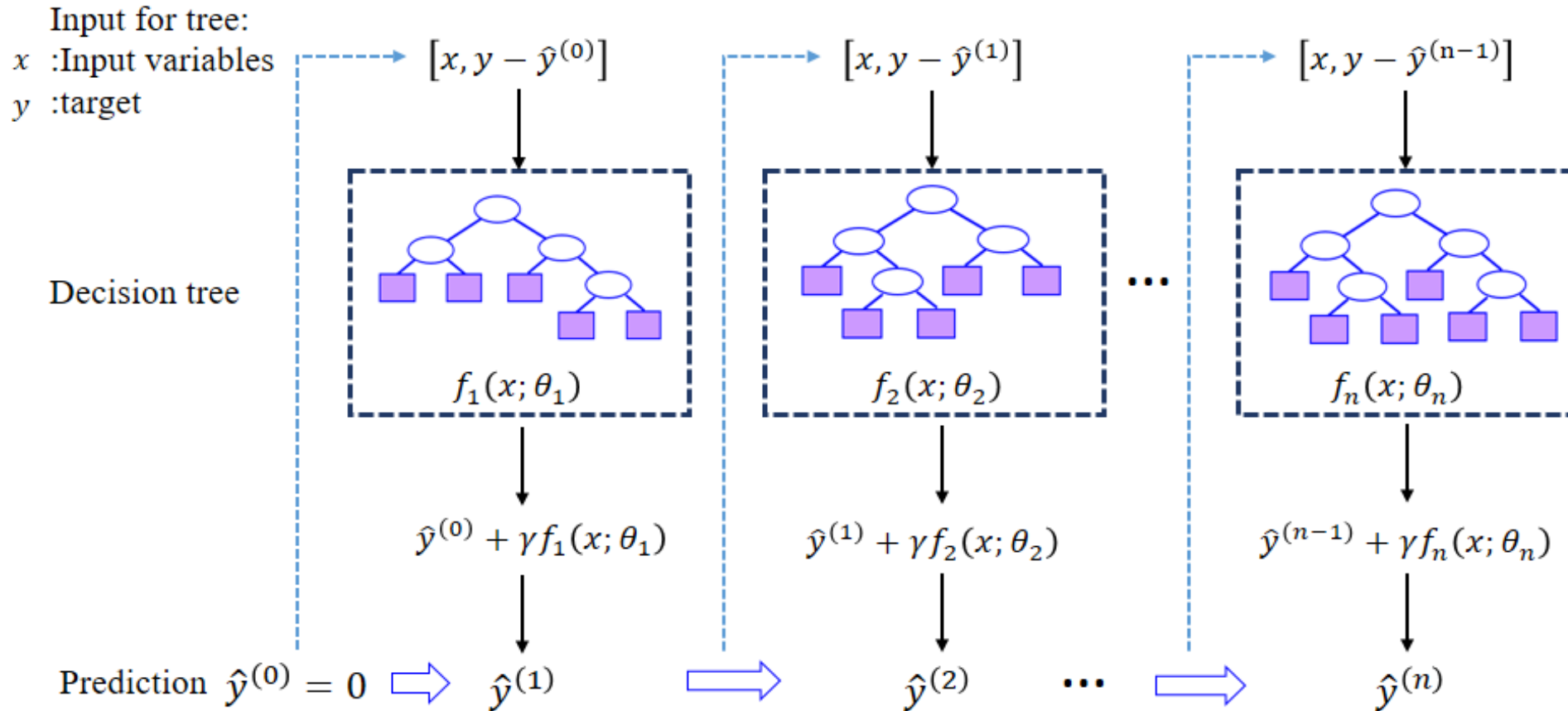
Opened in 1966, and railway added during retrofitting in 1999, Fatigue damage under

- Wind,
- Temperature,
- Train loads,
- Roadway traffic.

Machine learning-based method using monitoring data

- **Predict** (using comprehensive loads)
- **Interpret** (contribution, correlation,...)

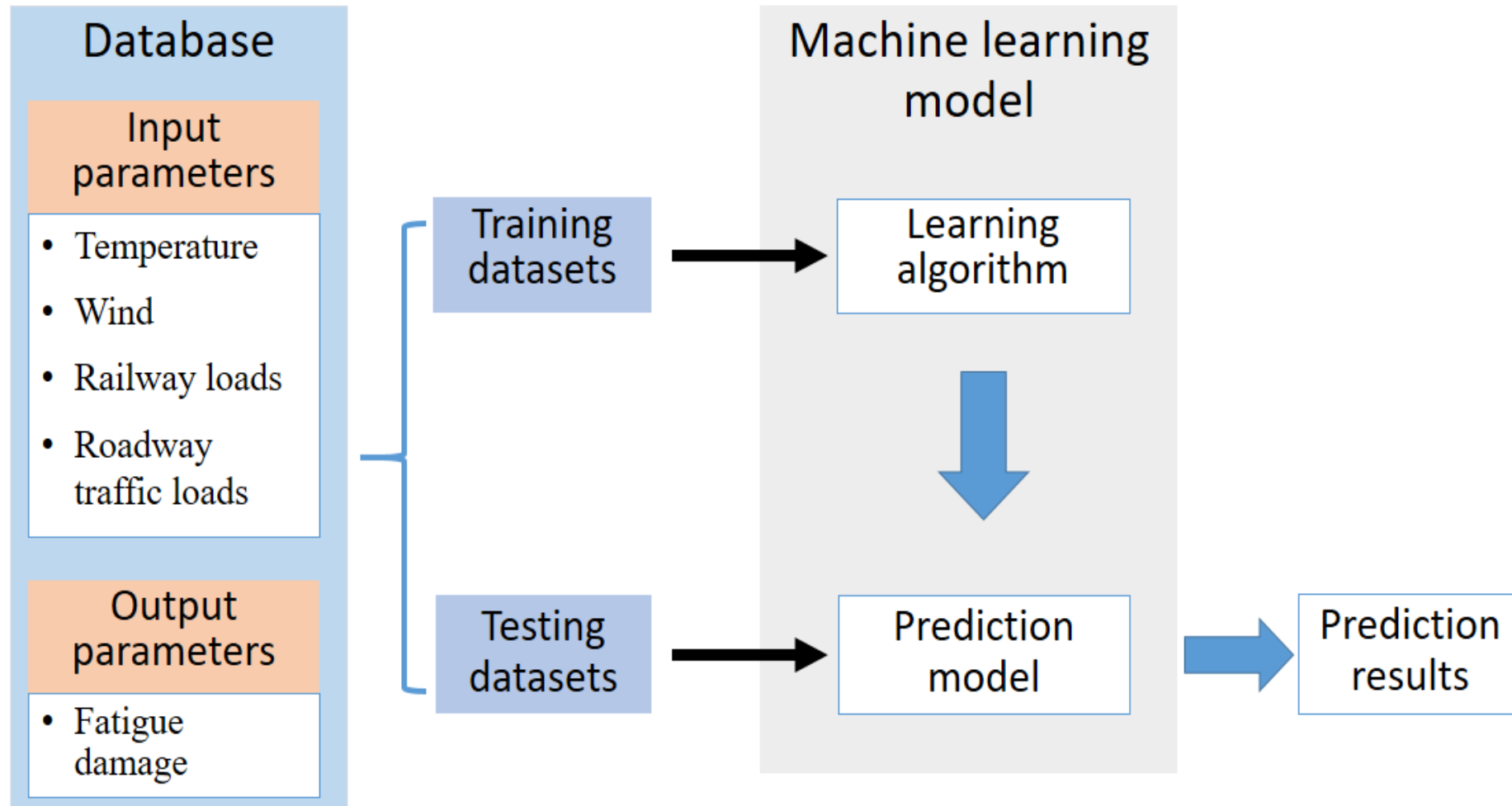
5 Data-driven fatigue damage prediction



where n denote the number of decision trees for boosting; θ_i is the structure of the i th decision tree that include the split, nodes, etc. $\hat{y}^{(i)}$ is the predicted i th output parameter; $f_i(x; \theta_i)$ is the output of the i th decision tree without shrinkage.

5 Data-driven fatigue damage prediction

Flowchart of the fatigue damage prediction method



5 Data-driven fatigue damage prediction

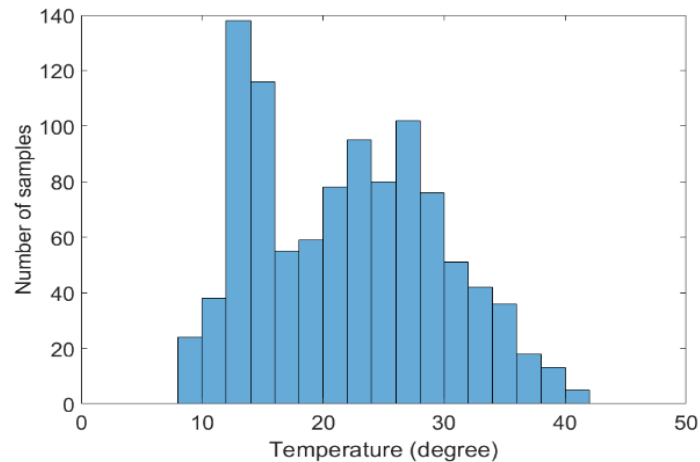
Data preparation

Hourly scale, 1000 datasets (60 days), covering

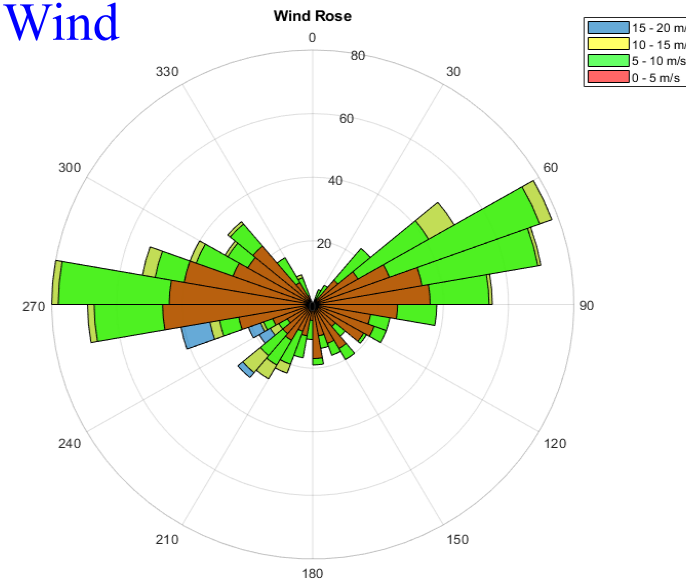
- July, September, December
- Weekdays and weekends

Input variables

Temperature

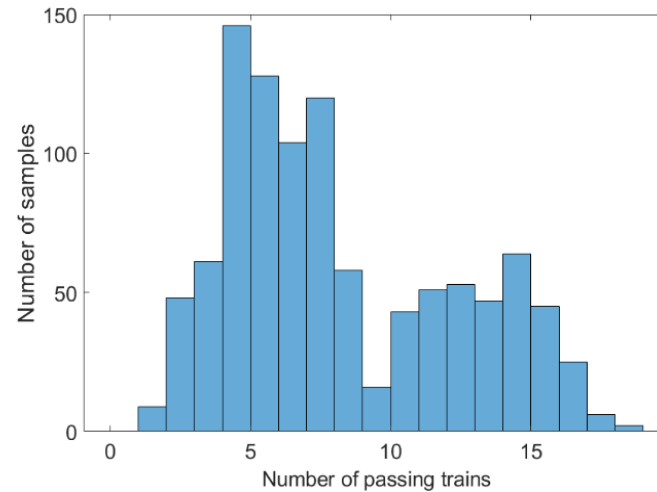


Wind

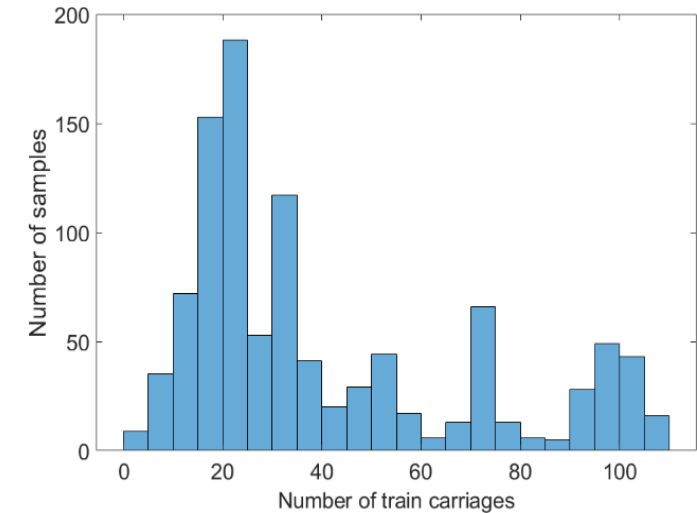


5 Data-driven fatigue damage prediction

Trainloads

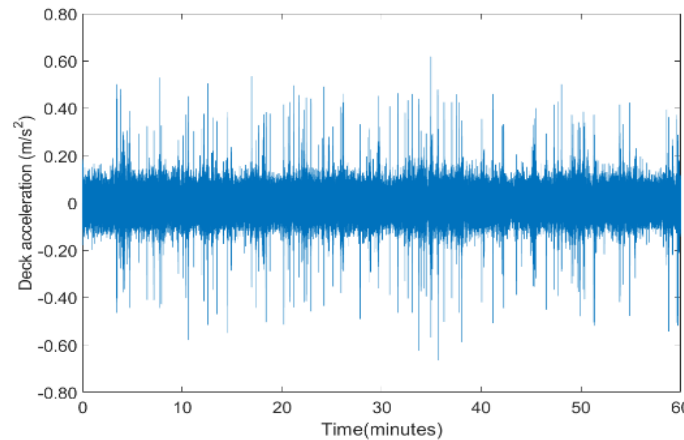


No. of passing trains

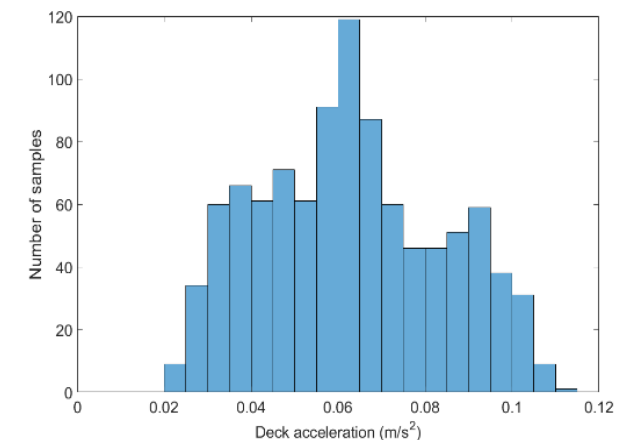


No. of train carriages

Roadway load
not measured,
represented by
deck vibration

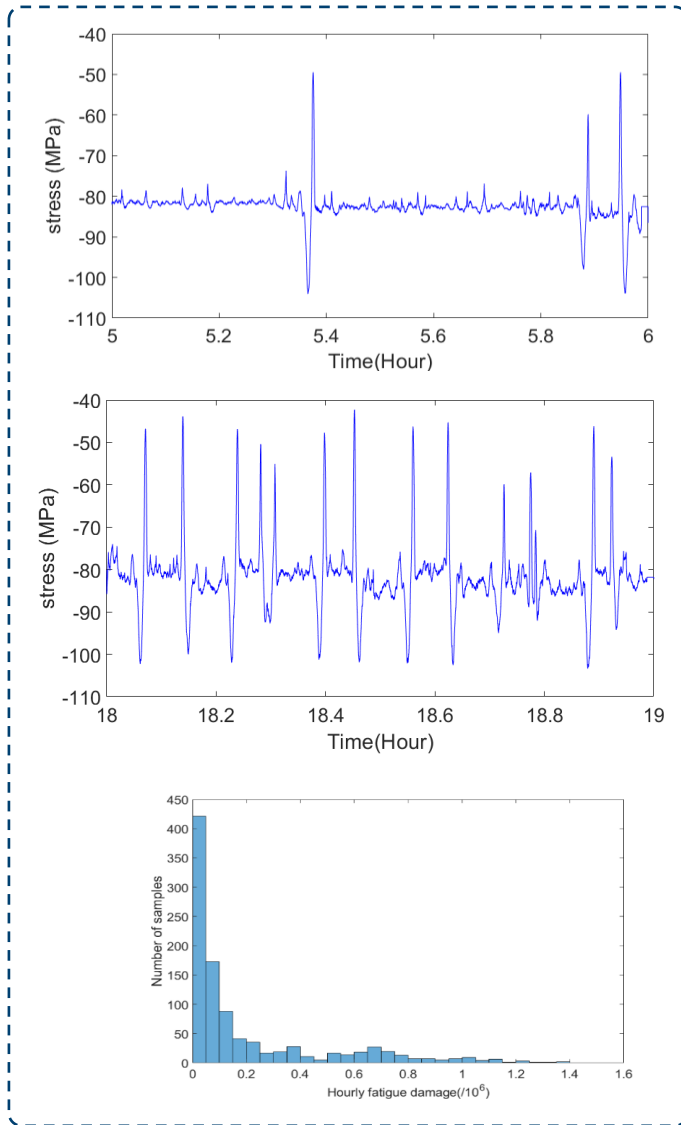


Deck vibration time history



Deck vibration RMS distribution

5 Data-driven fatigue damage prediction



$$D = \sum_i \frac{n_i}{N_i}$$

From monitoring data

From S-N curve

$$\Delta\sigma_R^m N_R = \Delta\sigma_C^m 2 \times 10^6 \quad \text{with } m = 3 \quad \text{for } N \leq 5 \times 10^6$$

$$\Delta\sigma_R^m N_R = \Delta\sigma_D^m 5 \times 10^6 \quad \text{with } m = 5 \quad \text{for } 5 \times 10^6 \leq N \leq 10^8$$

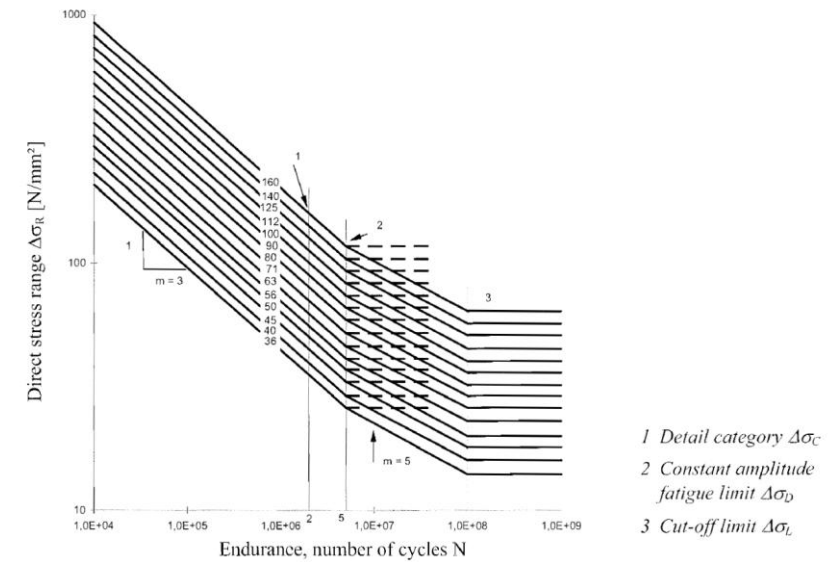


Figure 7.1: Fatigue strength curves for direct stress ranges

5 Data-driven fatigue damage prediction

1000 datasets: 800 for training and 200 for testing.

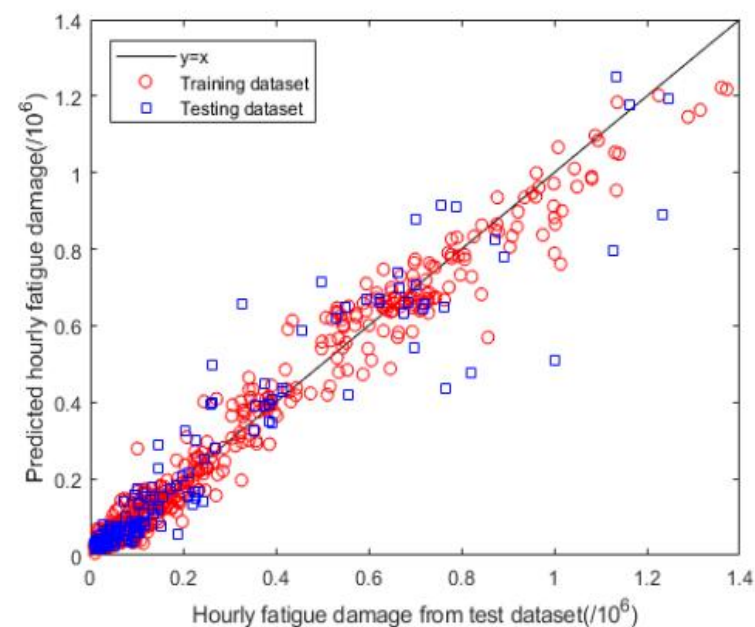
Performance metrics

$$R^2 = 1 - \frac{\sum_{i=1}^m (y_i - \hat{y}_i)^2}{\sum_{i=1}^m (\bar{y} - \hat{y}_i)^2}$$

$\hat{y}_i$, y_i predicted and the test values

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^m (y_i - \hat{y}_i)^2}$$

Prediction results



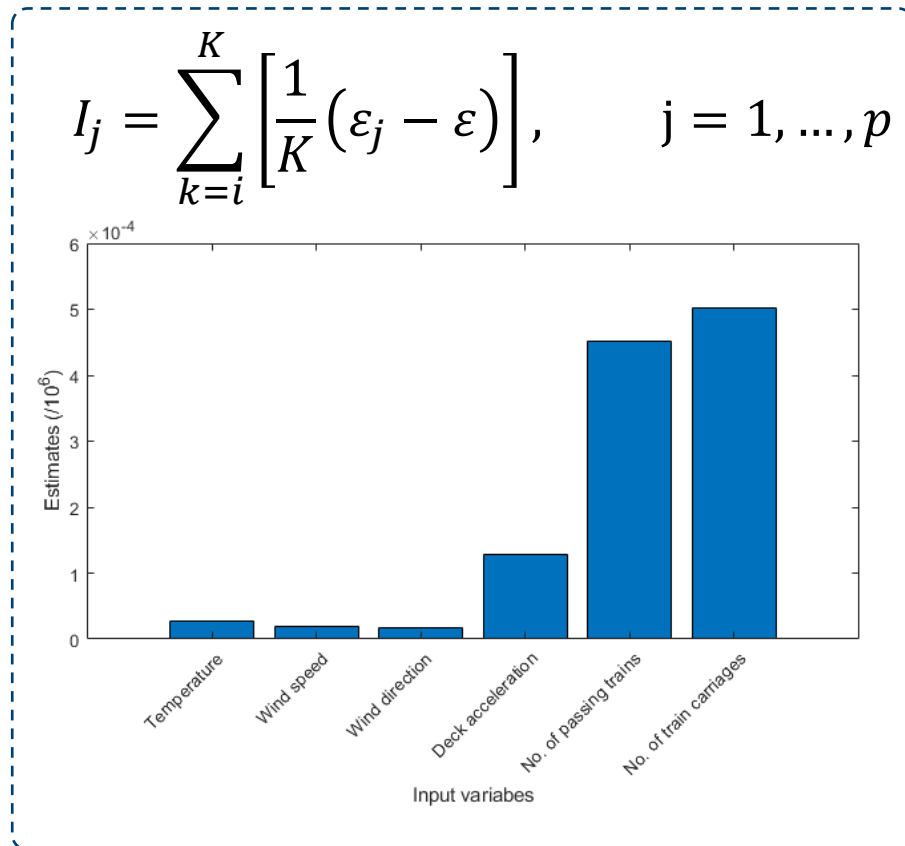
Comparison of different Machine learning algorithms

Model	R ²	RMSE (10 ⁻⁶)
GBRT	0.9180	0.0755
ANN	0.9131	0.0777
DT	0.8973	0.0855
SVM	0.8296	0.0949
RF	0.9024	0.0782

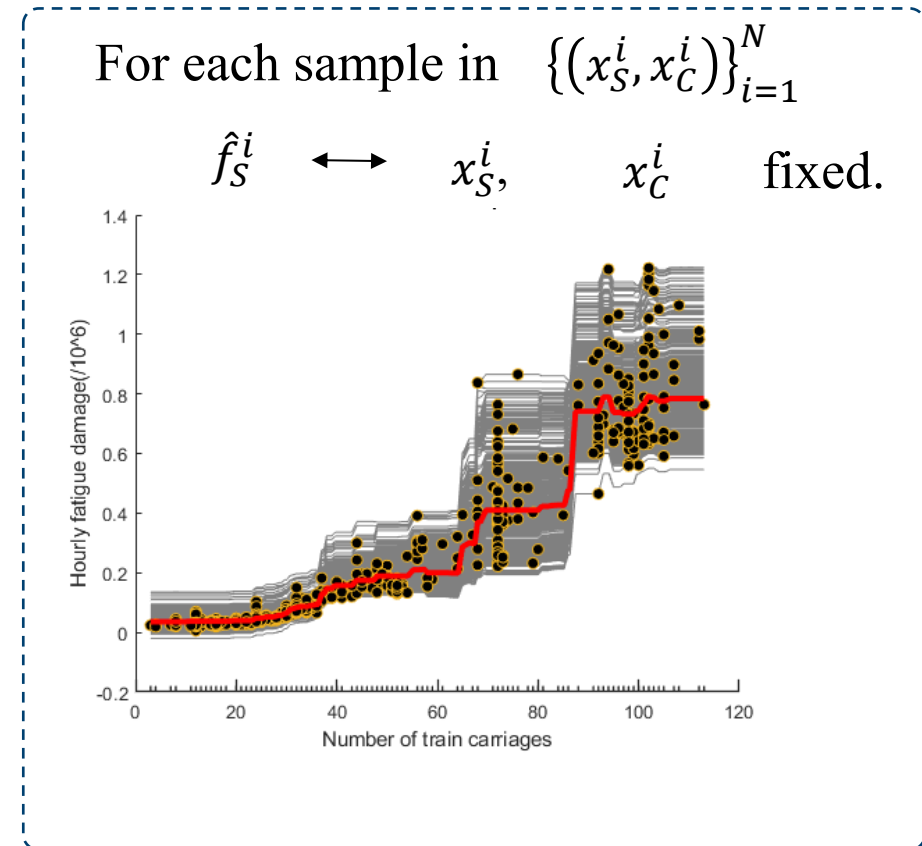
5 Data-driven fatigue damage prediction

Prediction result interpretation

Feature Importance Estimates



Individual Conditional Expectation



Trainloads have the most importance.

6 Automated bridge defect inspection using YOLO

Many existing bridges are subject to harsh environment, urgently requiring efficient and automated detection methods.



Traditional Manual Inspection

High-risk

Slow, disruptive

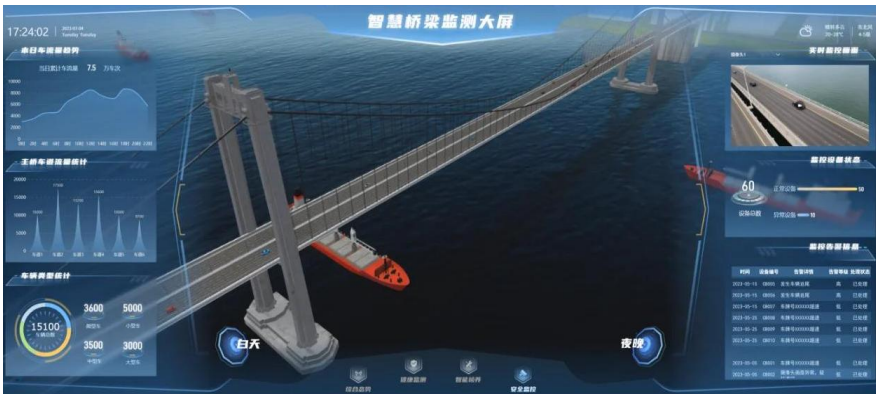
Subjective, imprecise

Limited, blind spots

Paper-based, fragmented

Reactive maintenance

VS



Modern, Intelligent Inspection

Remote, minimal human exposure

Rapid, minimal disruption

Data-driven, quantifiable

Comprehensive, full access

Digital, integrated

Predictive, proactive planning

6 Automated bridge defect inspection using YOLO

Dataset preparation for realistic bridge inspection scenarios



6,718 images

13,331 bounding boxes | YOLO format | split 7:1:2

Six defect categories

Biodegradation

Concrete-leaching

Efflorescence

Exposed-reinforcement-steel

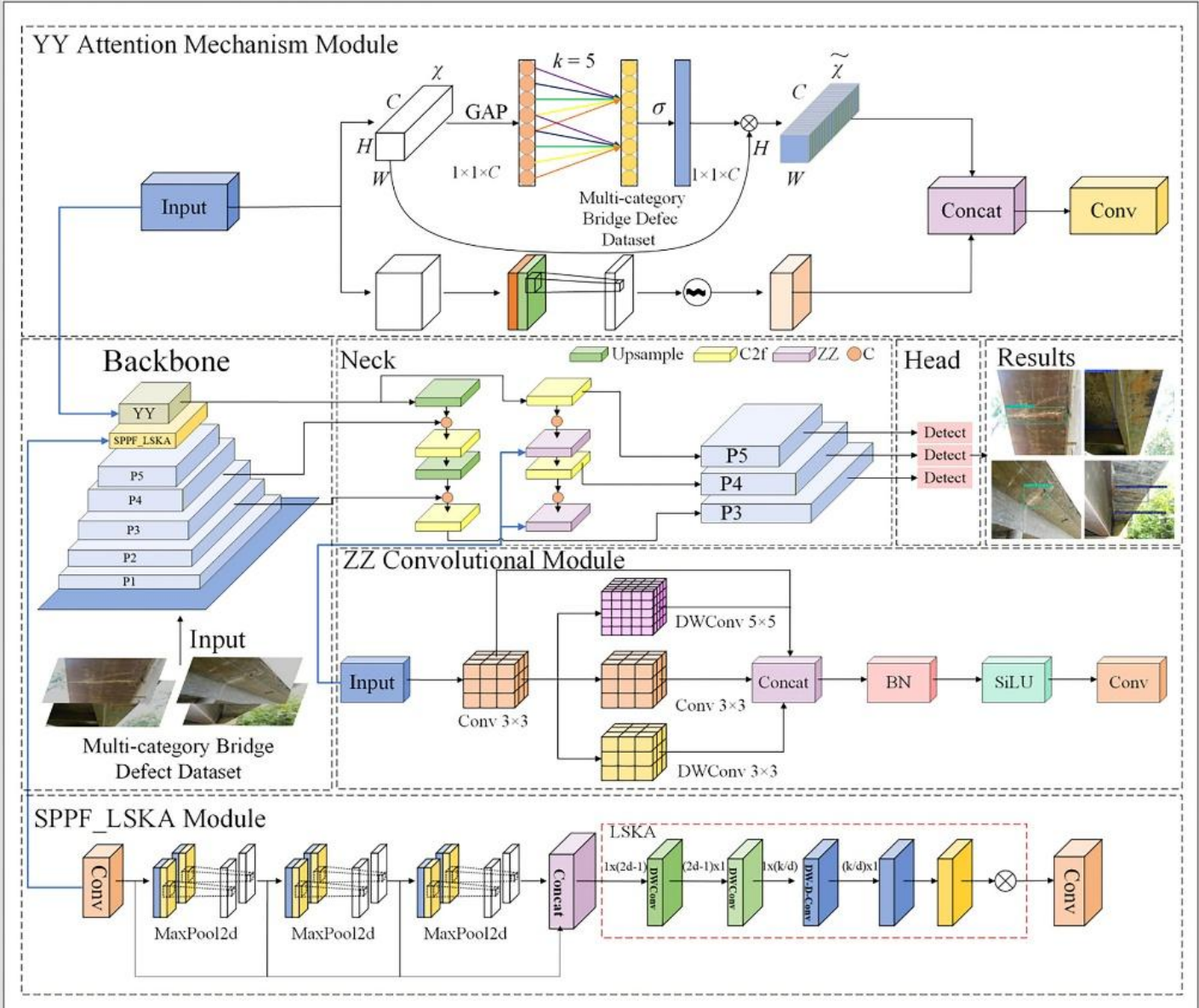
Formwork-Niche

Staining-or-infiltration

Real-world images are kept unprocessed: blurred backgrounds, mixed categories and dense small defects are retained.

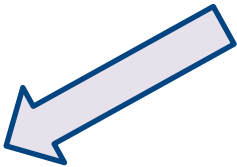
6 Automated bridge defect inspection using YOLO

Hierarchical collaboration across feature extraction, attention and semantic fusion



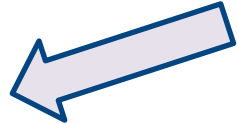
YY attention

Channel-spatial calibration



ZZ convolution

Multi-scale texture extraction

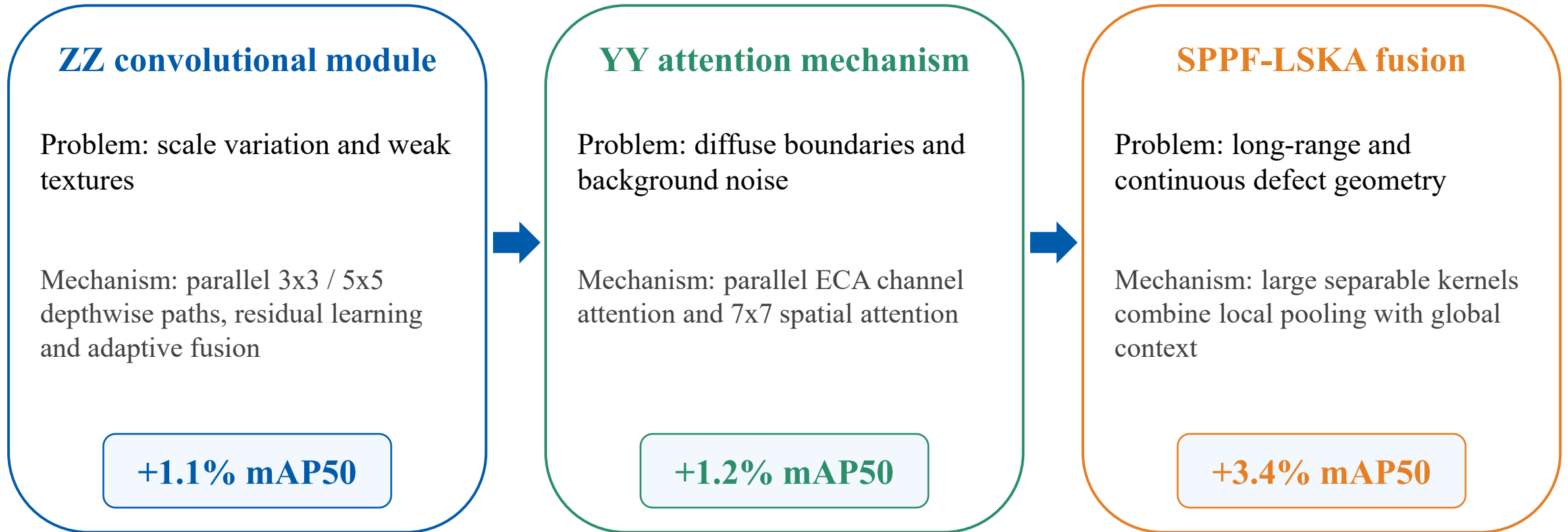


SPPF-LSKA

Long-range semantic fusion

6 Automated bridge defect inspection using YOLO

Why the three modules work together



Local texture → boundary calibration → long-range context → precise localization

6 Automated bridge defect inspection using YOLO

Ablation study on the Multi-category Bridge Defect Dataset

Configuration	mAP50	mAP50:95	FPS
YOLOv11n	39.9	17.7	198.2
+ ZZ	41.0	17.8	159.6
+ YY	41.1	17.4	183.2
+ SPPF-LSKA	43.3	18.1	176.2
+ ZZ + YY	41.9	17.7	169.2
YOLOv11n-ZY (+ ZZ + YY+ SPPF-LSKA)	45.6	33.0	161.7

+15.3 pp
mAP50:95 improvement

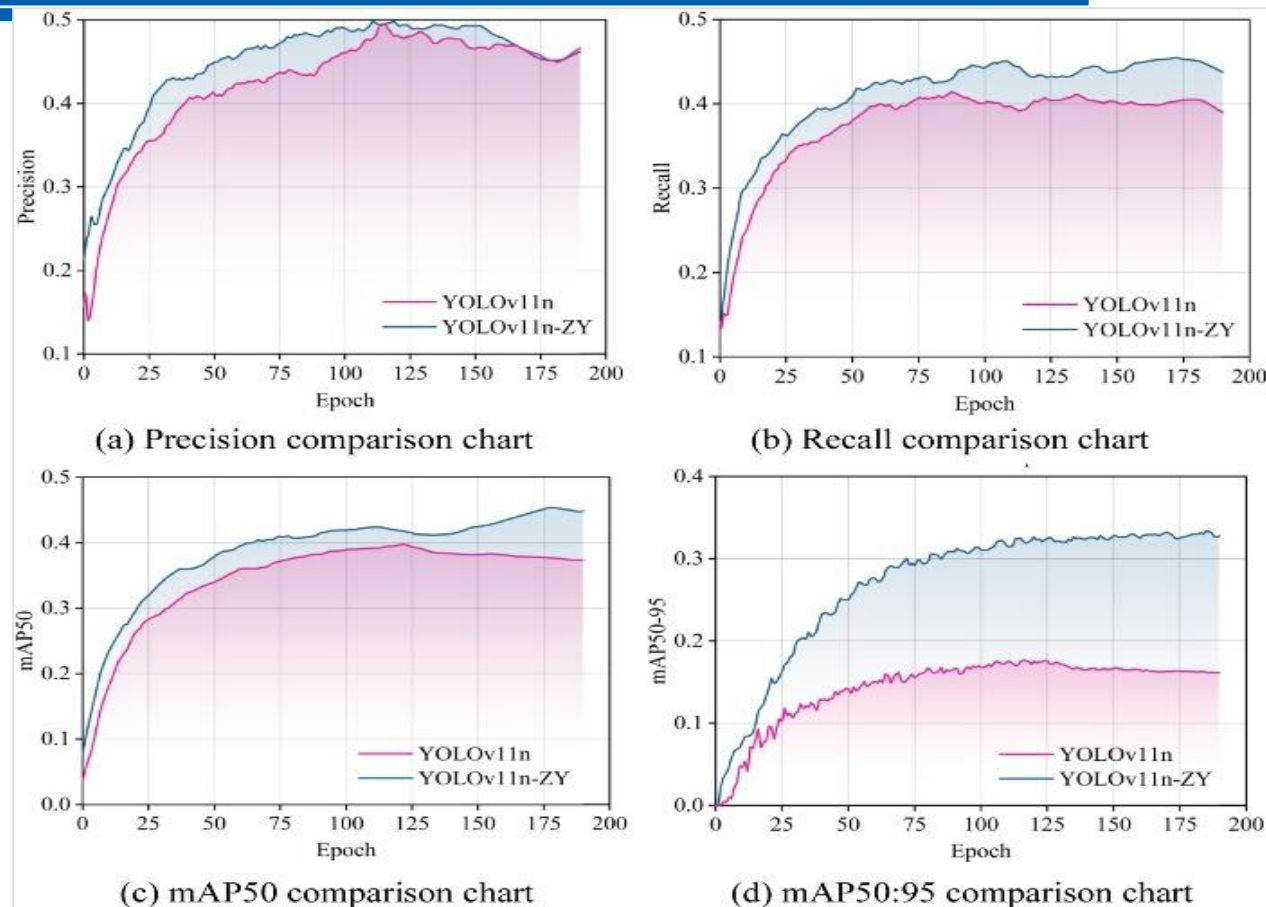


2.87 MB
model size

161.7 FPS
real-time capable

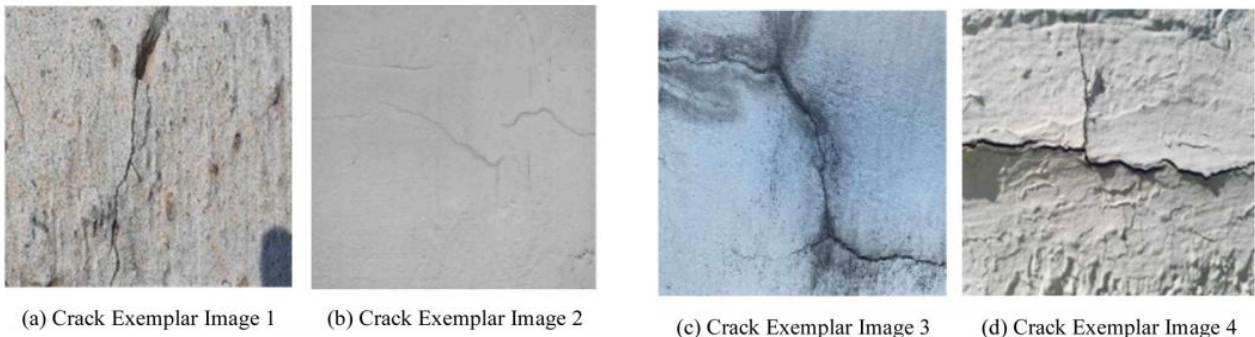
Joint optimization sharply improves localization accuracy while preserving a lightweight architecture.

6 Automated bridge defect inspection using YOLO



Generalization and benchmark comparison

Model	mAP50	Size / MB
YOLOv8n	38.7	3.01
YOLOv8s	38.8	11.13
YOLOv11n	39.9	2.58
YOLOv11s	39.0	9.42
YOLOv11n-ZY	45.6	2.87



Crack-seg Dataset

84.3%

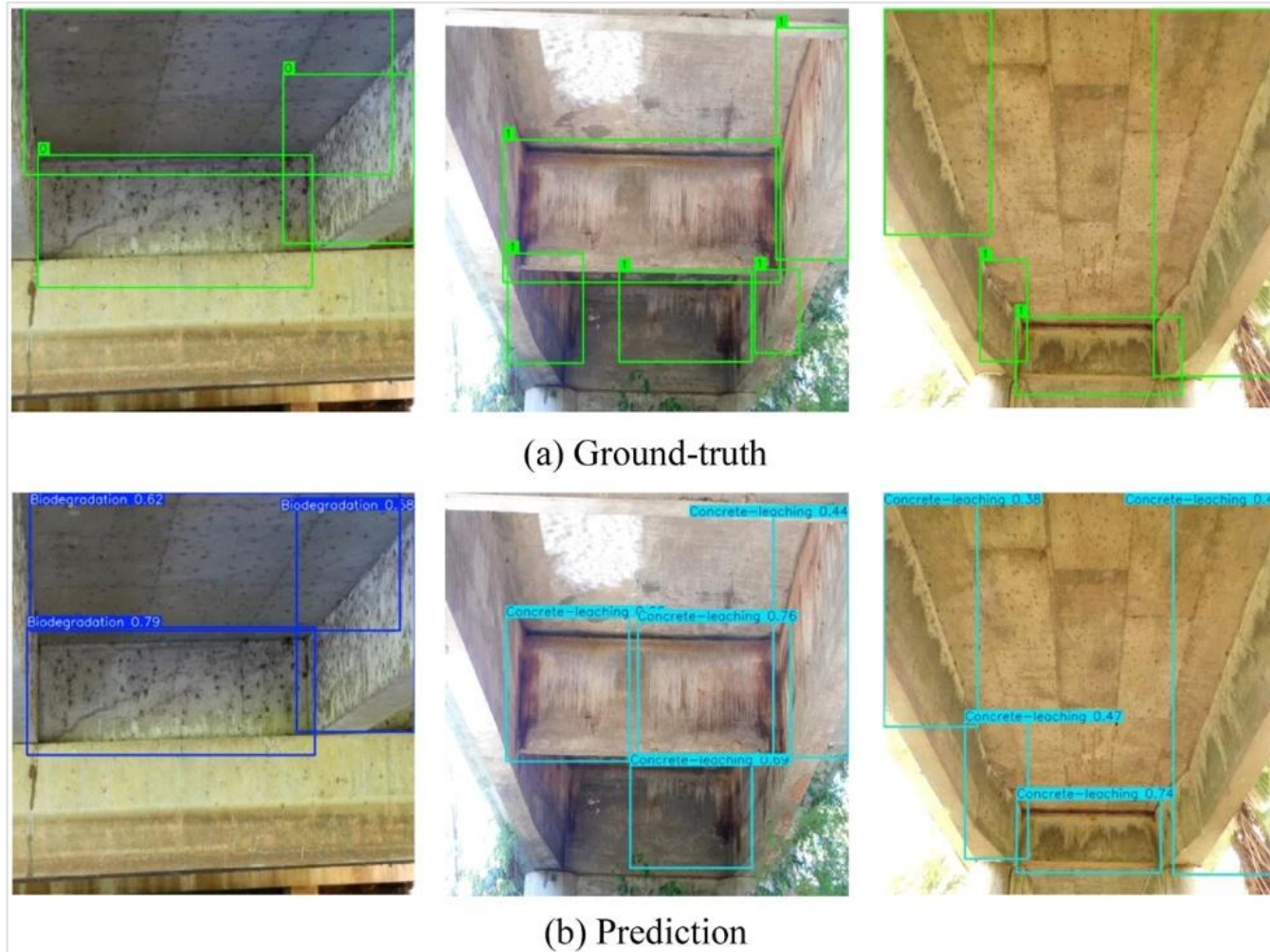
Crack-seg mAP50

+2.1 pp over baseline

Cross-dataset generalization confirmed

6 Automated bridge defect inspection using YOLO

Detection results and per-category localization gains



AP50:95 gains

Formwork-Niche

+22.4 pp

Biodegradation

+19.9 pp

Concrete-leaching

+13.9 pp

The strongest gains occur for spatially complex and context-dependent defects.

6 Automated bridge defect inspection using YOLO

Human-machine collaborative on-site inspection

Detection Page

Model Selected

Image Detection

Video Detection

Camera Detection

IOU Threshold Adjustment

Select File

Start Detection

Stop Detection

	Image Name	Class	Confidence	Bounding Box Coordinates
3	F:/ces/ql/yolov11-main/qxt/902.jpg	Efflorescence	0.89	(2538, 1282, 2687, 2007)
4	F:/ces/ql/yolov11-main/qxt/902.jpg	Formwork-Niche	0.73	(2320, 1090, 2482, 1432)
5	F:/ces/ql/yolov11-main/qxt/902.jpg	Efflorescence	0.54	(2268, 1349, 2600, 1508)
6	F:/ces/ql/yolov11-main/qxt/902.jpg	Formwork-Niche	0.33	(1848, 2113, 2751, 2574)

1 Multi-modal input

Images, video streams and live camera capture

2 Dynamic control

Adjust confidence and IoU thresholds during inspection

3 Human verification

Pause, review suspicious frames and use temporal consistency

Real-time, lightweight and field-deployable

7 Conclusions

- 1) Reliability-based vehicle weight limit determination method considering stochastic traffic model;
- 2) Bridge condition rating using NLP-based machine learning method.
- 3) Vision and machine learning-based method for train classification;
- 4) Data-driven fatigue damage prediction and physical interpretation;
- 5) YOLO-based real-time bridge defect inspection.

Thank you for your attention



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