面向交通基础设施检测的多源异构深度学习融合方法

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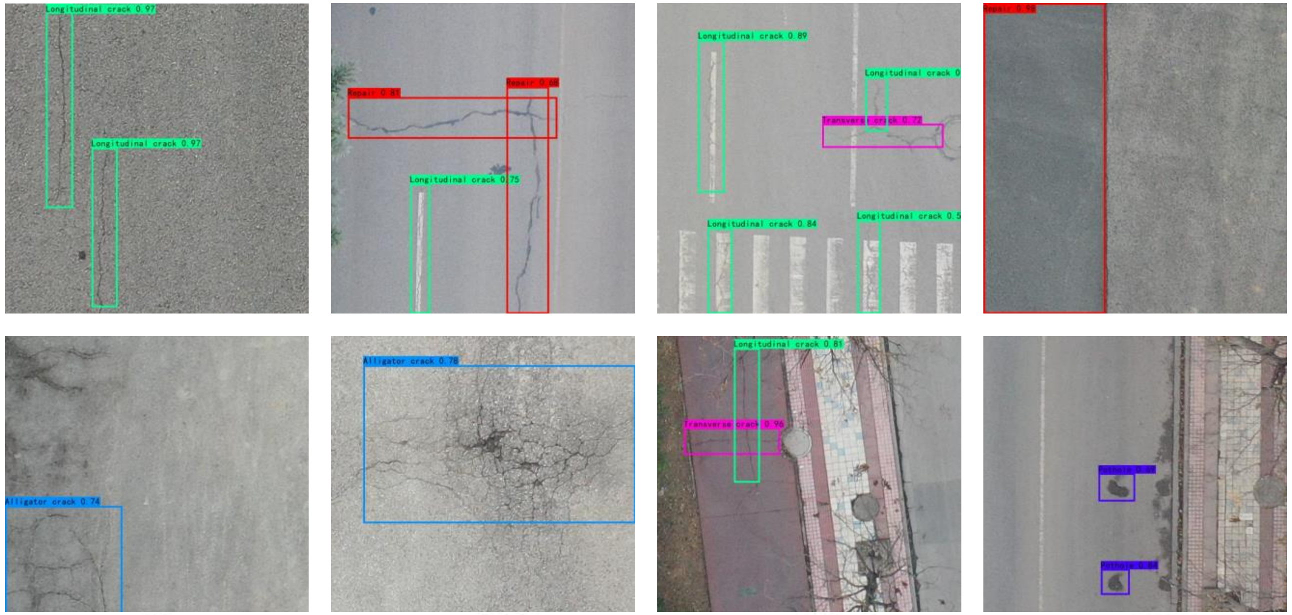
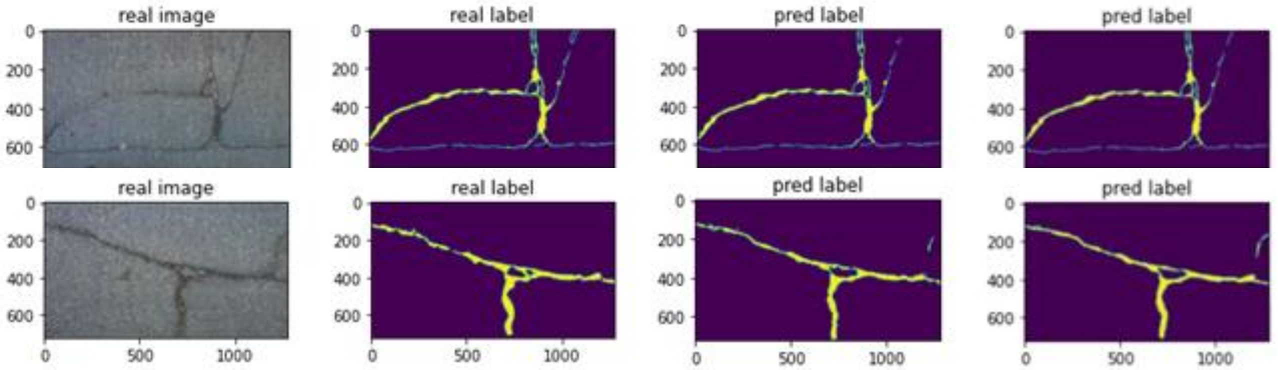
目 录

多源异构数据

路表图像



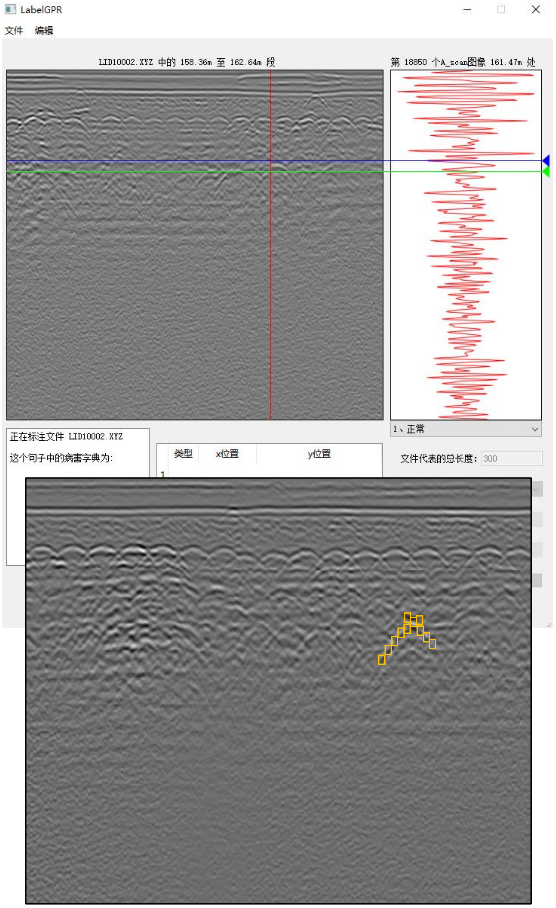


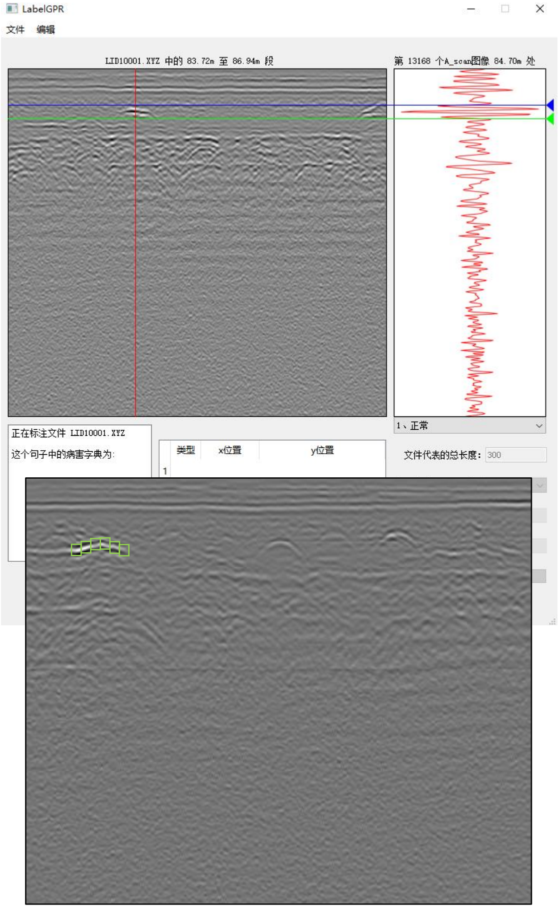
real image
real label
pred label
pred label
real image
real label
pred label
pred label

多源异构数据

时序数据

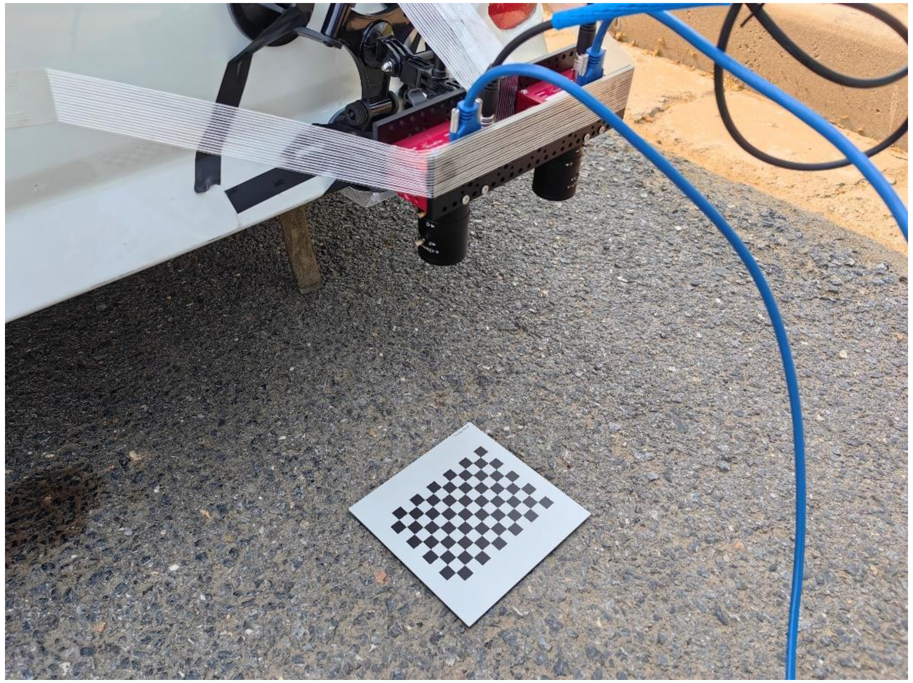

3D:Radar

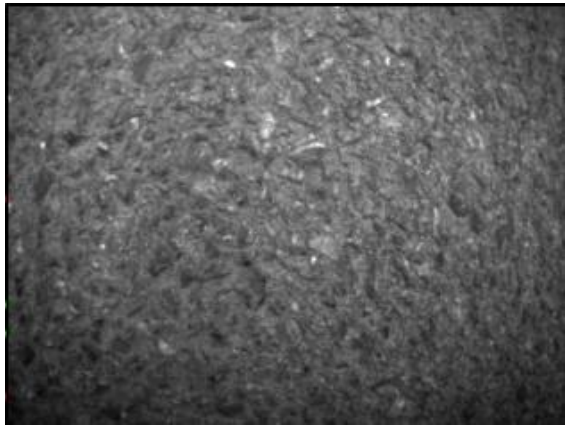

LabelGPR
文件 编辑
LID10002.XYZ 中的 158.36m 至 162.64m 段
第 18850 个A_scan图像 161.47m 处
1、正常
正在标注文件 LID10002.XYZ
这个句子中的病害字典为:
类型
x位置
y位置
1
文件代表的总长度:
300

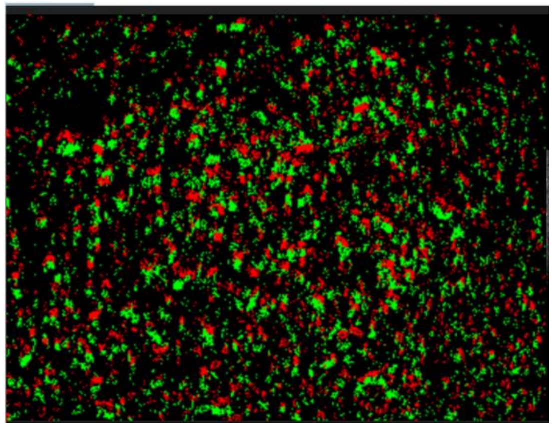

LabelGPR
文件 编辑
LID10001.XYZ 中的 83.72m 至 86.94m 段
第 13168 个A_scan图像 84.70m 处
1、正常
正在标注文件 LID10001.XYZ
这个句子中的病害字典为:
类型
x位置
y位置
1
文件代表的总长度:
300

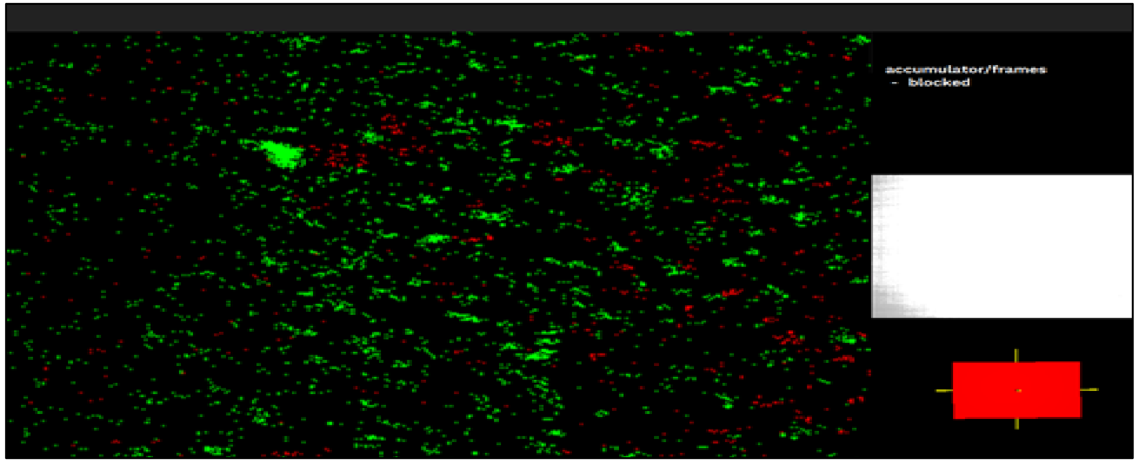
多源异构数据

高维数据



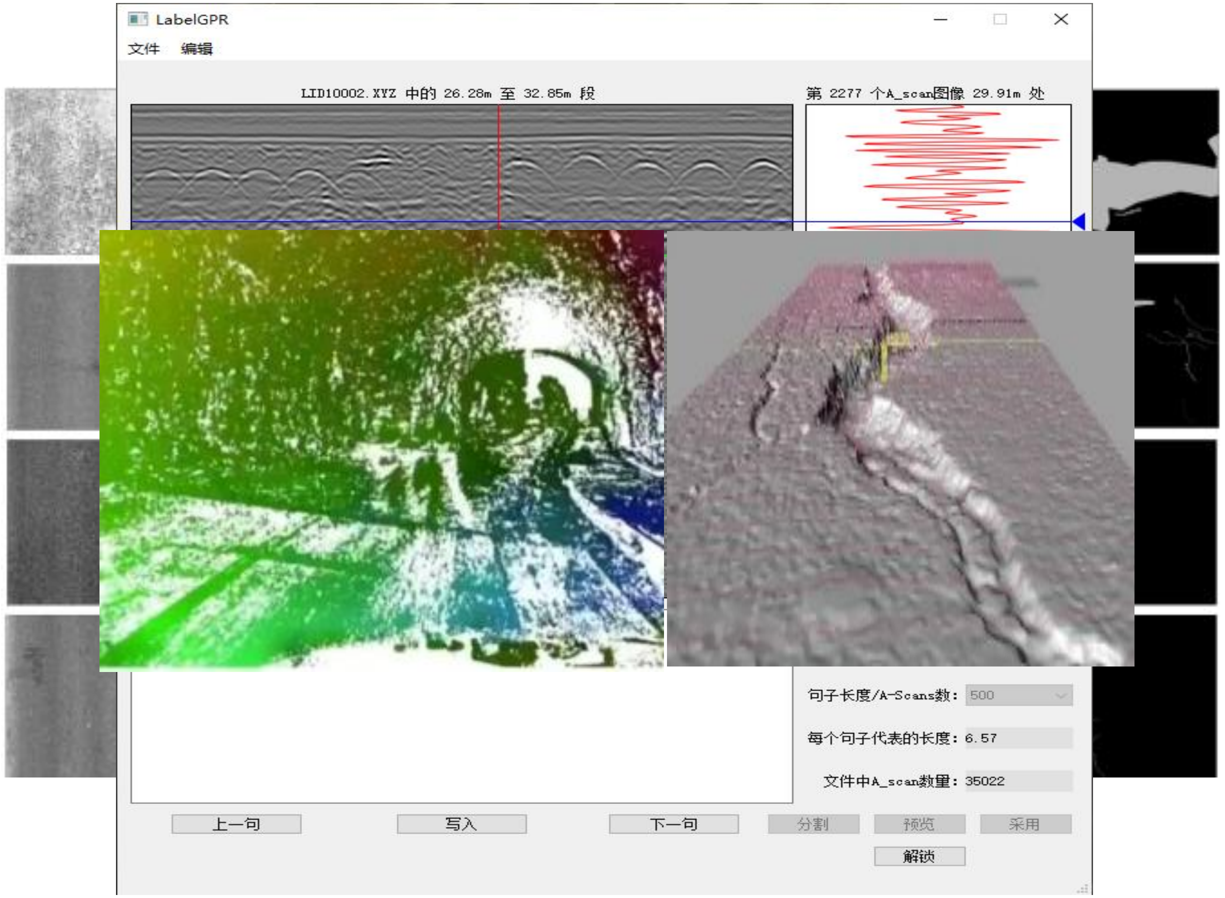






多源异构数据

- 路表图像[1]: 多功能车图像、无人机航拍图像等
- NDT时序数据 [2]: 探地雷达信号、超声波信号、应力应变数据等
- 高维数据[3]: 路面三维点云、多目事件数据等



[1] Tong et al. (2022). Pavementscapes: a large-scale hierarchical image dataset. arXiv:2208.00775.

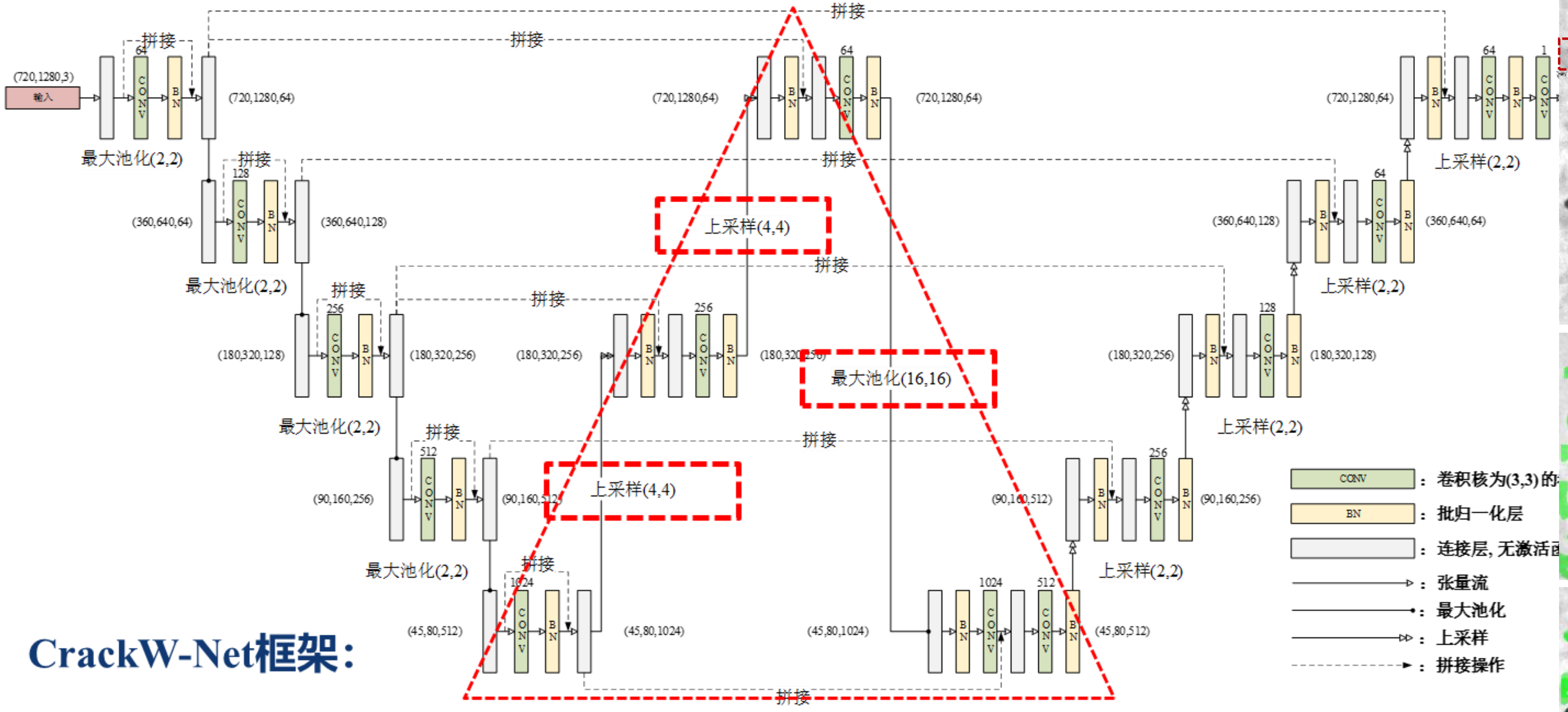
[2] Tong et al. (2020). Advances of deep learning applications in ground-penetrating radar: A survey. CBM.

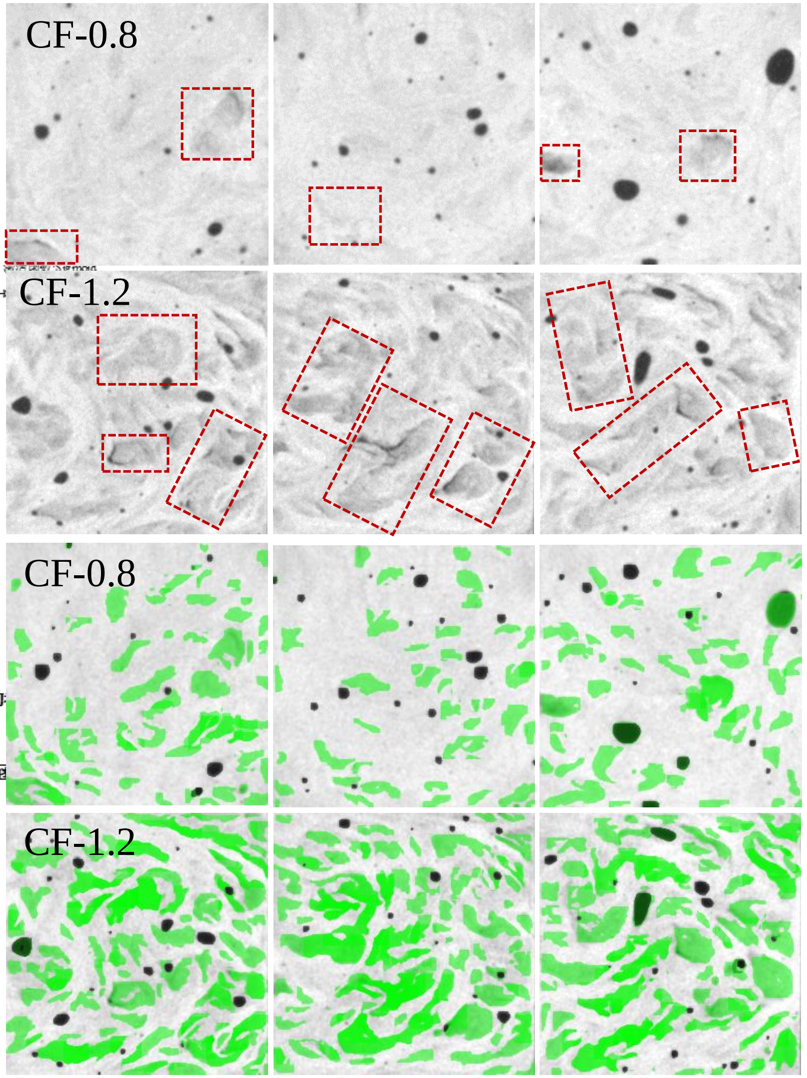
[3] Li et al. (2021). Classification of Pavement Disease 3D Point Cloud Images Based on Deep Learning Network.

多源异构深度神经网络

图像分割

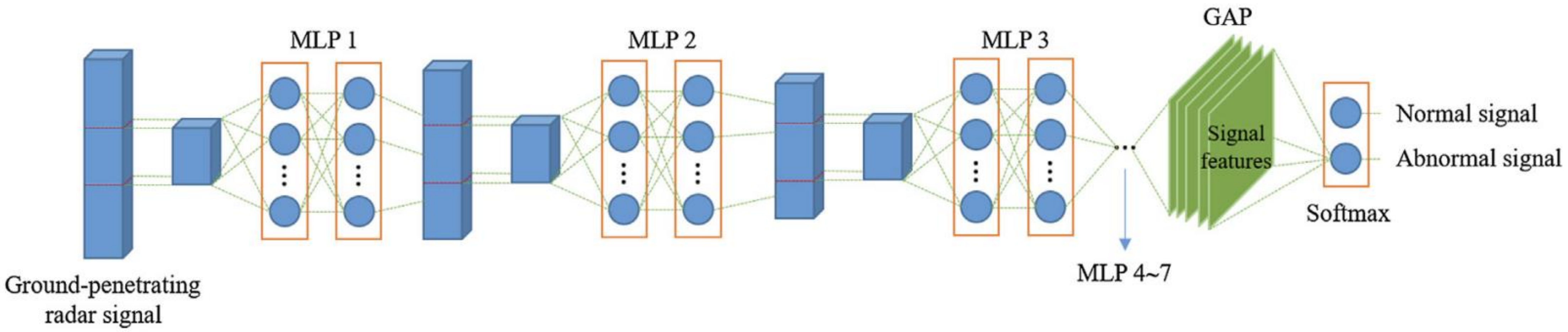
CrackW-Net框架：

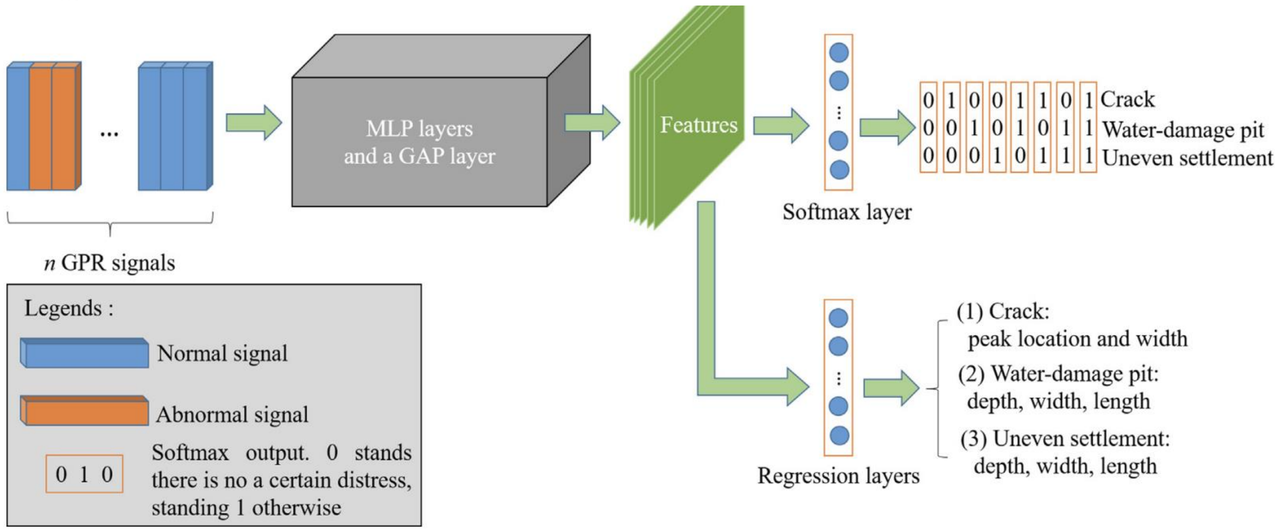


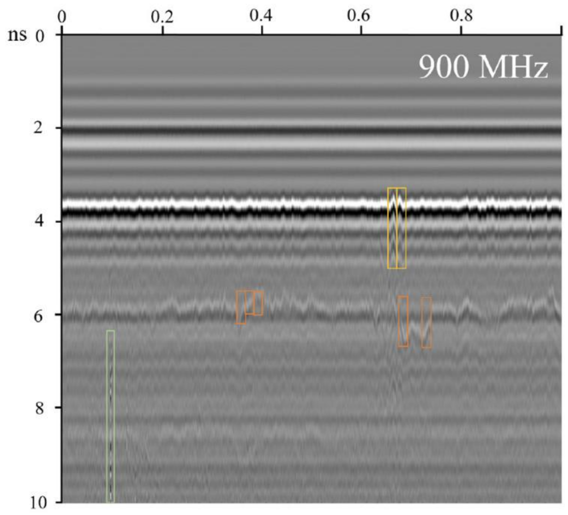


多源异构深度神经网络

信号处理

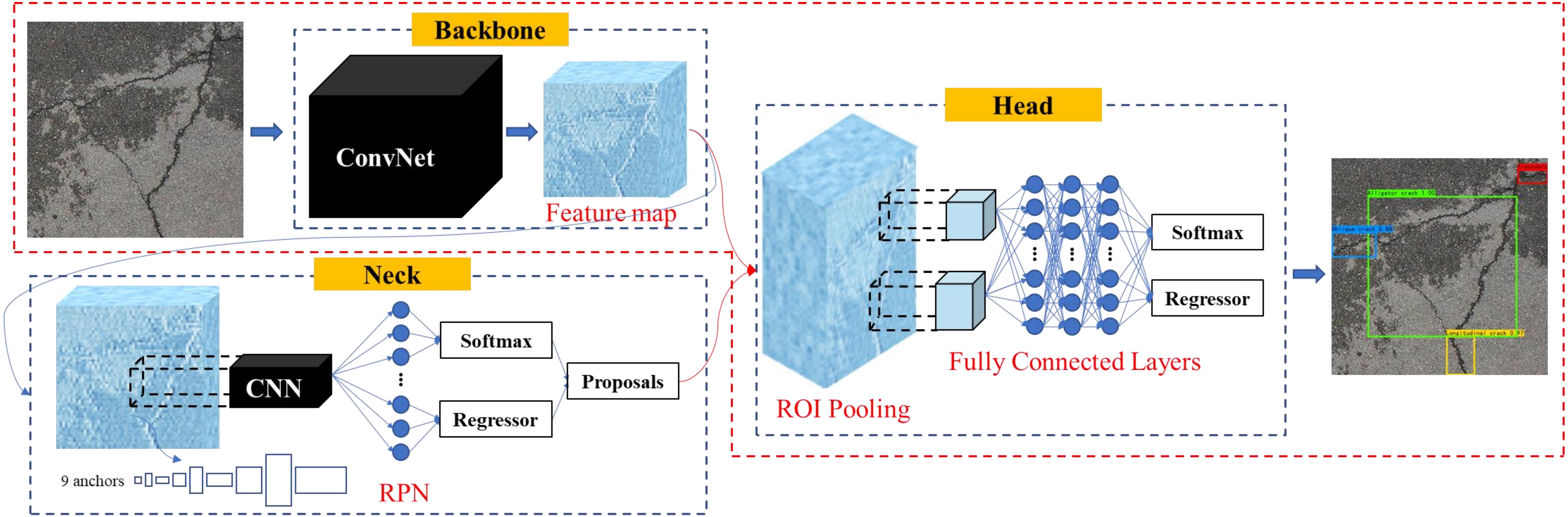






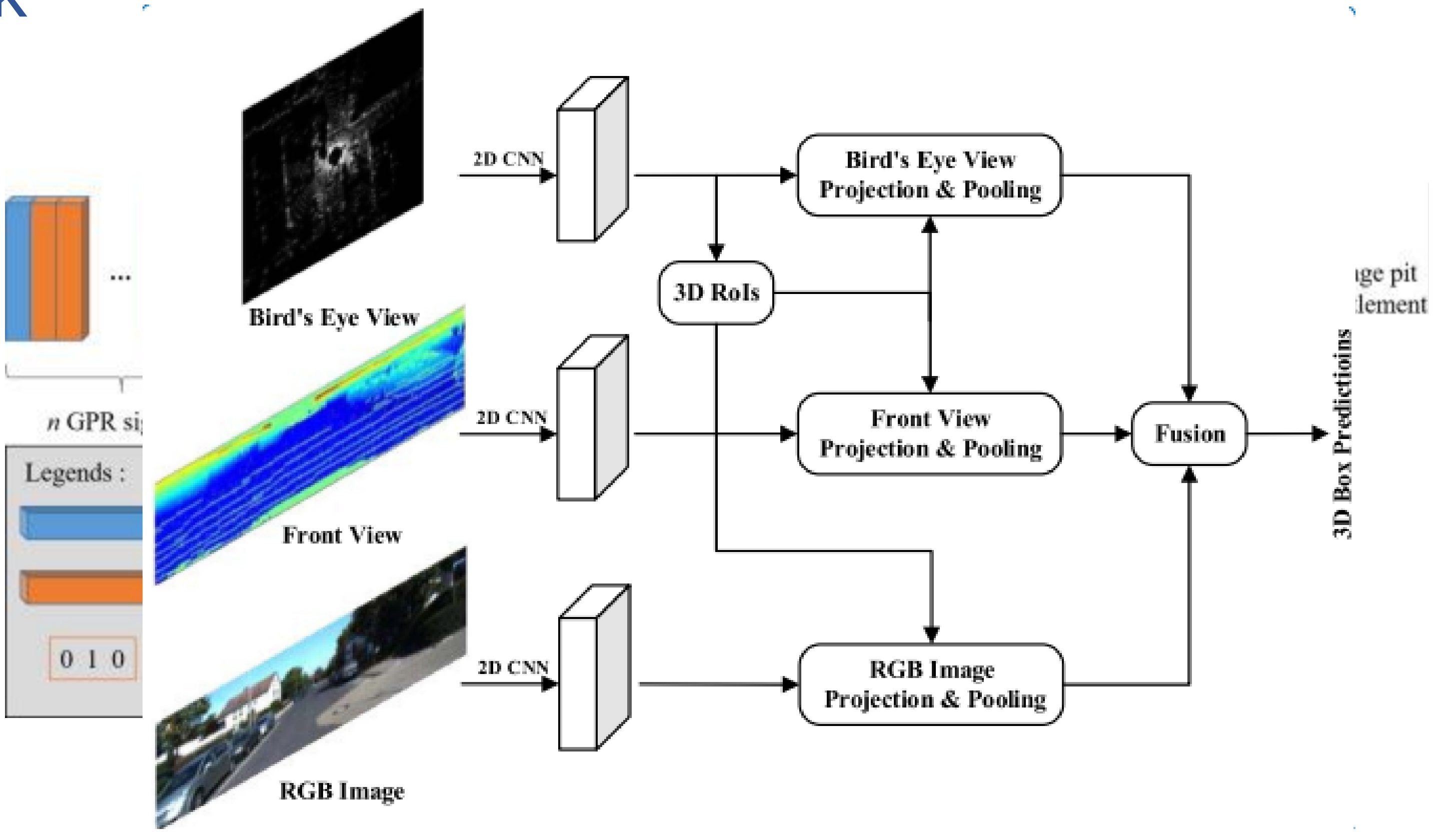
多源异构深度神经网络

高维分析



多源异构深度神经网络

- 图像分割 [3]: W-Unet、Crack-net、ES-transformer
- 信号处理 [4]: NIN、RNN、LSTM
- 高维分析 [5]: RPN、BEV、Point-based methods



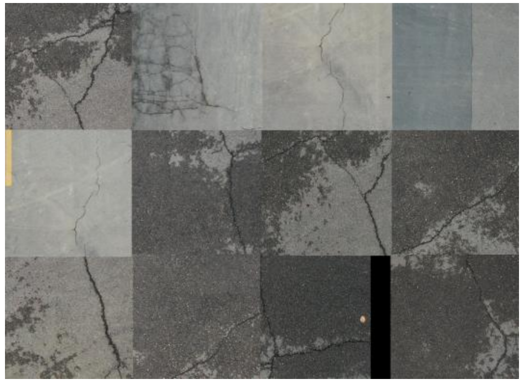
[3] Tong et al. (2023). Evidential transformer for pavement distress segmentation. CACAIE.
[4] Tong et al. (2009). Pavement-distress detection using ground-penetrating radar and network in networks. CBM
[5] J. Deng et al. (2009). ImageNet: A Large-Scale Hierarchical Image Database. CVPR.

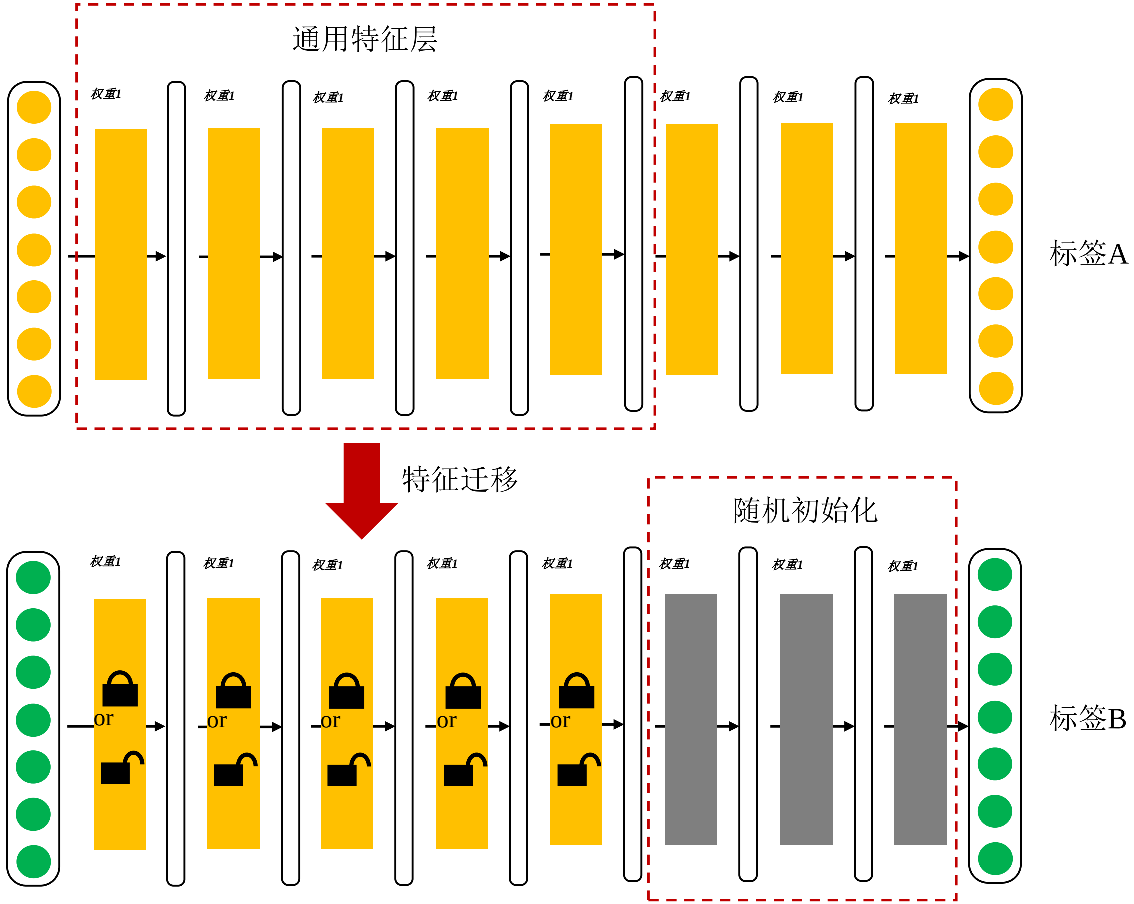
如何重复利用数据和网络？

迁移学习

COCO Dataset

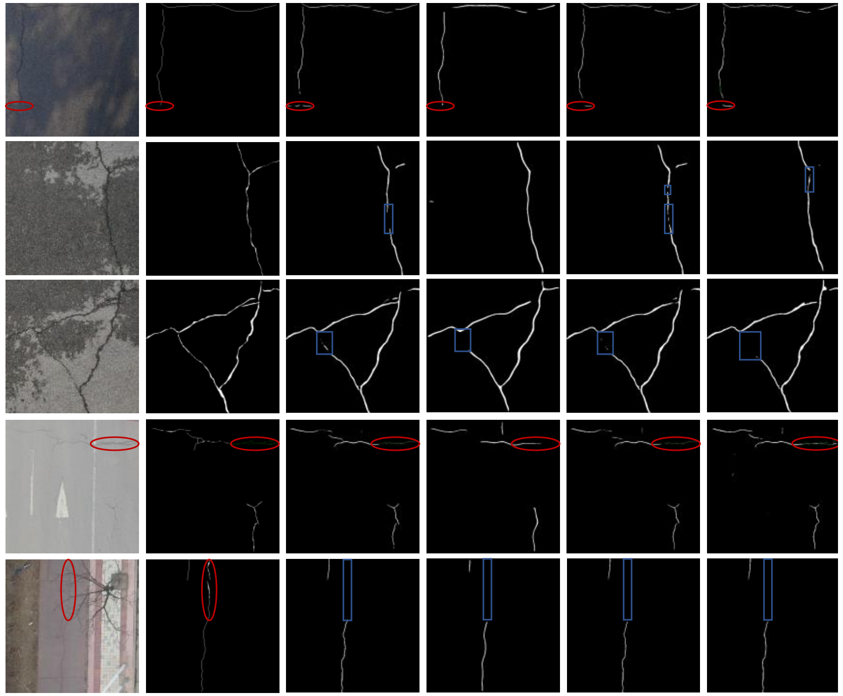
路面病害数据集



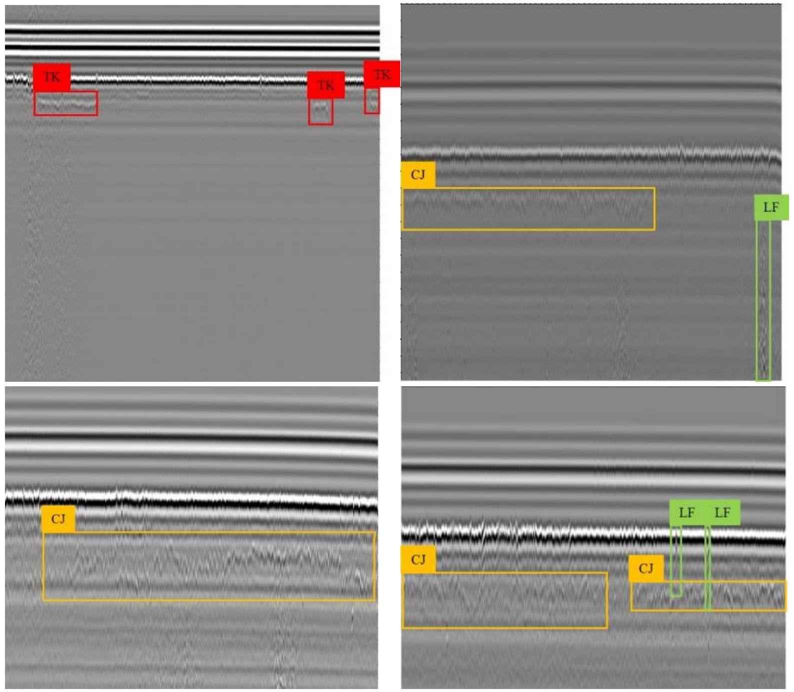


如何重复利用数据和网络？

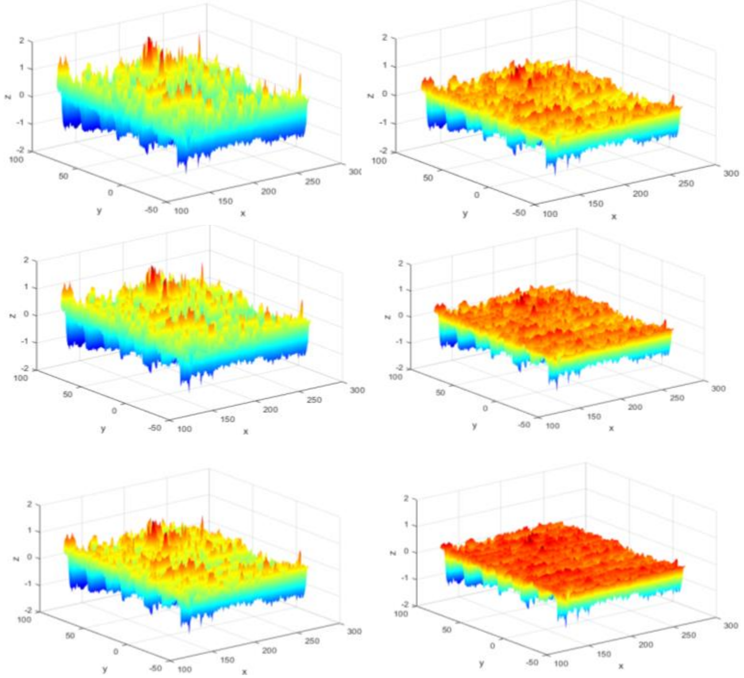
多源数据集组合



病害图片



雷达信号



高维特征

如何重复利用数据和网络？

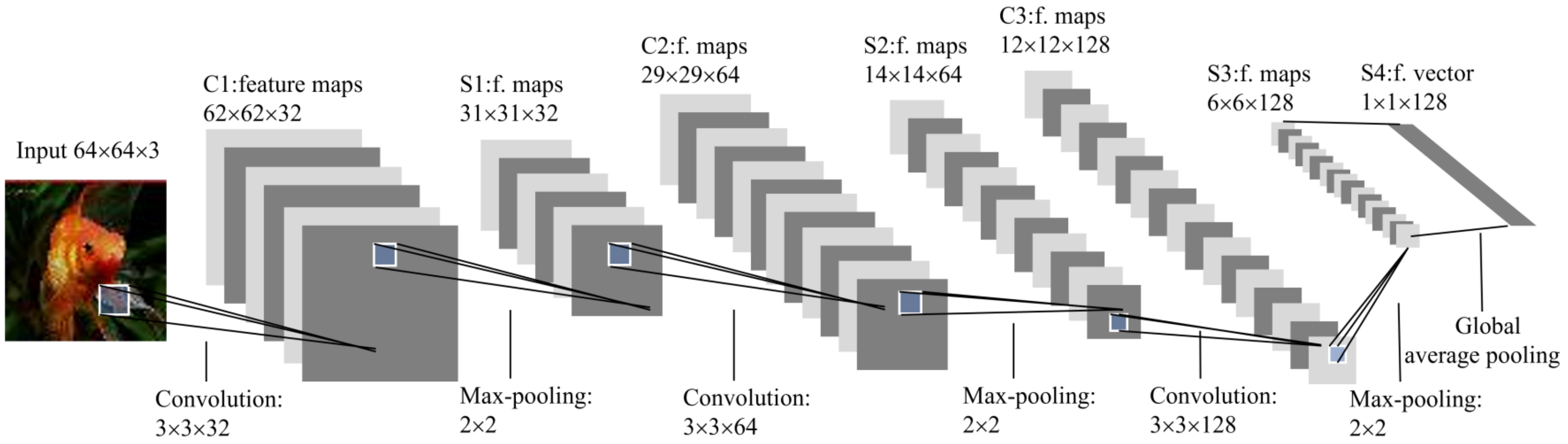
融合多源异构模型

如何重复利用数据和网络？

- 迁移学习
  - 运用已有知识来学习新知识，核心是找到已有知识和新知识之间的相似性
  - 学习过程中已有知识容易损失
- 多源数据集组合
  - 需要重新训练模型
  - 需要处理不精确标签问题
- 融合多源异构模型
  - 不同模型的输出结果必须兼容
  - 需要具备异常值检测能力
  - 融合结果可能是次优解

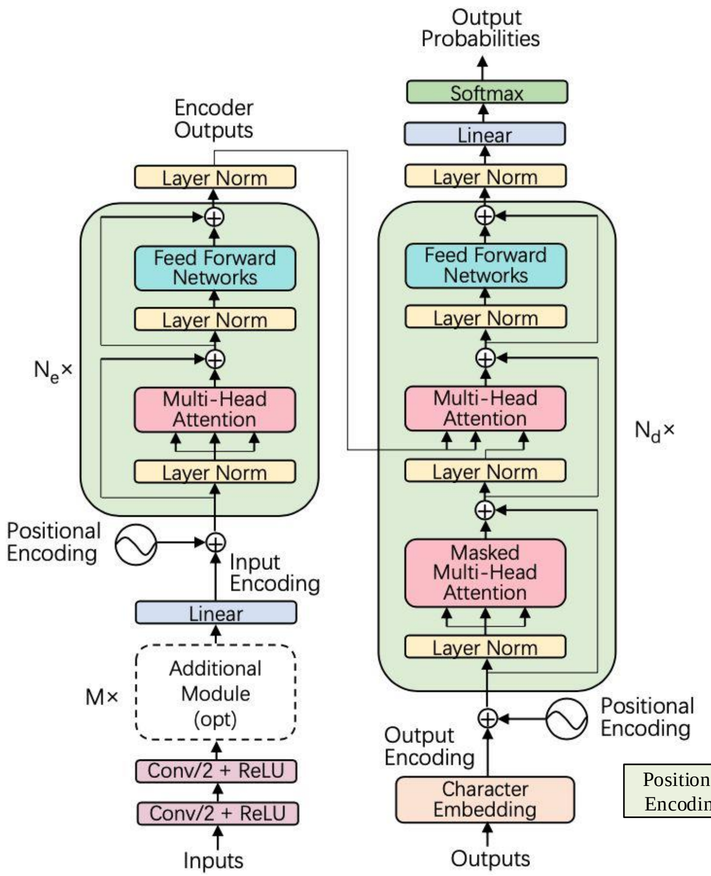
目录

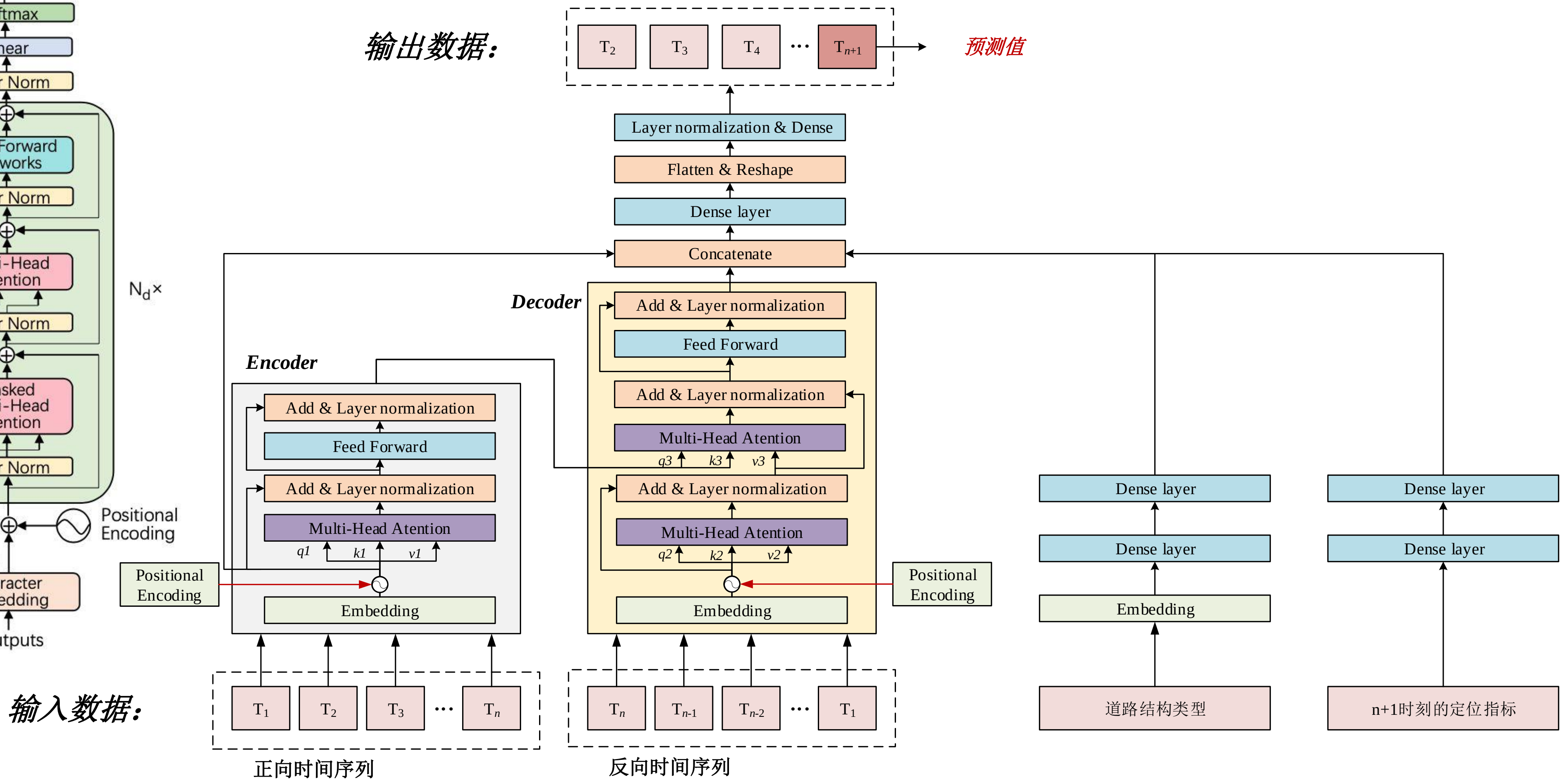
深度神经网络



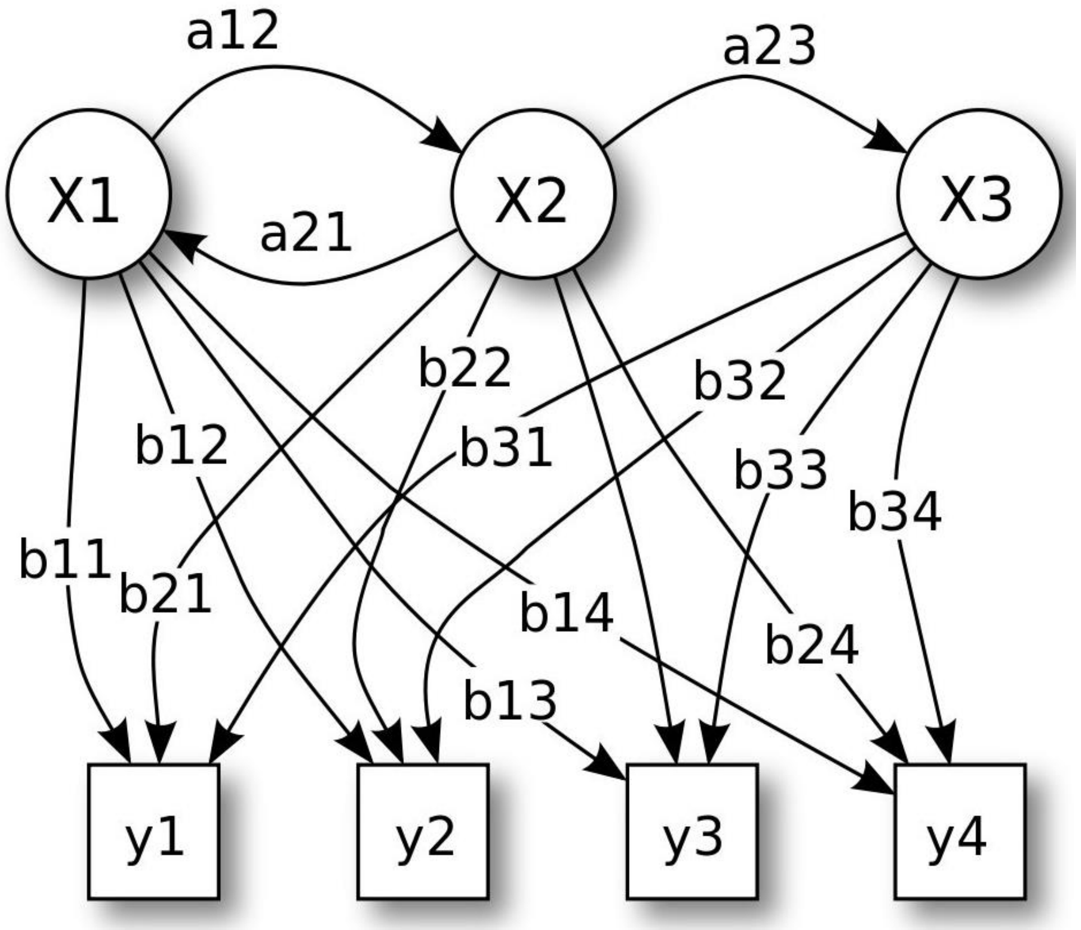
输入 → 特征提取 → $X \in \mathbb{R}^n$ → 置信度输出 → P^{Ω}

深度神经网络


Output Probabilities
Softmax
Linear
Layer Norm
Encoder Outputs
Feed Forward Networks
Multi-Head Attention
Masked Multi-Head Attention
N_e×
N_d×
Positional Encoding
Input Encoding
Output Encoding
Additional Module (opt)
M×
Conv/2 + ReLU
Character Embedding
Inputs
Outputs


输出数据:
T_2 T_3 T_4 … T_{n+1}
预测值
Layer normalization & Dense
Flatten & Reshape
Dense layer
Concatenate
Decoder
Encoder
Add & Layer normalization
Feed Forward
Multi-Head Atention
q1 k1 v1
q2 k2 v2
q3 k3 v3
Positional Encoding
Embedding
Dense layer
输入数据:
T_1 T_2 T_3 … T_n
T_n T_{n-1} T_{n-2} … T_1
道路结构类型
n+1时刻的定位指标
正向时间序列
反向时间序列

深度神经网络融合方法



贝叶斯概率分布

$$P(A|B) = \frac{P(AB)}{P(B)} \qquad P(B) = \sum_{i=1}^{n} P(A_i)P(B|A_i)$$

$$P(A_i|B) = \frac{P(A_i)P(B|A_i)}{\sum_{j=1}^{n} P(A_j)P(B|A_j)}$$

Dempster-Shafer 证据理论

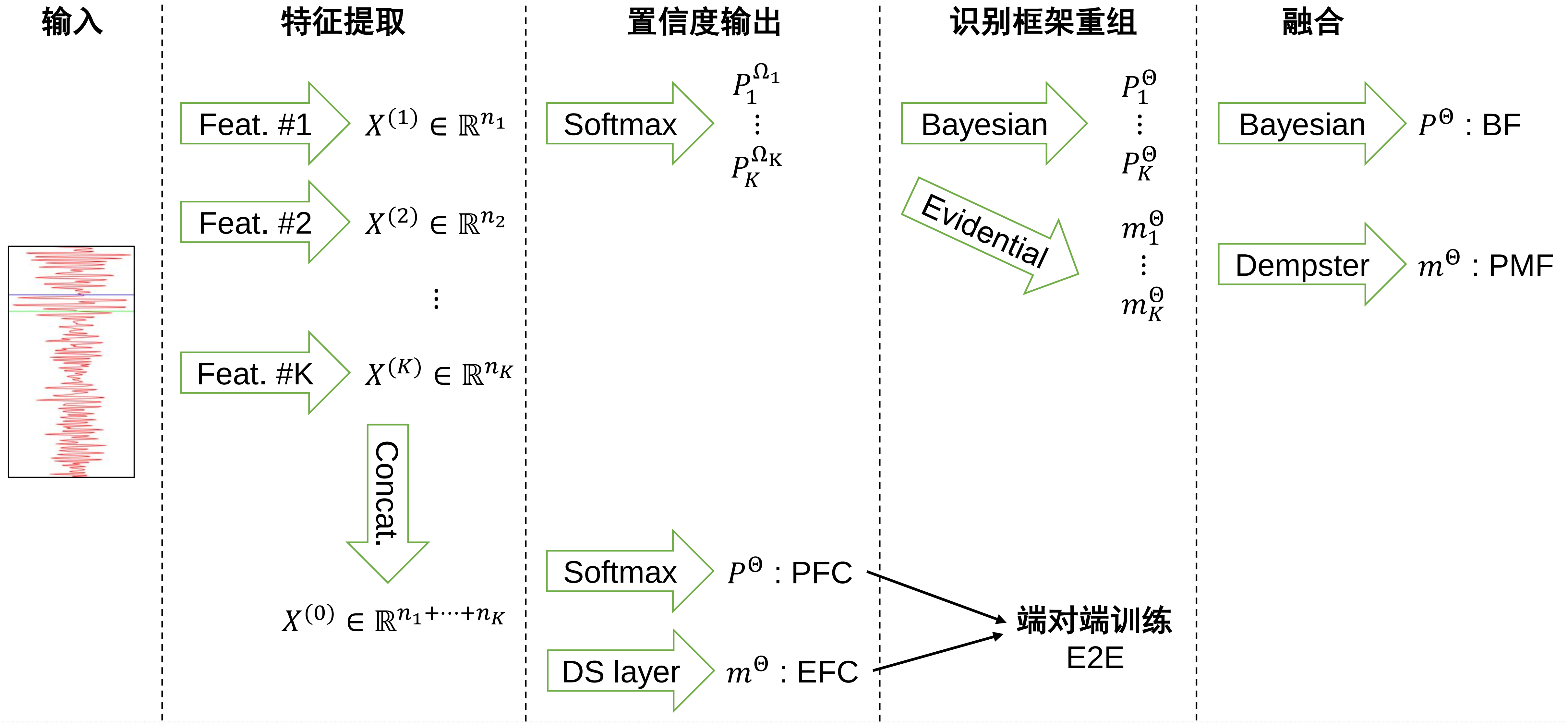
证据合成公式：

$$m(A) = m_1 \oplus m_2(A) = m_2 \oplus m_1(A) = \frac{1}{K}\sum_{B\cap C} m_1(B)m_2(C)$$

归一化常数：

$$K = \sum_{B\cap C\neq\varnothing} m_1(B)m_2(C) = 1 - \sum_{B\cap C\neq\varnothing} m_1(B)m_2(C)$$

深度神经网络融合方法



输入
特征提取
置信度输出
识别框架重组
融合
Feat. #1
$X^{(1)} \in \mathbb{R}^{n_1}$
Feat. #2
$X^{(2)} \in \mathbb{R}^{n_2}$
Feat. #K
$X^{(K)} \in \mathbb{R}^{n_K}$
Concat.
$X^{(0)} \in \mathbb{R}^{n_1+\cdots+n_K}$
Softmax
$P_1^{\Omega_1}$
$P_K^{\Omega_K}$
Softmax
P^{Θ} : PFC
DS layer
m^{Θ} : EFC
Bayesian
P_1^{Θ}
P_K^{Θ}
Evidential
m_1^{Θ}
m_K^{Θ}
端对端训练
E2E
Bayesian
P^{Θ} : BF
Dempster
m^{Θ} : PMF

识别框架

- 定义重组函数(refining) $\rho: 2^{\Omega} \rightarrow 2^{\Theta}$ 是一个从识别框架Ω到另一个识别框架Θ的映射：
  - $\{\rho(\{\omega\}) | \omega \in \Omega\} \subseteq 2^{\wedge}\Theta$ is a partition of Θ
  - $\forall A \subseteq \Omega, \rho(A) = \bigcup_{\omega \in A} \rho(\{\omega\})$
- 识别框架Θ是识别框架Ω的重组框架(refinement)
- 重组函数案例：
  - $\Omega = \{$裂缝, 路表变形$\}$
  - $\Theta = \{$横向裂缝, 纵向裂缝, 网状裂缝, 块状裂缝, 车辙, 沉陷, 波浪拥包$\}$
  - $\rho(\{$裂缝$\}) = \{$横向裂缝, 纵向裂缝, 网状裂缝, 块状裂缝$\}$
  - $\rho(\{$路表变形$\}) = \{$车辙, 沉陷, 波浪拥包$\}$
- 两个识别框架是互相兼容 (compatible)↔识别框架有相同的重组框架

贝叶斯融合

- P^{Ω}: $\mathbb{P}(\text{裂缝}) = p$; $\mathbb{P}(\text{路表变形}) = 1 - p$
- P^{Θ}:
  - $\mathbb{P}(\{\text{横向裂缝}, \text{纵向裂缝}, \text{网状裂缝}, \text{块状裂缝}\}) = p$
  - $\mathbb{P}(\{\text{车辙}, \text{沉陷}, \text{波浪拥包}\}) = 1 - p$

无差异原则：每个元素的概率均等

- P^{Θ}:
  - $\mathbb{P}(\text{横向裂缝}) = \mathbb{P}(\text{纵向裂缝}) = \cdots = p/c$
  - $\mathbb{P}(\text{车辙}) = \mathbb{P}(\text{沉陷}) = \cdots = \mathbb{P}(\text{波浪拥包}) = (1 - p)/d$

证据融合

- 概率到信度函数m^{Θ}:
  - $m(\{$横向裂缝, 纵向裂缝, 网状裂缝, 块状裂缝, $\}) = p$
  - $m(\{$车辙, 沉陷, 波浪拥包$\}) = 1 - p$
- 信度函数m^{Ω}在识别框架Θ的**扩展信度函数(vacuous extension)** $m^{\Omega\uparrow\Theta}$:

$$m^{\Omega\uparrow\Theta}(B) = \begin{cases} m^{\Omega}(A) & \text{if } \exists A \subseteq \Omega, B = \rho(A), \\ 0 & \text{otherwise} \end{cases}$$

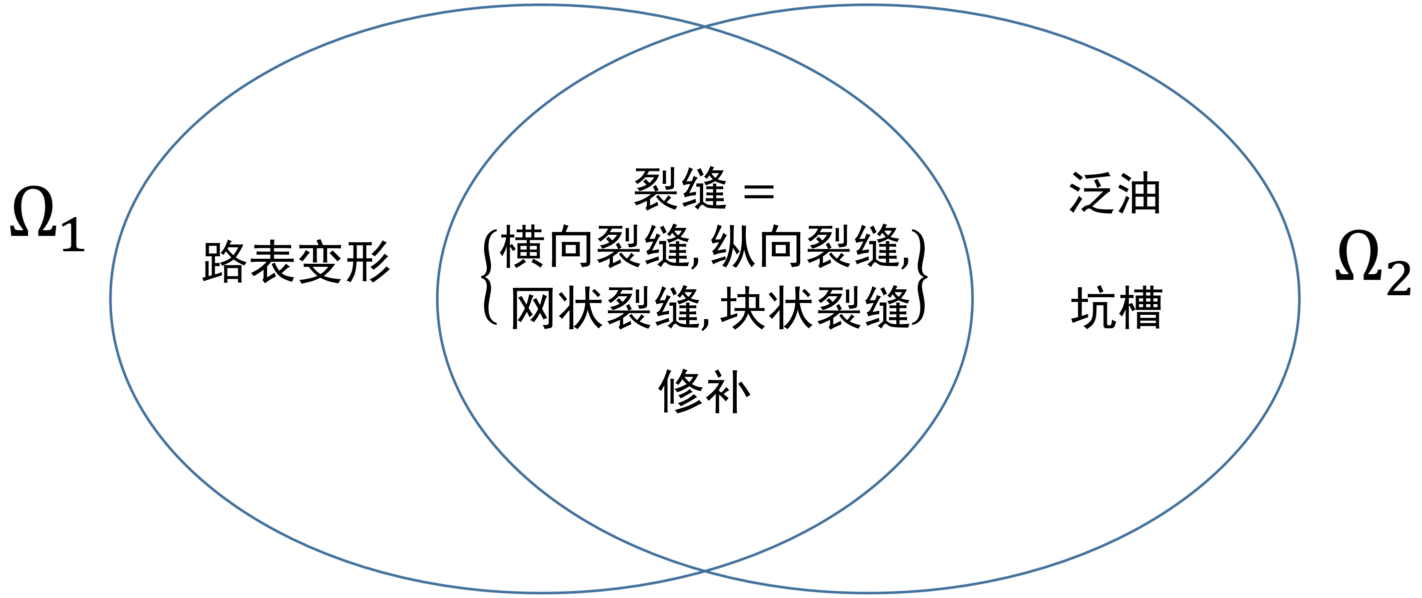
- 来自不同识别框架Ω_1,Ω_2 ,..., Ω_v的扩展信度函数$m^{\Omega 1\uparrow\Theta}$,$m^{\Omega 2\uparrow\Theta}$ ..., $m^{\Omega v\uparrow\Theta}$ 采用**Dempster准则**融合：

$$m^{\Theta}(B) = K_v \sum_{B=A1\cap A2\cap\cdots\cap Av} m^{\Omega 1\uparrow\Theta}(A1) m^{\Omega 1\uparrow\Theta}(A2) \cdots m^{\Omega v\uparrow\Theta}(Av)$$

$$K_v = \sum_{A1\cap A2\cap\cdots\cap Av\neq\emptyset} m^{\Omega 1\uparrow\Theta}(A1) m^{\Omega 1\uparrow\Theta}(A2) \cdots m^{\Omega v\uparrow\Theta}(Av)$$

不相容的识别框架

- $\Omega_1 = \{裂缝, 路表变形, 修补\}$
- $\Omega_2 = \{横向裂缝, 纵向裂缝, 网状裂缝, 块状裂缝, 修补, 泛油, 坑槽\}$



不相容的识别框架

- $\Omega_1^* = \{$裂缝, 路表变形, 修补$\} \cup \{\text{everything else } 1\}$

$\neq$

- $\Omega_2^* = \{$横向裂缝, …, 块状裂缝, 修补, 泛油, 坑槽$\} \cup \{\text{everything else } 2\}$

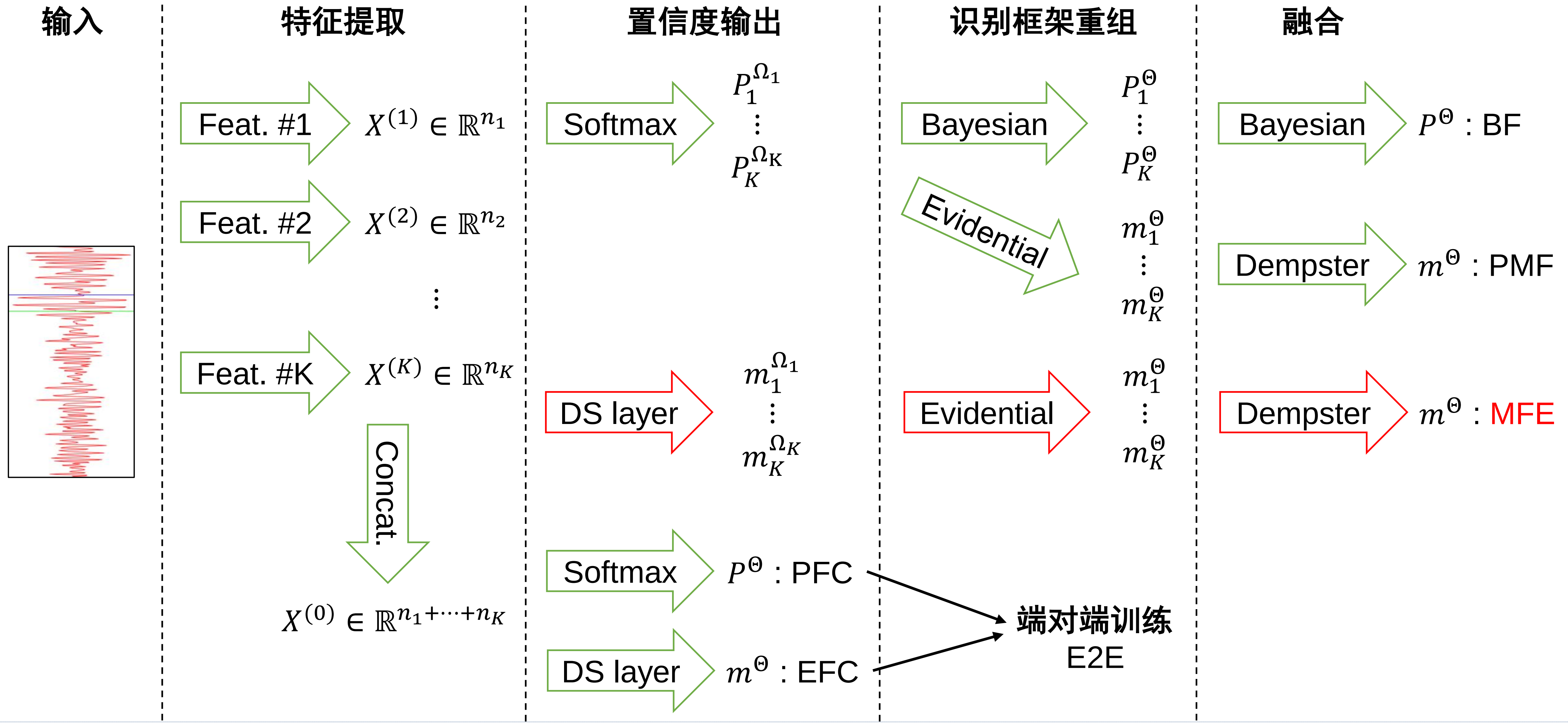
$\neq$

- Ω_1^* 和 Ω_2^* 变成互相兼容 (compatible)

- Common refinement Θ:

$\Theta = \{$横向裂缝, …, 修补, 泛油, 坑槽路表变形, 修补$\} \cup \{\text{everything else } 3\}$

深度神经网络融合方法



输入
特征提取
置信度输出
识别框架重组
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Feat. #1
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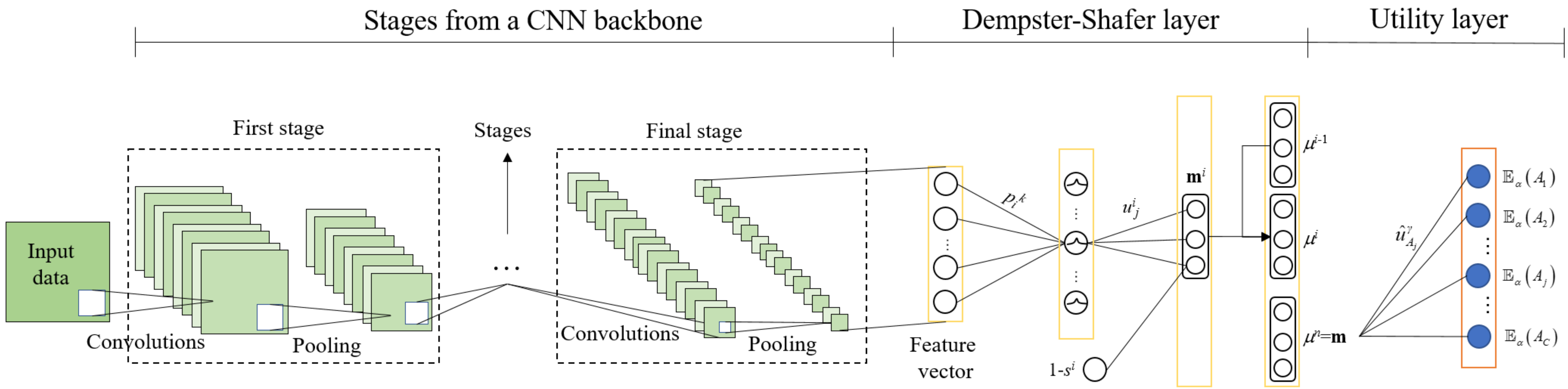
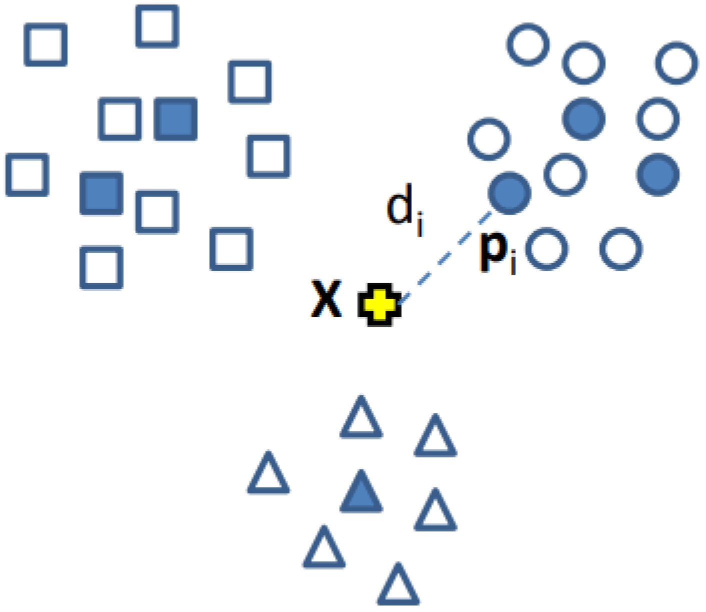
Feat. #2
$X^{(2)} \in \mathbb{R}^{n_2}$
⋮
Feat. #K
$X^{(K)} \in \mathbb{R}^{n_K}$
Concat.
$X^{(0)} \in \mathbb{R}^{n_1+\cdots+n_K}$
Softmax
$P_1^{\Omega_1}$ ⋮ $P_K^{\Omega_K}$
DS layer
$m_1^{\Omega_1}$ ⋮ $m_K^{\Omega_K}$
Softmax
P^{Θ} : PFC
DS layer
m^{Θ} : EFC
Bayesian
P_1^{Θ} ⋮ P_K^{Θ}
Evidential
m_1^{Θ} ⋮ m_K^{Θ}
Evidential
m_1^{Θ} ⋮ m_K^{Θ}
端对端训练
E2E
Bayesian
P^{Θ} : BF
Dempster
m^{Θ} : PMF
Dempster
m^{Θ} : MFE

证据深度神经网络



[6] Z. Tong, Ph. Xu and T. Denœux. An evidential classifier based on Dempster-Shafer theory and deep learning. *Neurocomputing*, Vol. 450, pages 275–293, Aug. 2021.

证据结构层



- 采用r个prototypes代表训练集
- 任一prototype $\boldsymbol{p}_i$具有对任一类别ω_j的置信度$h_{i,j}$，$\sum_j h_{i,j} = 1$
- 任一prototype $\boldsymbol{p}_i$对样本$\boldsymbol{x}$类别的置信度随着和$d_i = \|\boldsymbol{x} - \boldsymbol{p}_i\|$相似度增加而减小 。

[7] T. Denoeux. A neural network classifier based on Dempster-Shafer theory. IEEE transactions on SMC A, 30(2):131-150, 2000.

证据结构层

- 相似度支持计算:

$$s_i[\boldsymbol{x}] = \frac{\exp(-\eta_i \|\boldsymbol{x} - \boldsymbol{p}_i\|^2)}{1 + \exp(-\xi_i)}, \forall i \in \{1, \dots, r\}$$

- prototype $\boldsymbol{p}_i$的信度函数计算:

$$m_i[\boldsymbol{x}](\{\omega_j\}) = h_{i,j} s_i[\boldsymbol{x}], \forall \omega_j \in \Omega$$

$$m_i[\boldsymbol{x}](\Omega) = 1 - s_i[\boldsymbol{x}]$$

- r个prototypes的信度函数融合:

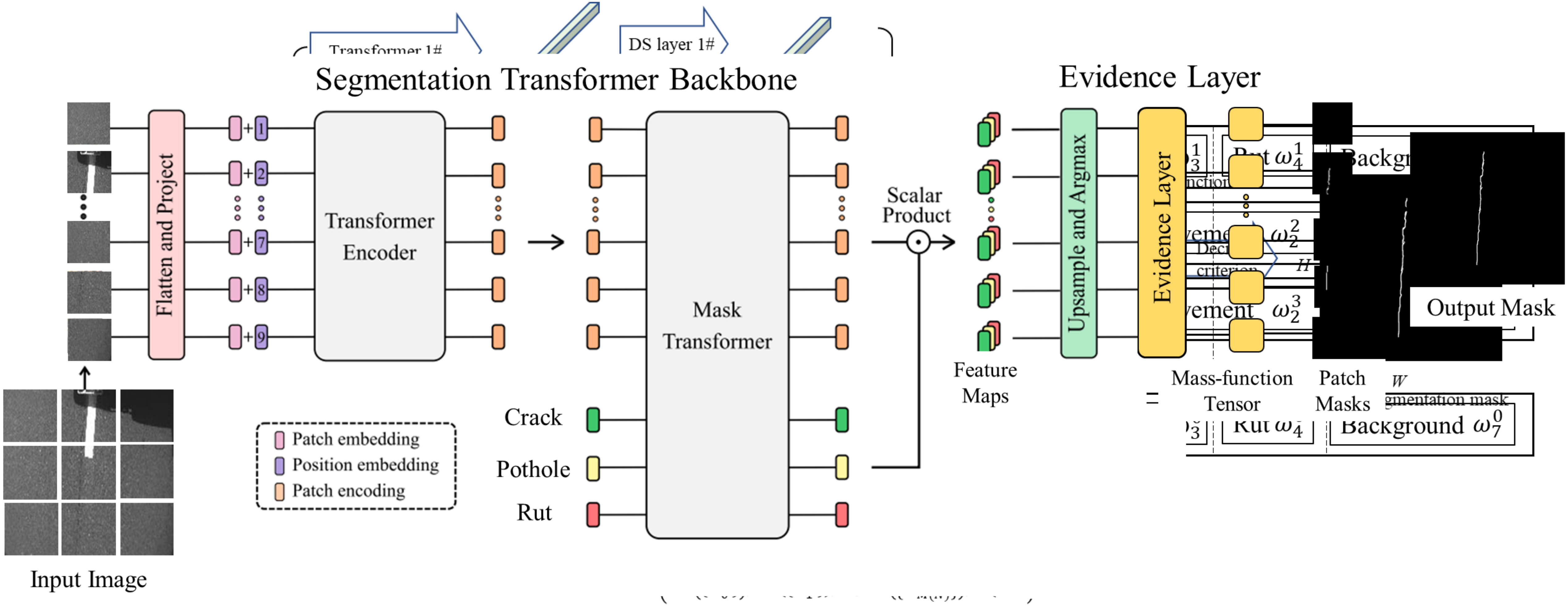
$$m = m_1 \oplus m_2 \oplus \cdots \oplus m_r$$

- 证据结构层的融合信度函数：

$$\sum_{A \subseteq \Omega / \emptyset} m(A) = 1$$

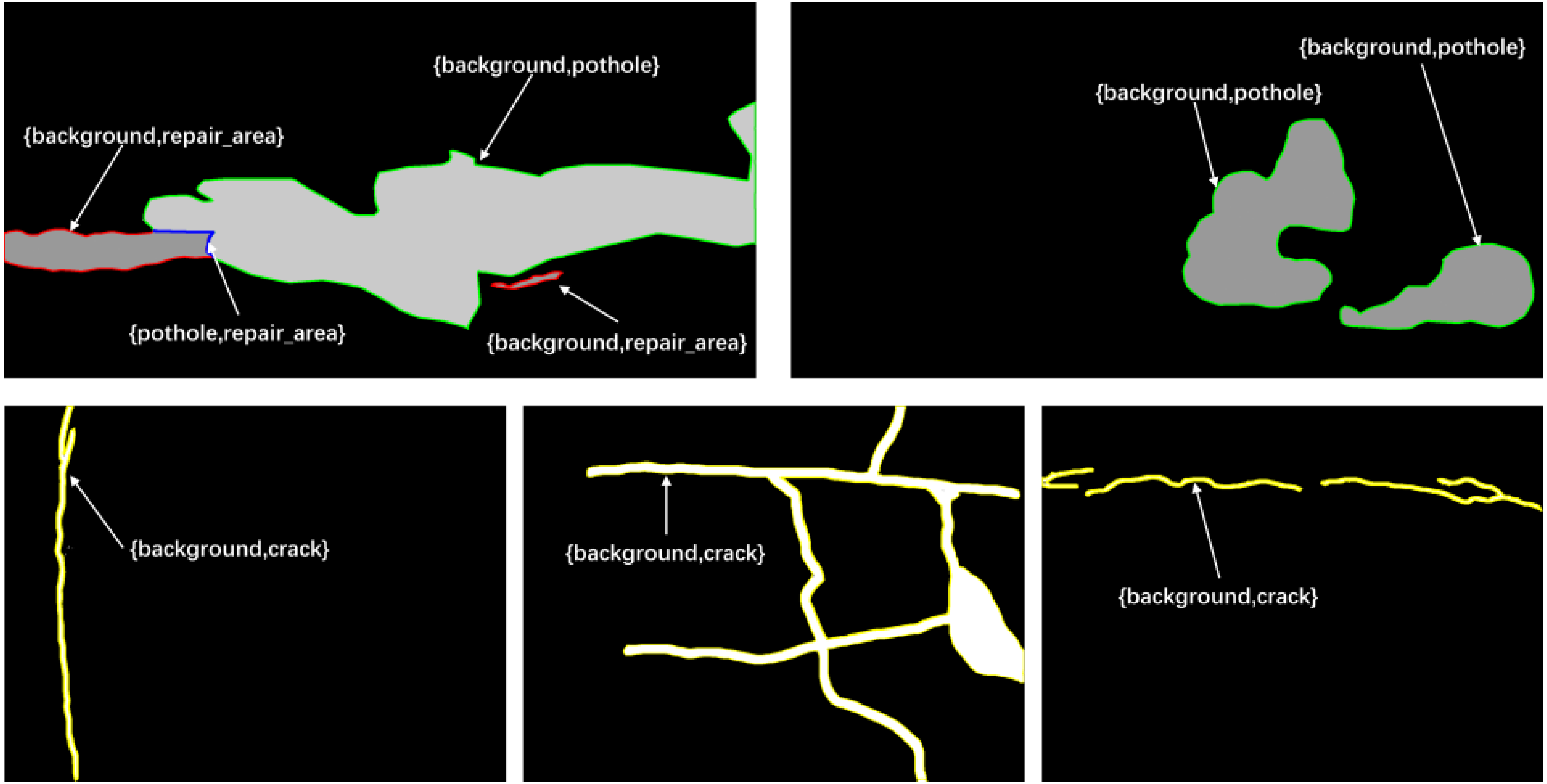
目 录

面向路面病害分割的多源深度神经网络融合

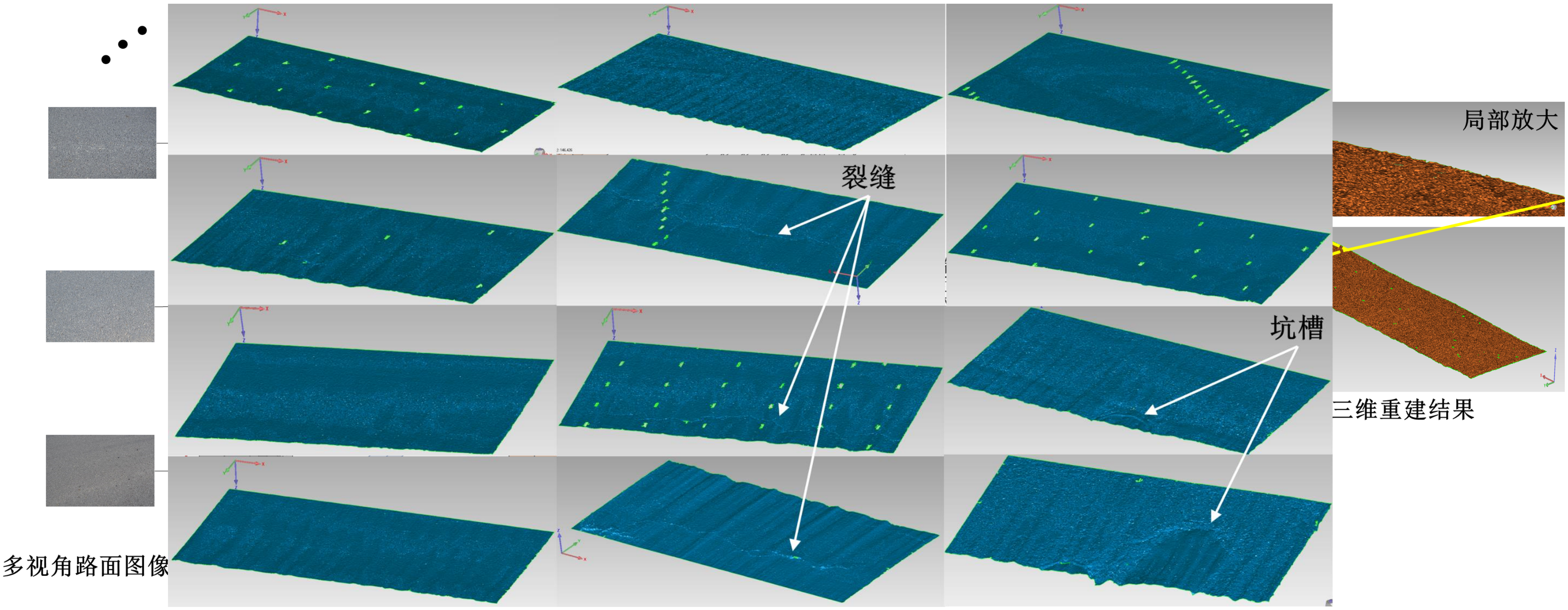


[3] Tong Zheng, Ma Tao, et al. (2023). Evidential transformer for pavement distress segmentation. CACAIE.

面向路面病害分割的多源深度神经网络融合

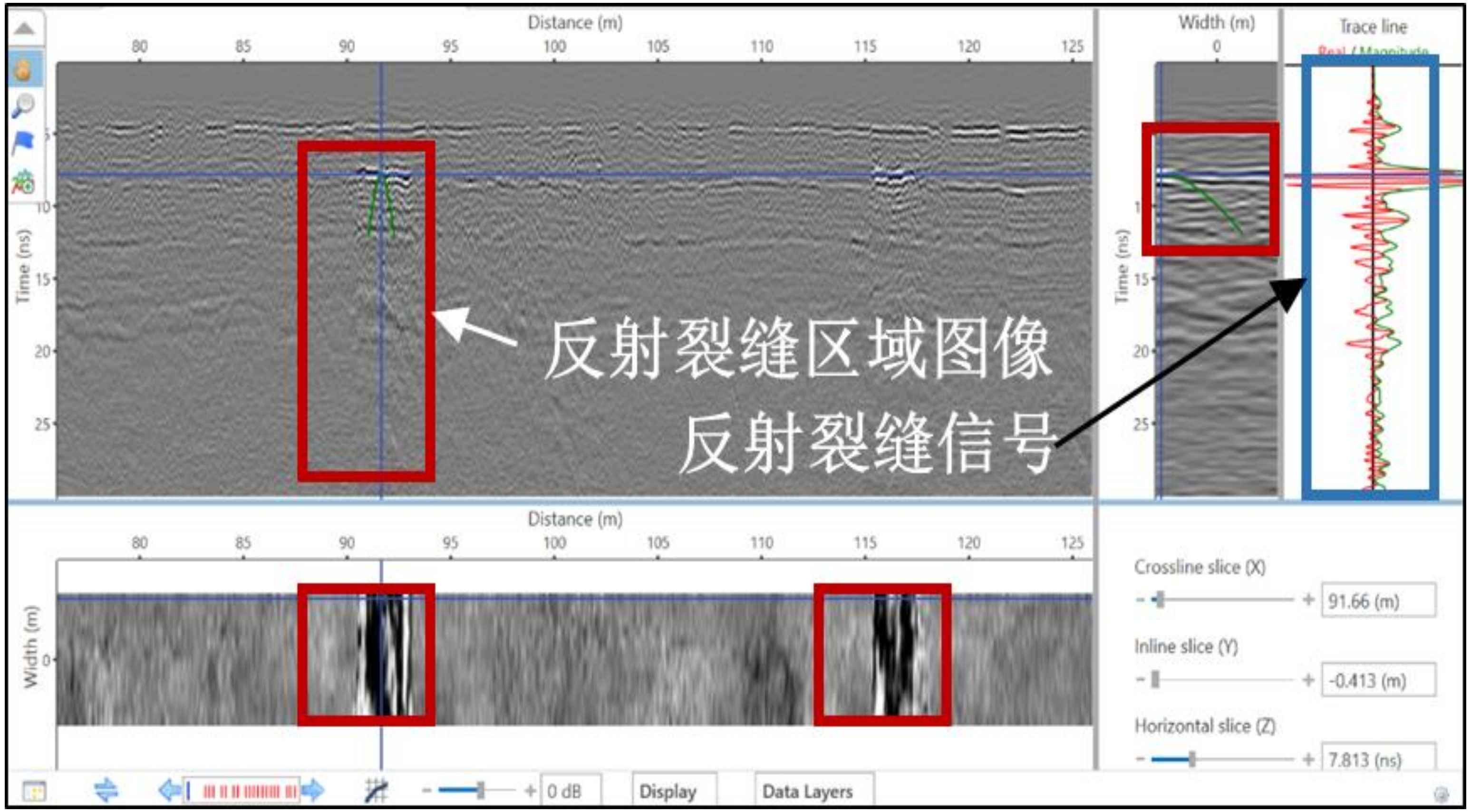


面向多目异源数据的深度神经网络融合

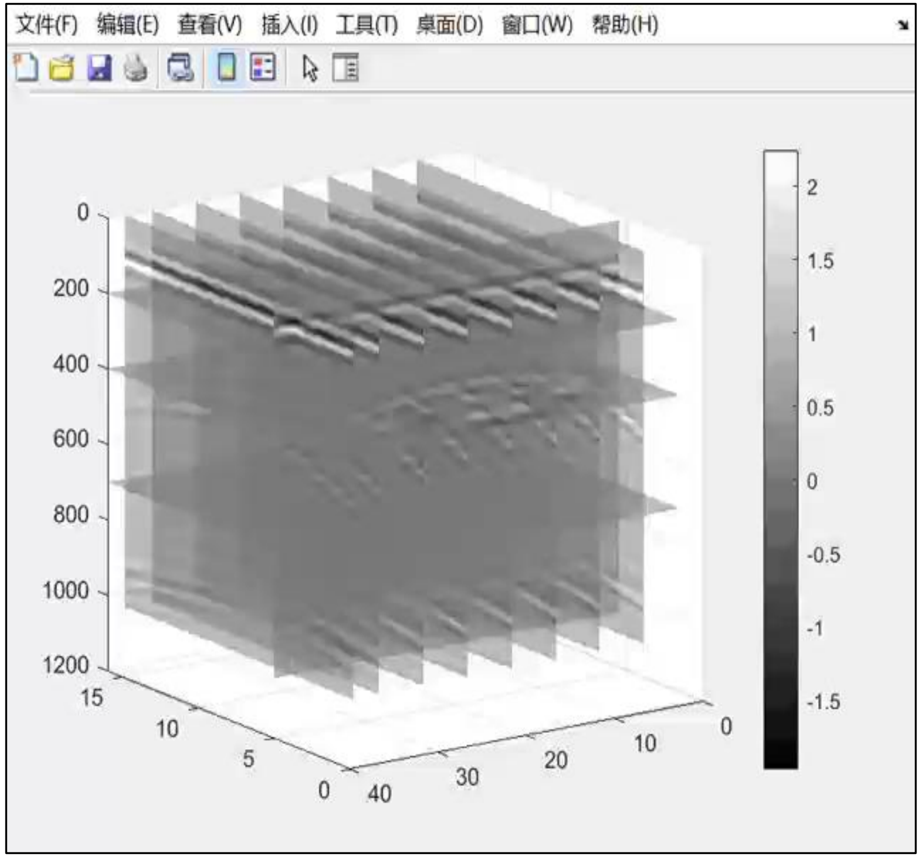


[7]马涛,童峥,张一鸣,张伟光(2023).基于多目视觉深度神经网络的路面宏观纹理三维重建方法. 中国公路学报.

多维数据融合

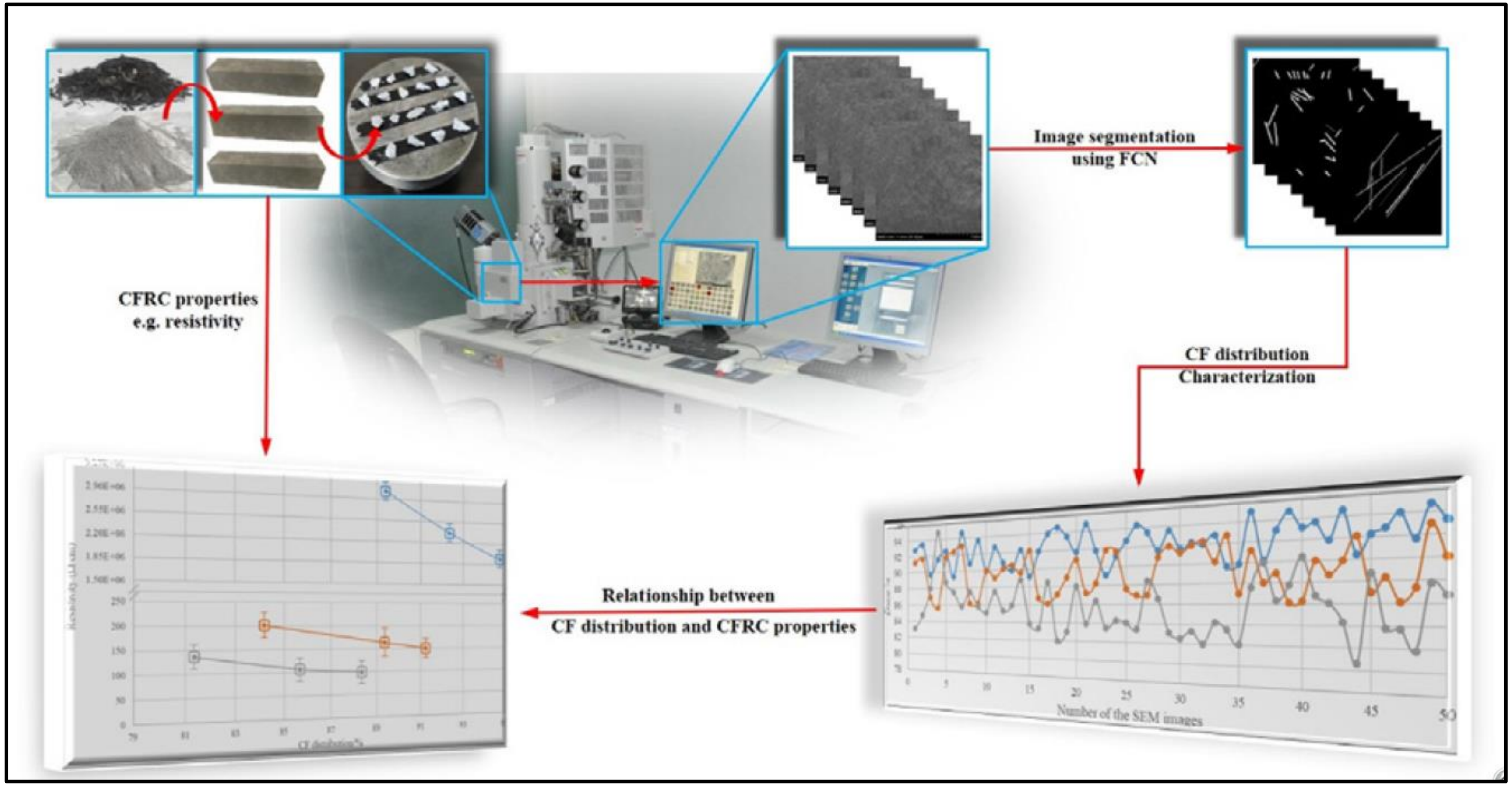


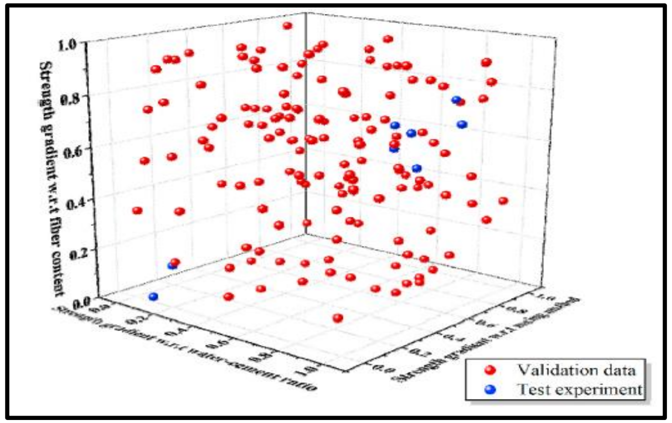
Distance (m)
Width (m)
Trace line
Time (ns)
反射裂缝区域图像
反射裂缝信号
Distance (m)
Width (m)
Crossline slice (X)
91.66 (m)
Inline slice (Y)
-0.413 (m)
Horizontal slice (Z)
7.813 (ns)
0 dB
Display
Data Layers

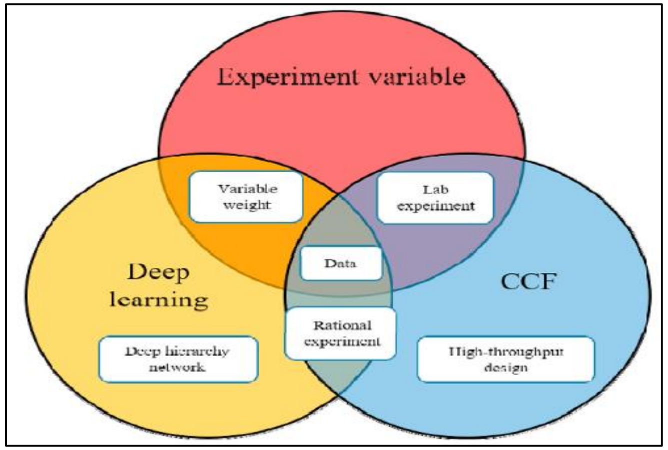


文件(F) 编辑(E) 查看(V) 插入(I) 工具(T) 桌面(D) 窗口(W) 帮助(H)

多源异构数据融合







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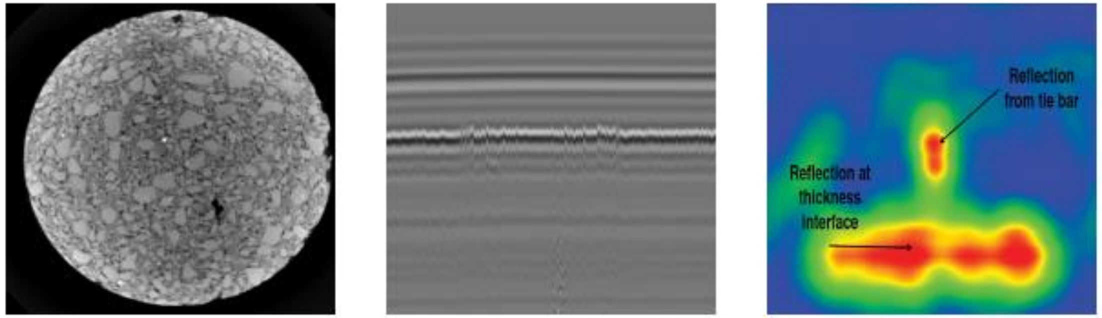
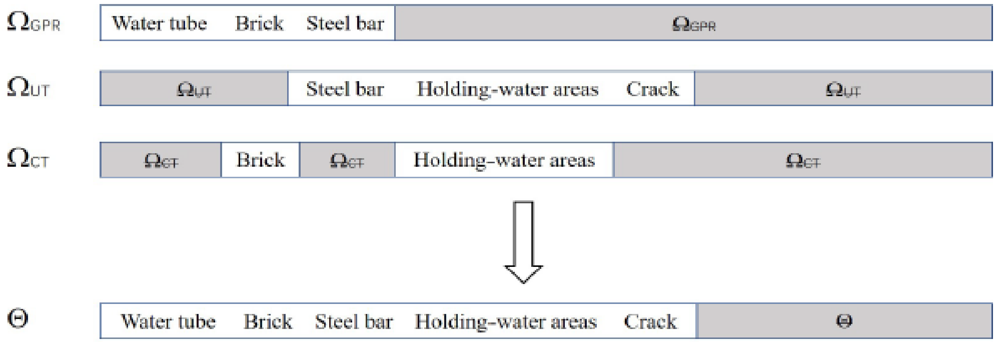
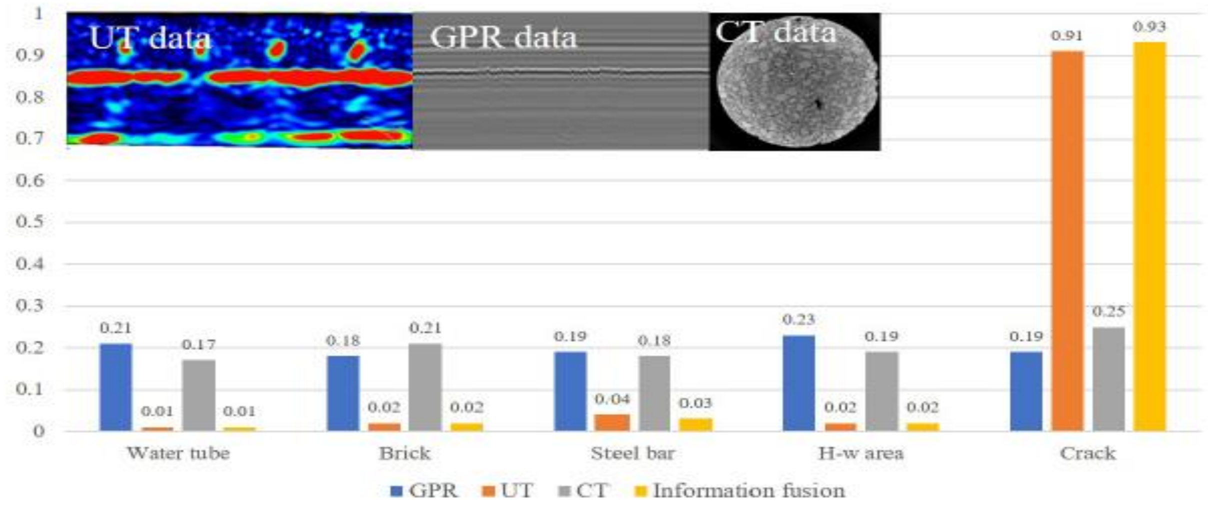
多源异构数据融合

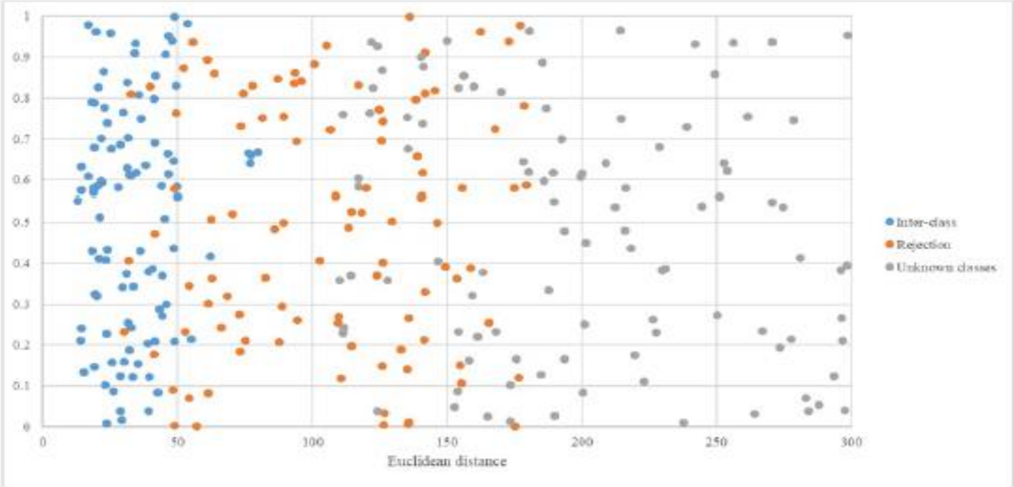


(a) CT image (b) GPR image (c) UT image



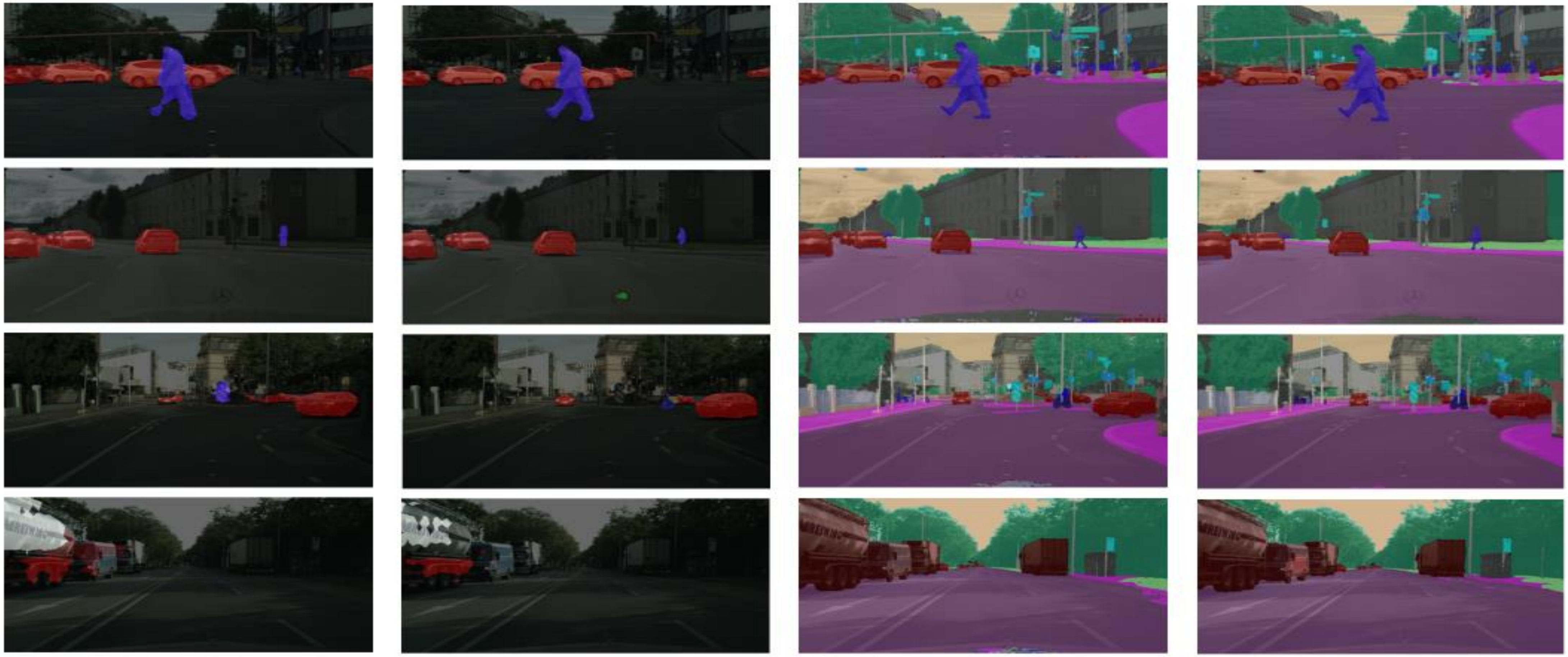
不同无损检测设备检测结果融合





结果示例

多源异构数据融合



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In Proceedings of the 6th International Conference on Belief Functions (BELIEF), pages 168-176, Shanghai, France, October 15-19, 2021..

结论

- 证据理论可用于多源异构深度神经网络融合
- 证据理论可融合多源异构交通基础设施检测数据
- 证据深度神经网络融合在保证原模型精度的基础上发展出了更加泛化的模型
- 证据深度神经网络融合重复利用已有深度学习模型，避免重复开发

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- Z. Tong, Ph. Xu and T. Denœux. An evidential classifier based on Dempster-Shafer theory and deep learning. *Neurocomputing*, Vol. 450, pages 275–293, Aug. 2021.
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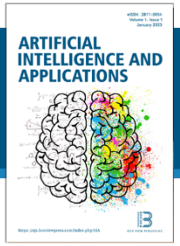

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