

Harnessing Explainability to Build Resilient Ensembles

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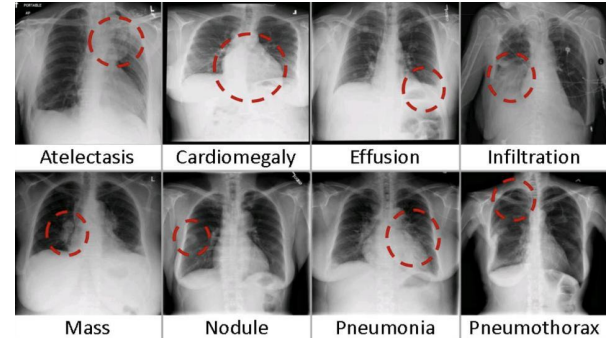
Training Data Faults

70% of Lyft dataset missing, mislabelled [Kang et al, 2022]



Autonomous Vehicles

20% of ChestX-ray mislabelled [Tang et al, 2021]



Healthcare

Training Data Faults

Image	Label
	Speed 80km/h Stop sign
	Stop sign Speed 80km/h
	No entry

Mislabeling

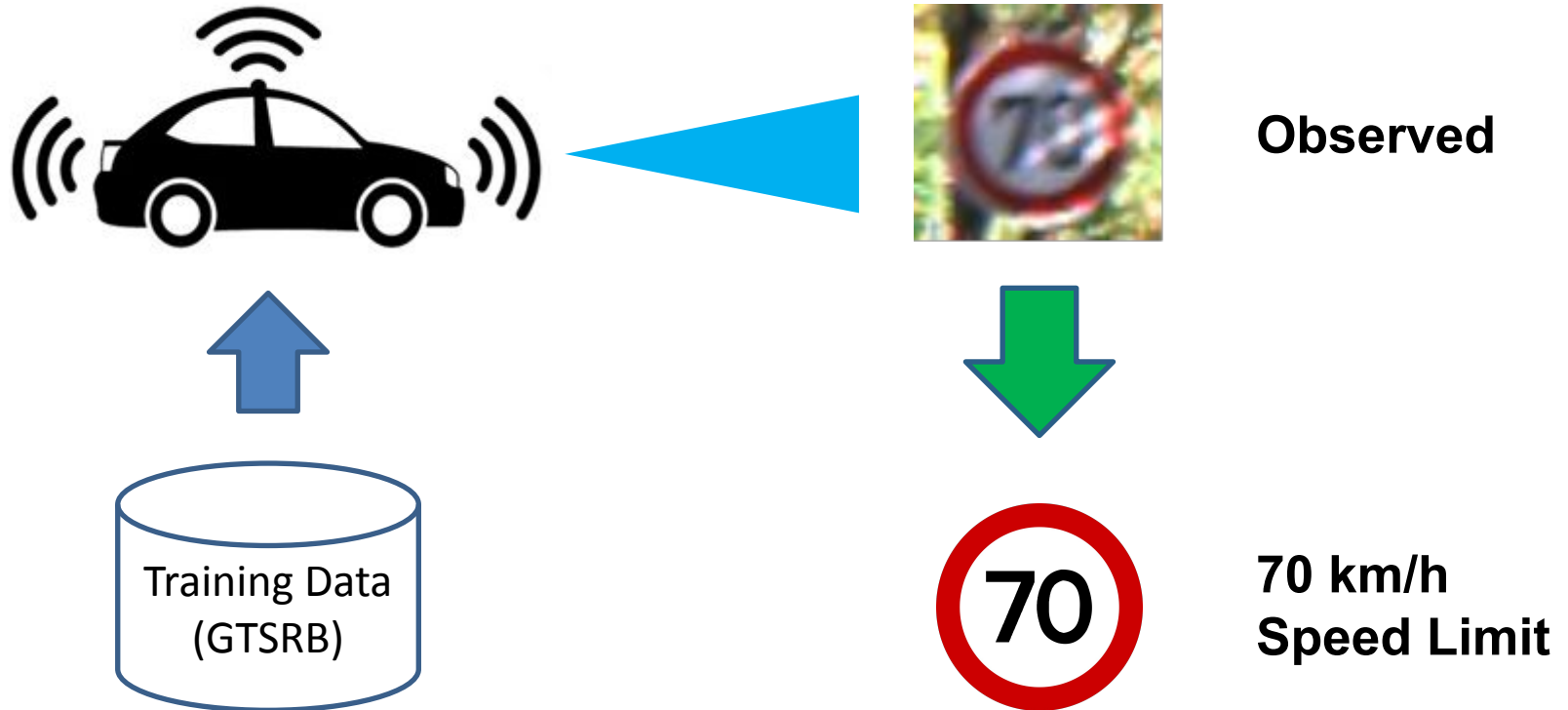
Image	Label
	Speed 80km/h
	Stop sign
	No entry

Removal

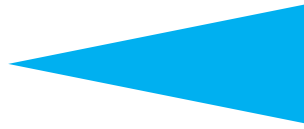
Image	Label
	Speed 80km/h
	Stop sign
	No entry
	No entry

Repetition

Autonomous Vehicle Example

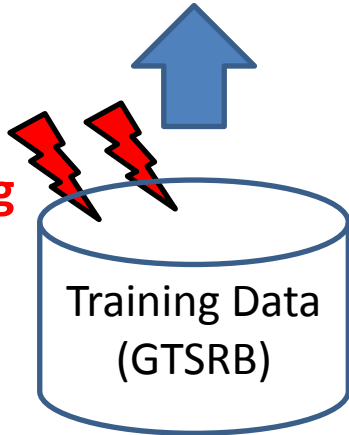


Random Mislabelling



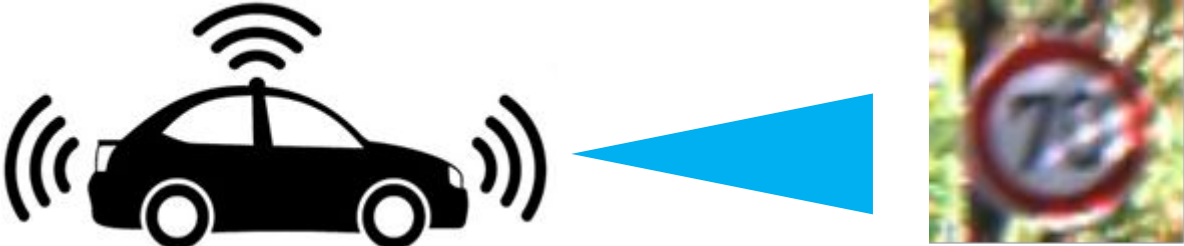
Observed

30%
Random
Mislabelling

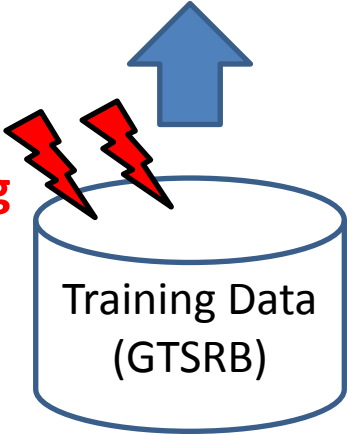


Road Bend
to the Right

Resilience against Faulty Training Data



**30%
Random
Mislabelling**



Resilience

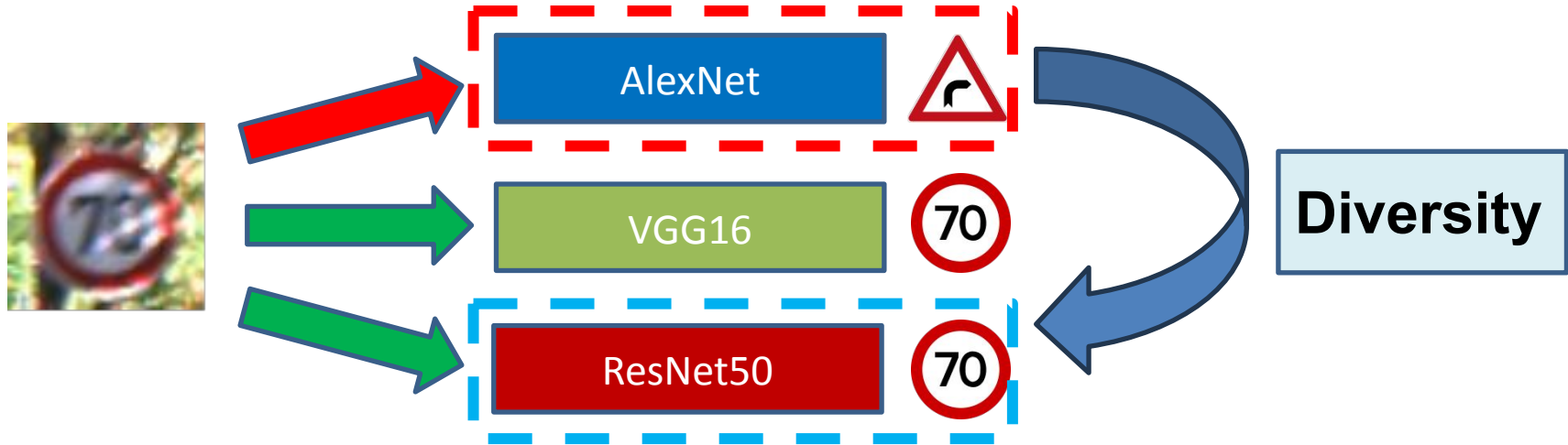
How to mitigate training data faults with minimal human effort?



Our Solution: Build Resilient Ensembles

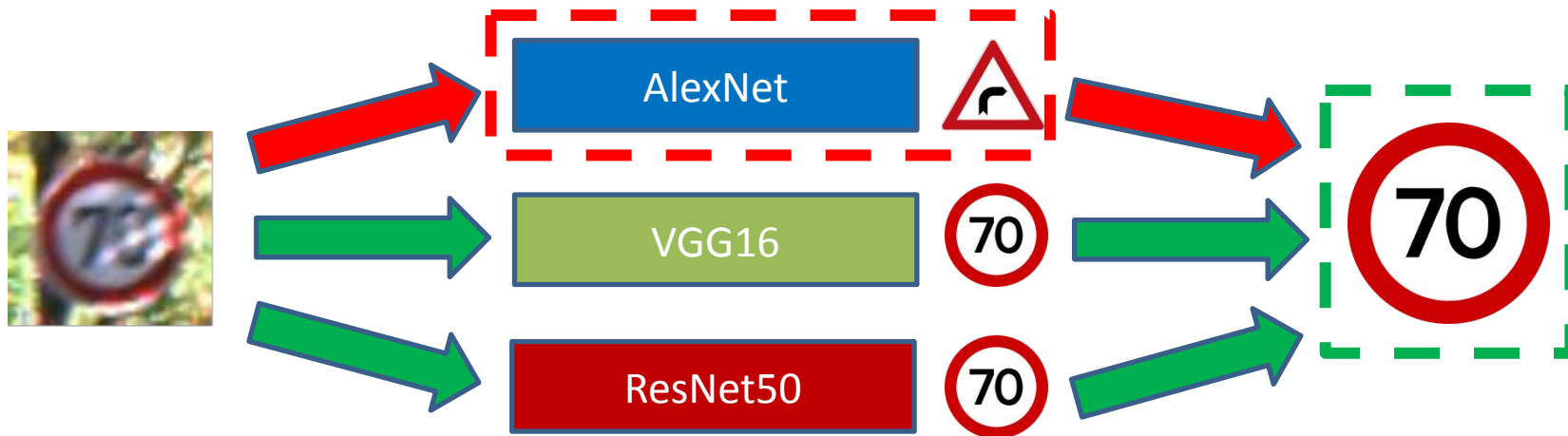
Our Work: The Fault in Our Data Stars: Studying Mitigation Techniques against Faulty Training Data in ML Applications **[DSN'22]**

Resilient Ensembles (NVP)



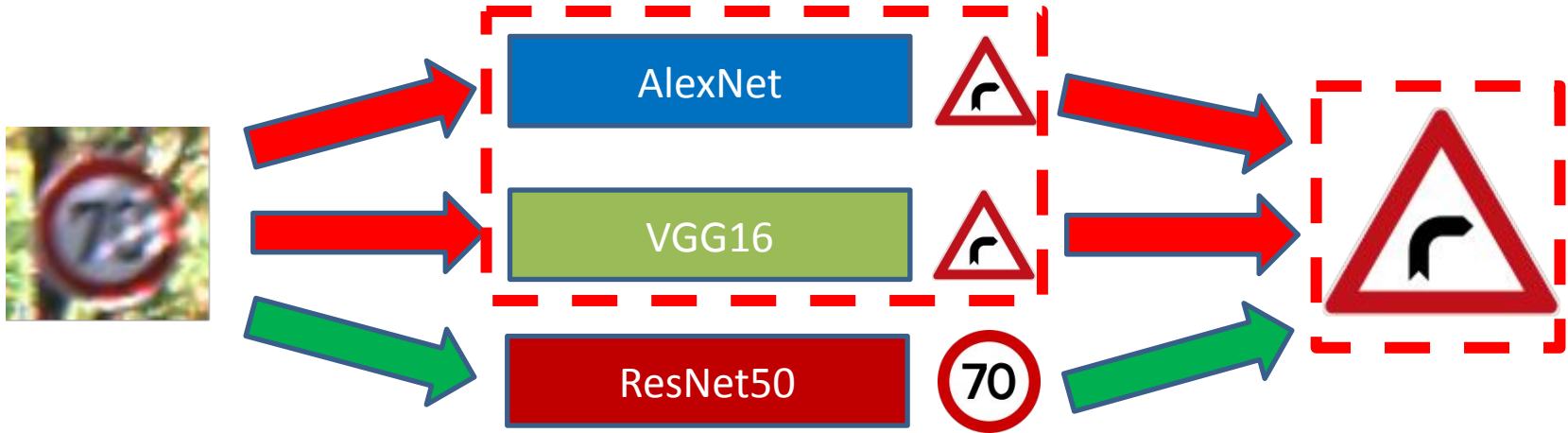
Our Work: The Fault in Our Data Stars: Studying Mitigation Techniques against Faulty Training Data in ML Applications [DSN'22]

Resilient Ensembles

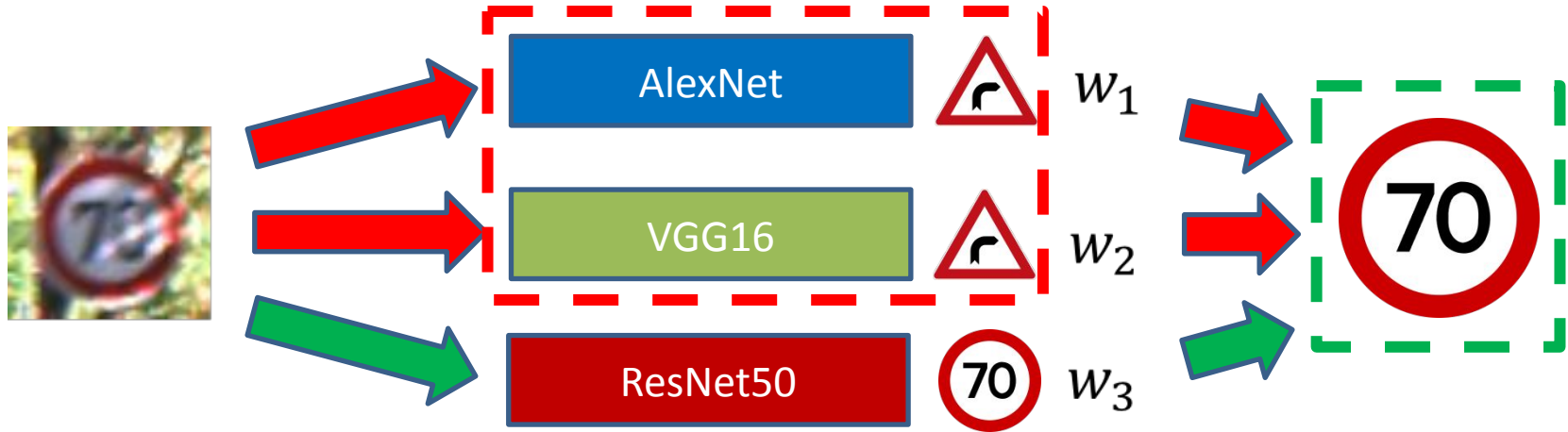


Our Work: Understanding the Resilience of Neural Network Ensembles against Faulty Training Data [QRS'21]

When Ensembles Misclassify?



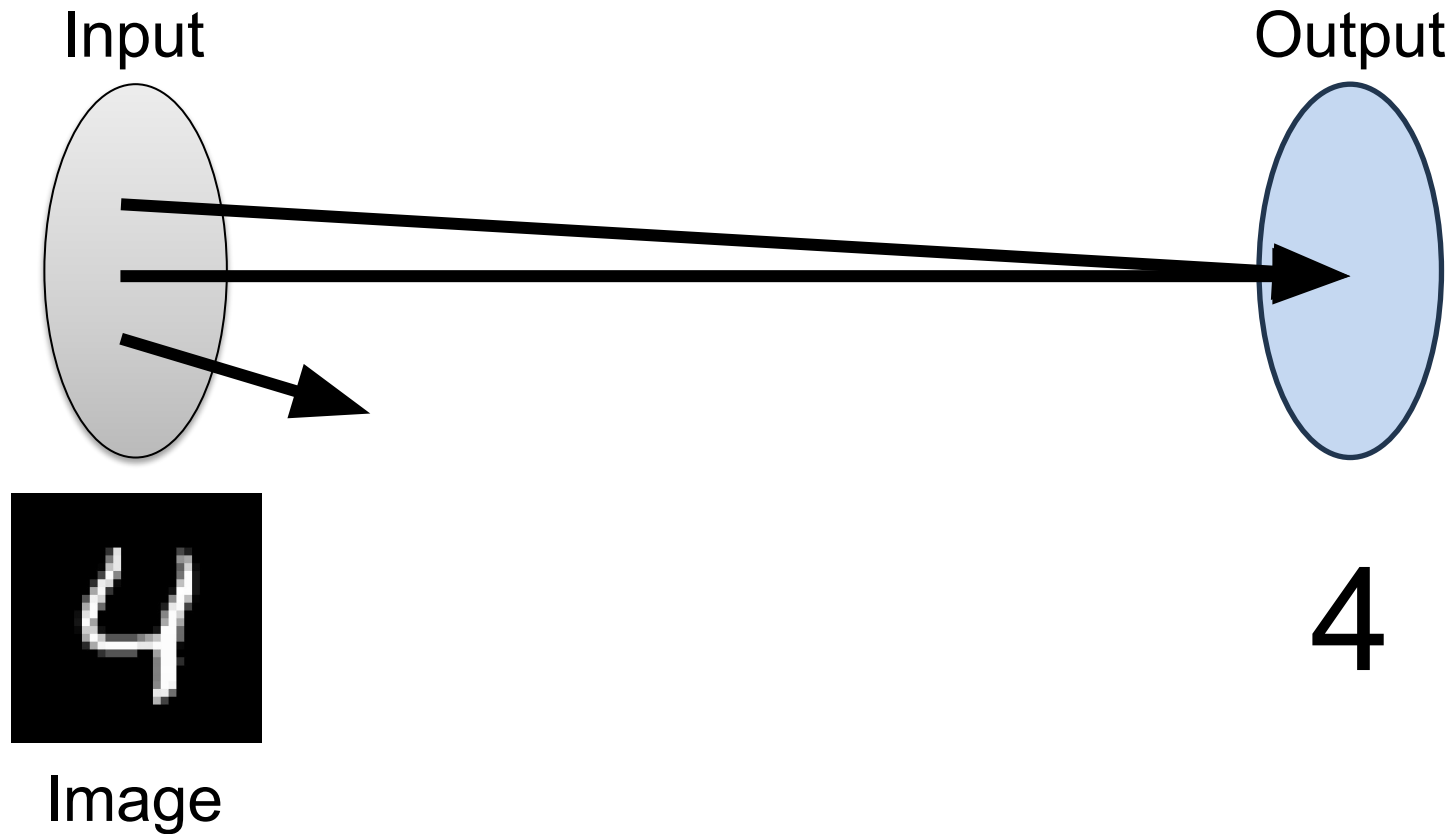
Dynamically Weighted Ensembles



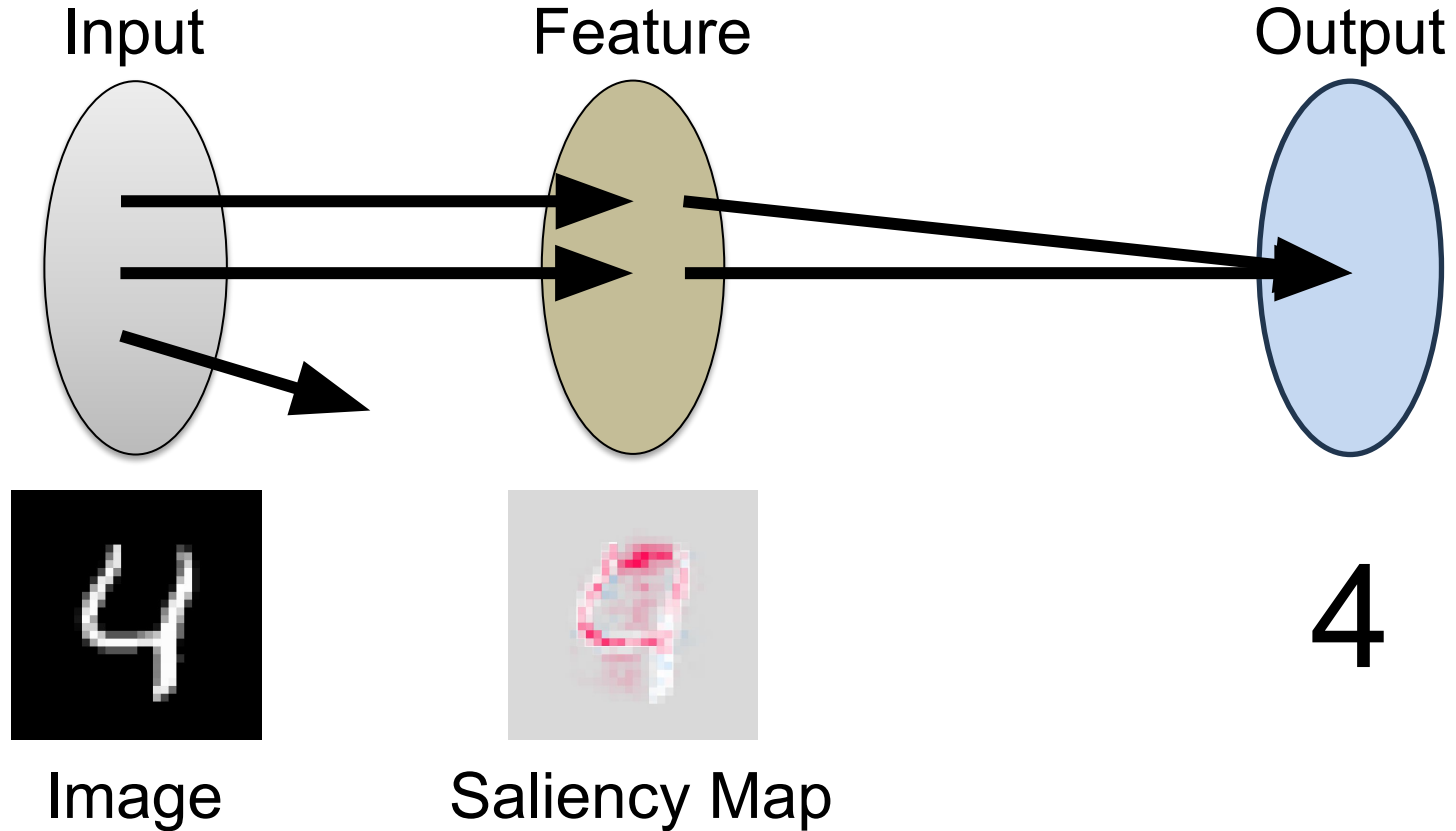
How to determine weights?
Feature Space Diversity?

$$w_1, w_2 < w_3$$

Input - Output Space

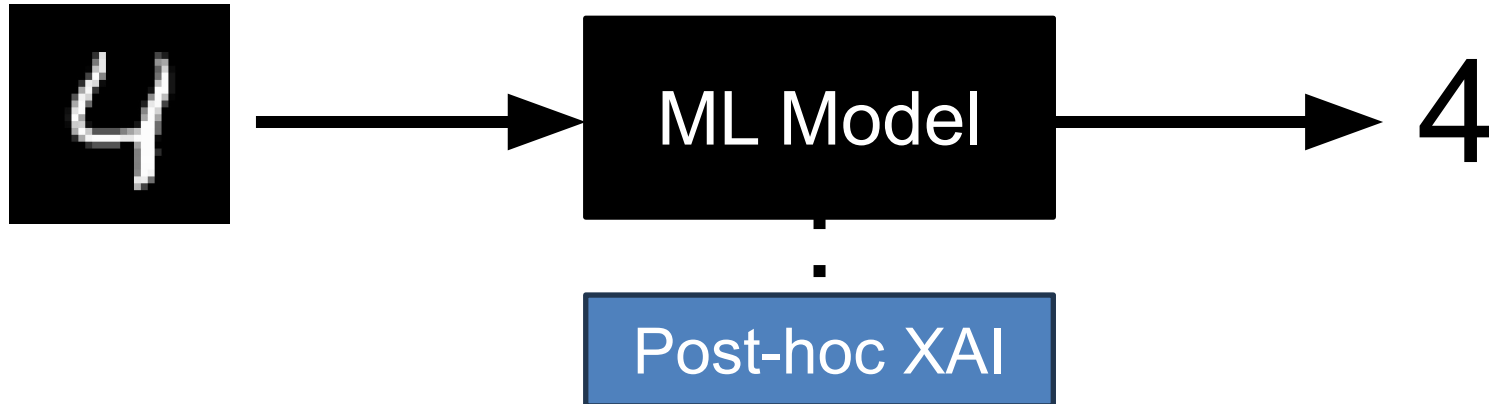


Feature Space



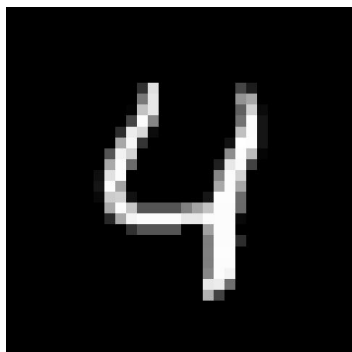
Explainable AI (XAI)

- Local post-hoc techniques (black box ML):
 - SHAP
 - Counterfactual Explanations
 - Integrated Gradients

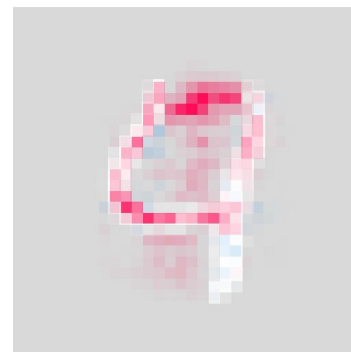


SHAP

- Which pixels contribute most to decision?

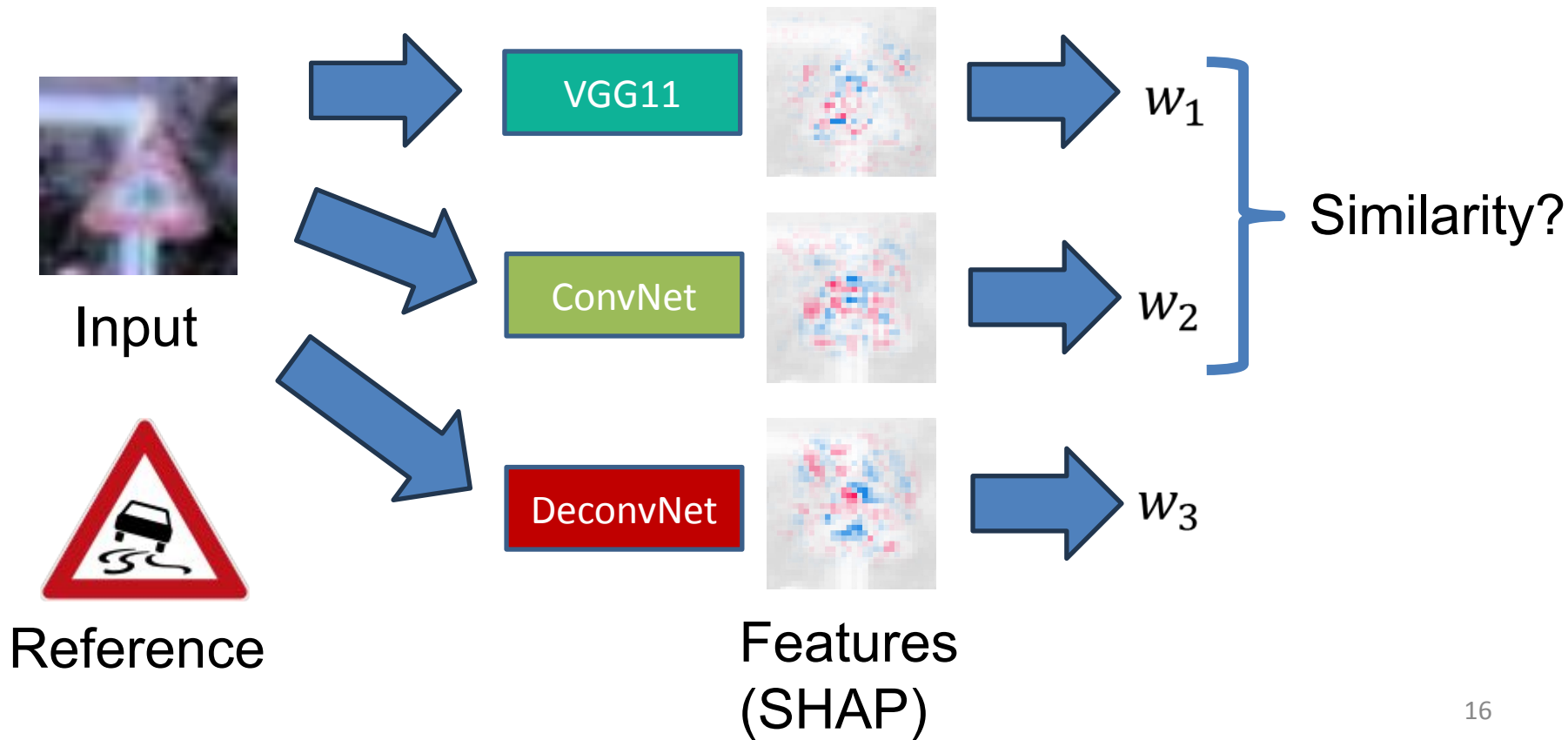


Input

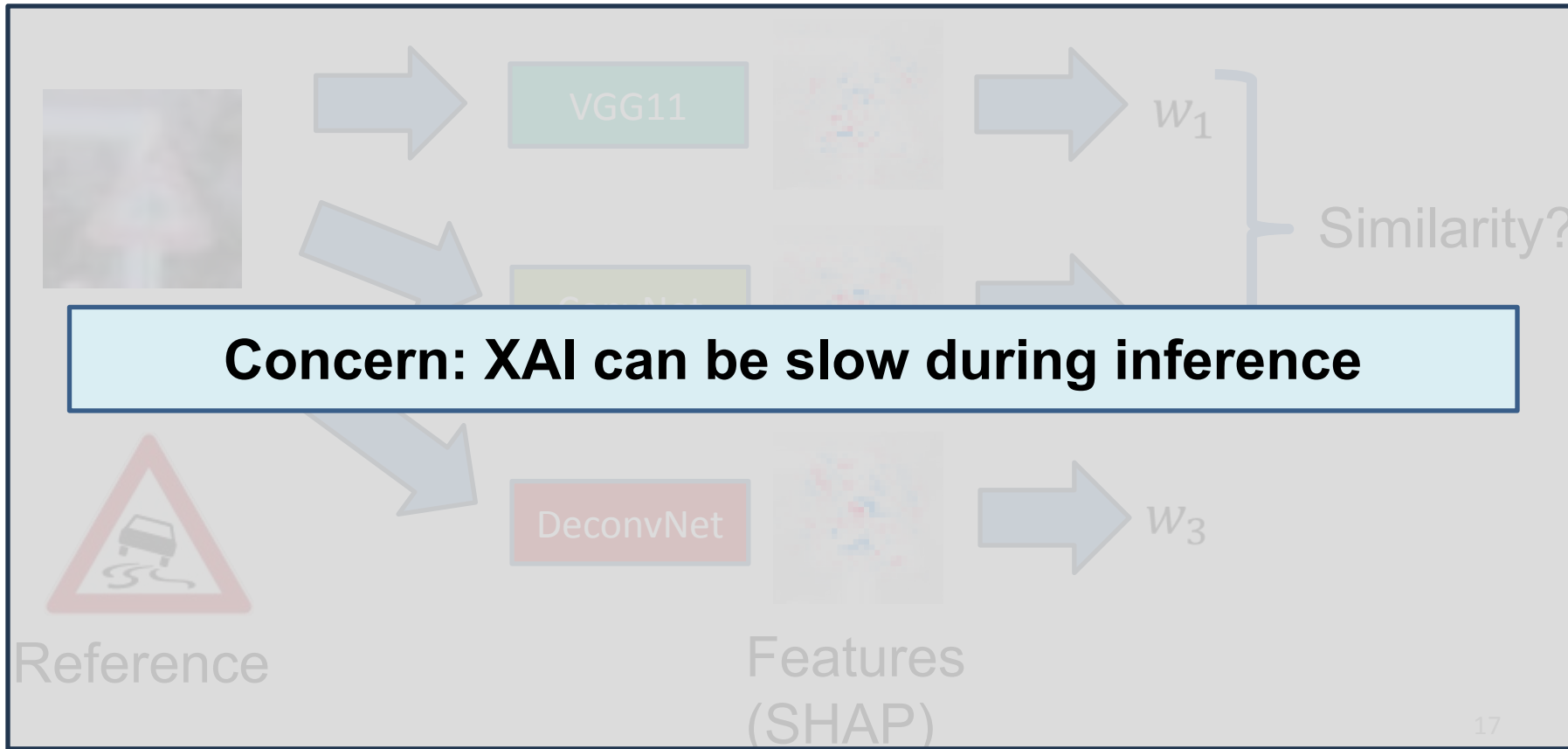


Features (Saliency Map)

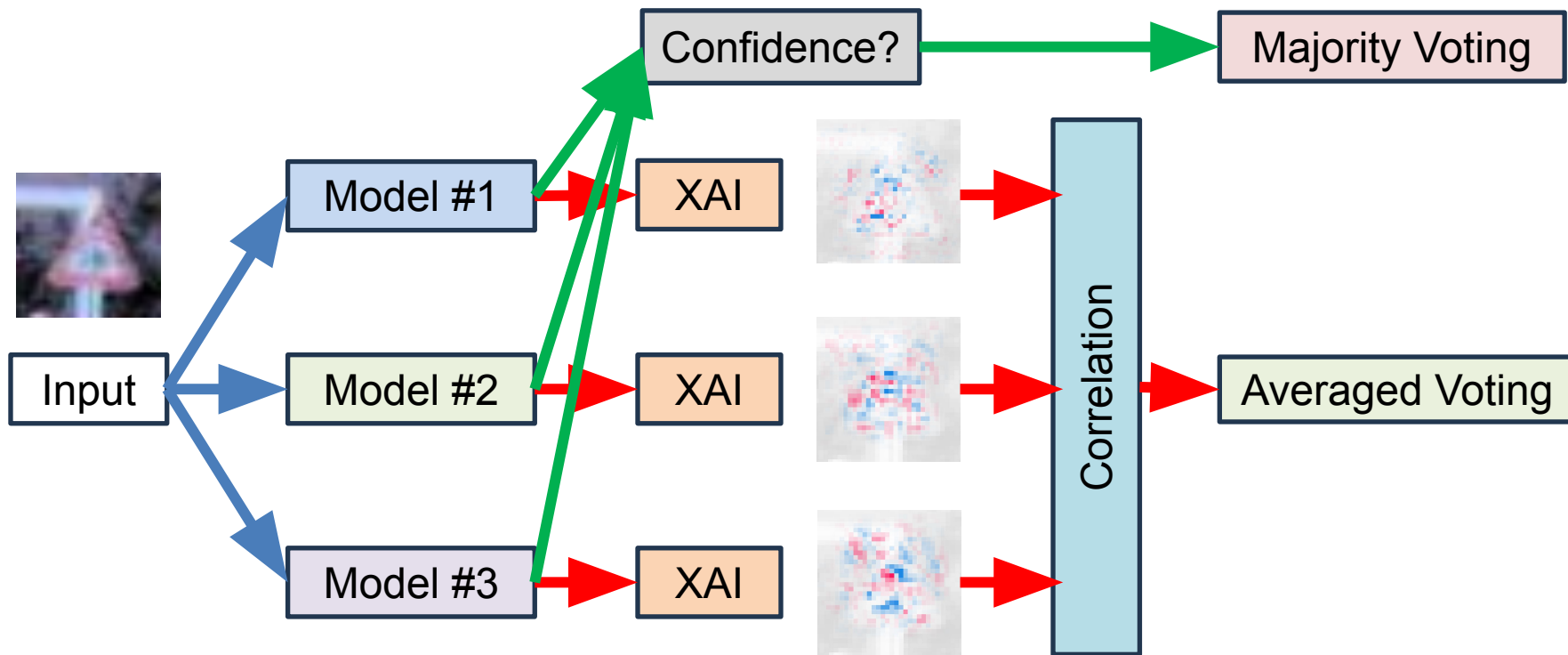
Example: Feature Diversity using SHAP



Example: Feature Diversity using SHAP



Optimized Workflow



Intuition: SHAP Correlations

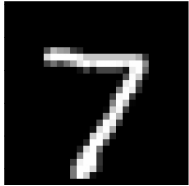
- Similarity Metric: R^2 Correlation
- Benchmark: GTSRB with 30% Mislabelling

	ConvNet	DeconvNet	VGG11
ConvNet	1	0.72	0.53
DeconvNet	X	1	0.36
VGG11	X	X	1

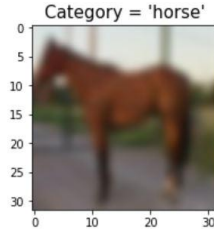
From Similarity to Weights

- Saliency maps \rightarrow matrices (M_1, M_2)
- Distance between M_1 and M_2
 - R^2
 - Cosine similarity
 - Wasserstein Distance (Earth Mover's Distance)

Exp Setup: Evaluation Datasets



MNIST
Handwritten
Digits



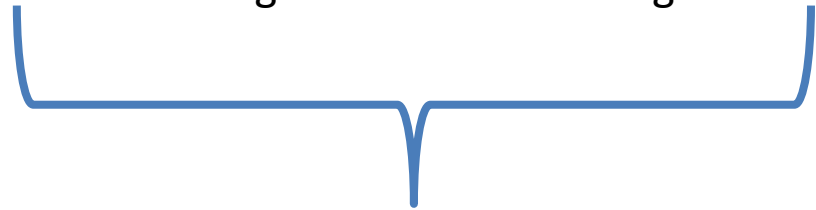
CIFAR-10
Object
Identification



GTSRB
Self-Driving Cars



Pneumonia
Medical Diagnosis



Safety-Critical Applications

Exp Setup: Deep Neural Networks

ML Model Name	Depth (# of Layers)
ConvNet	Shallow
DeconvNet	Shallow
MobileNet	Deep
ResNet18	Deep
ResNet50	Deep
VGG11	Deep
VGG16	Deep

Research Questions



Feasibility

1. How many ensemble predictions are low confidence?
2. How diverse are ensembles in the feature space, compared to prediction confidence?

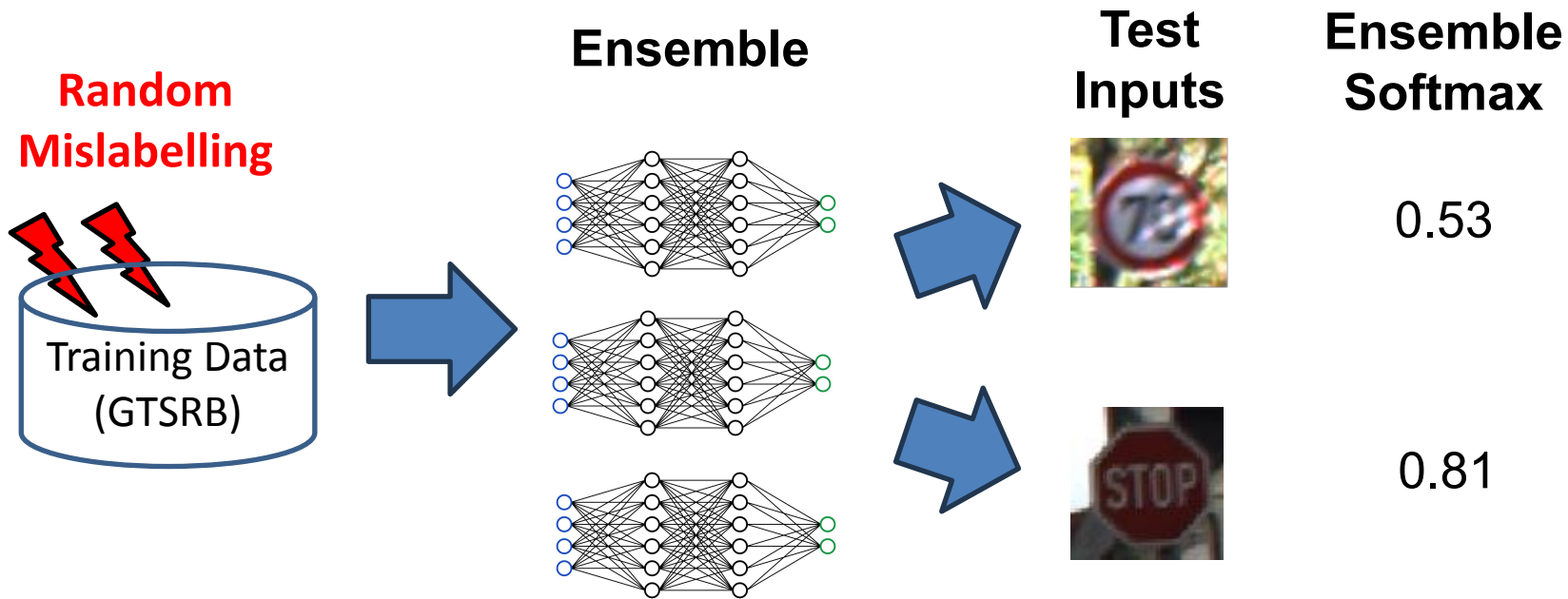
Runtime

3. When to use XAI?

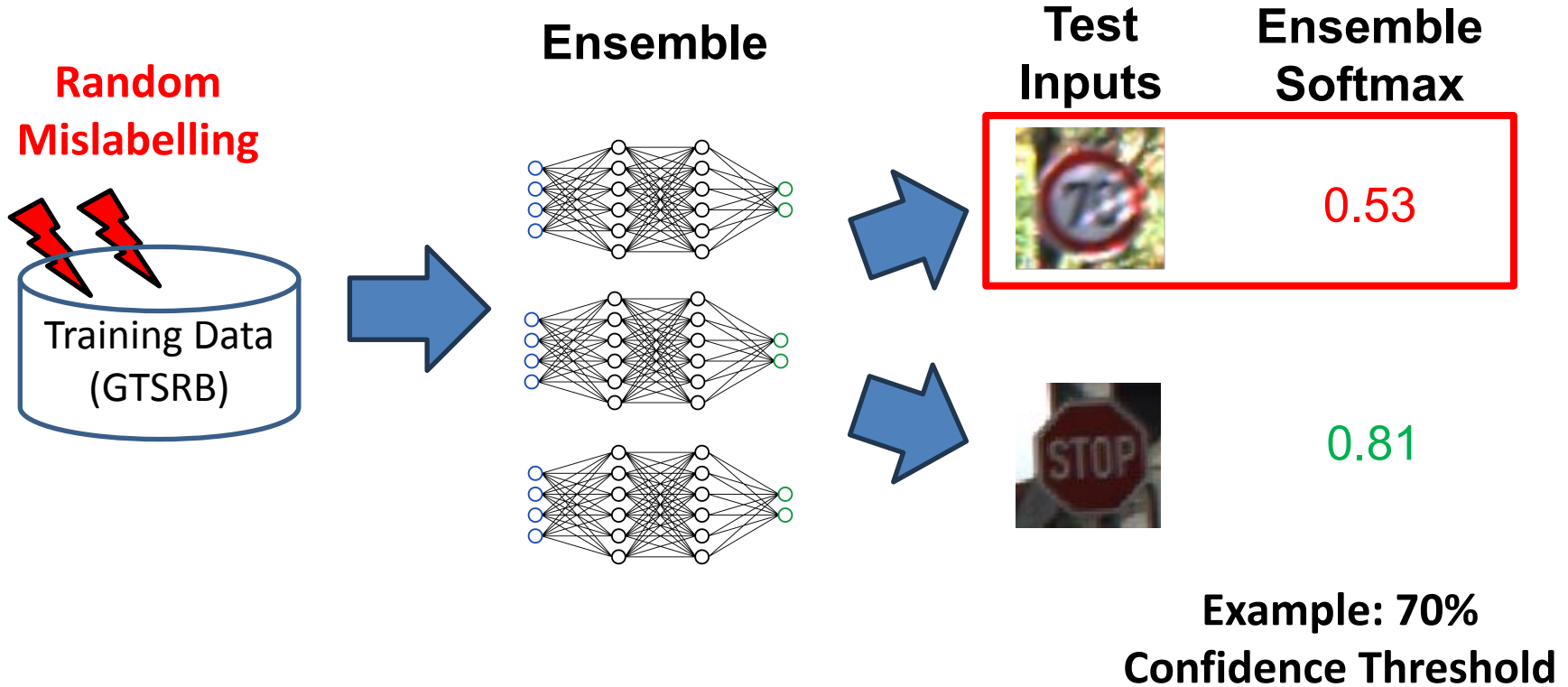
Design

4. Which XAI technique?
5. How to determine dynamic weights?

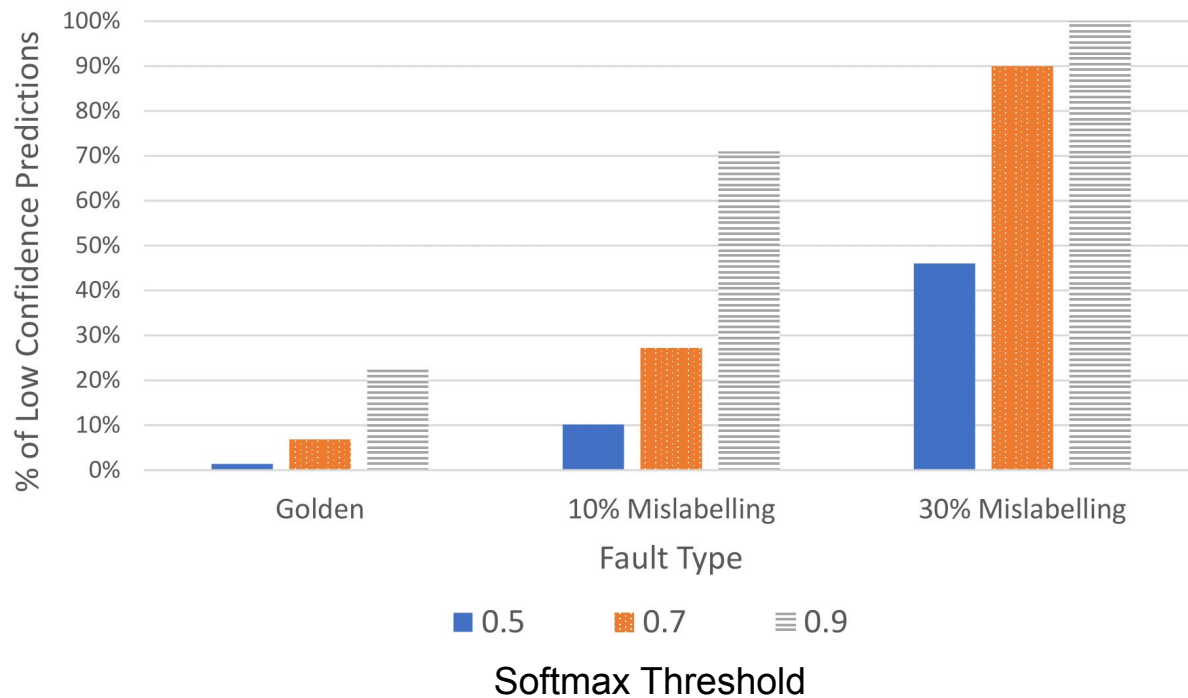
RQ1: Confidence under Training Faults



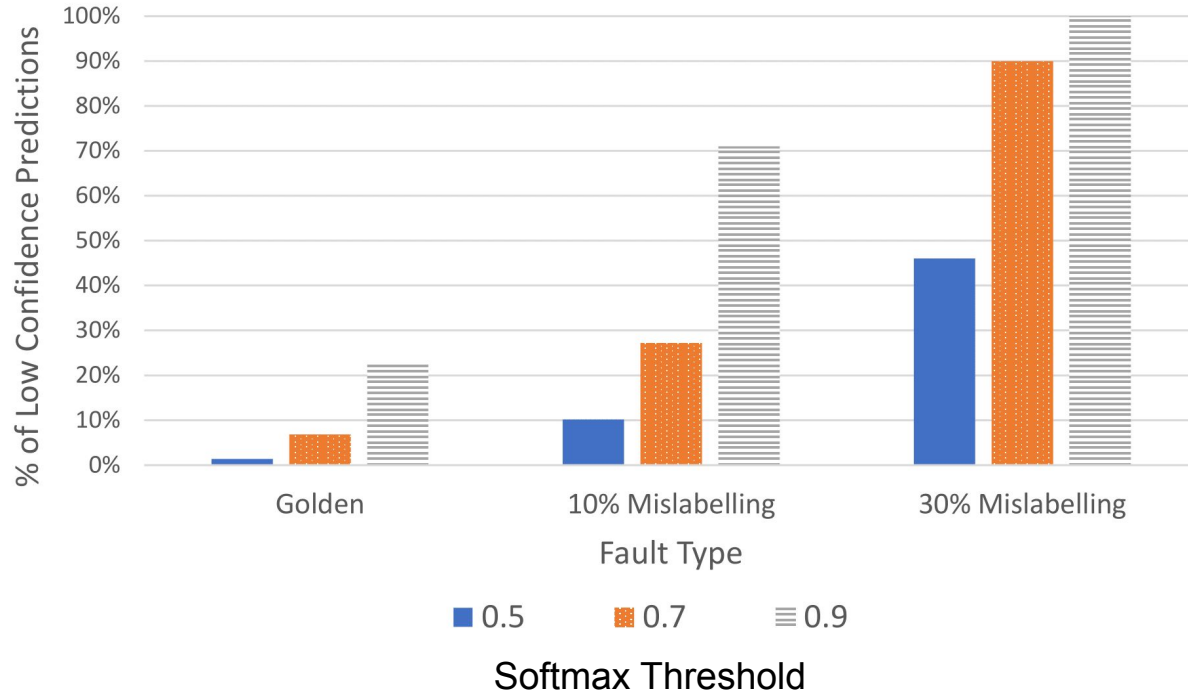
RQ1: Confidence under Training Faults



RQ1: Confidence under Training Faults



RQ1: Confidence under Training Faults



Prediction confidence drops as faulty training data increases

RQ2: Confidence - Feature Correlation

- How diverse are ensembles in the feature space compared to their prediction confidence?

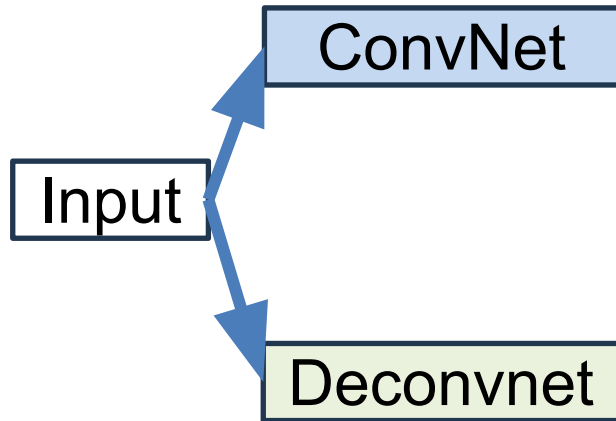
RQ2: Confidence - Feature Correlation

Goal:

We could use SHAP with confidence to determine dynamic weights

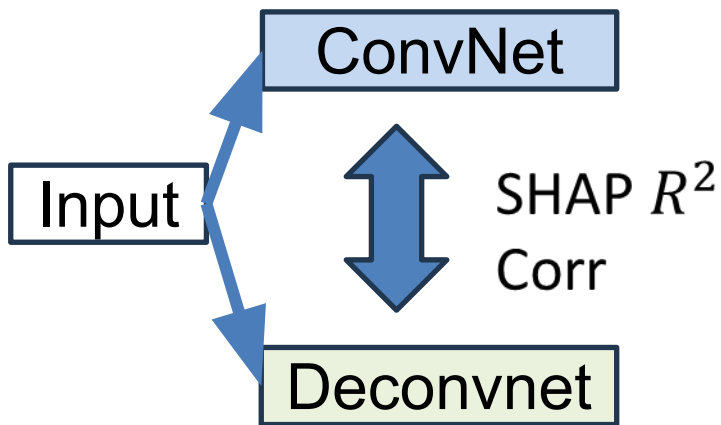
RQ2: Confidence - Feature Correlation

GTSRB, 30% mislabelling



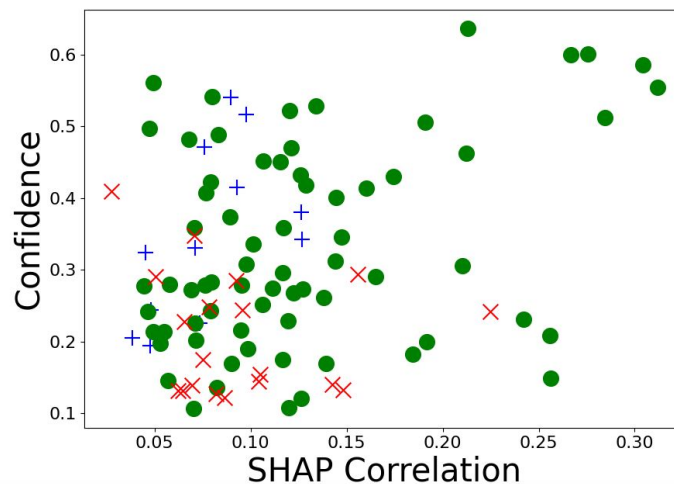
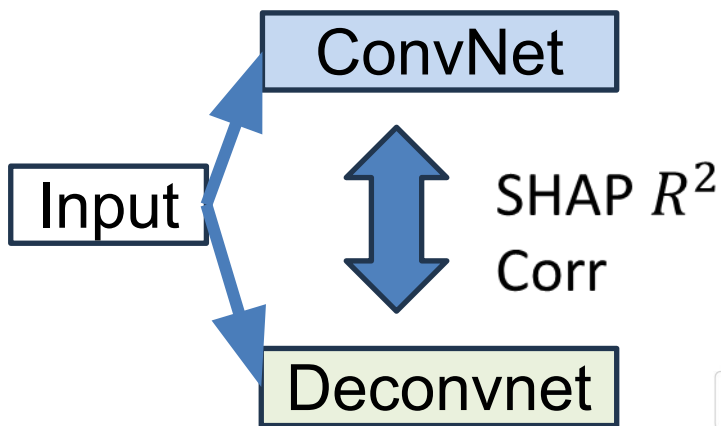
RQ2: Confidence - Feature Correlation

GTSRB, 30% mislabelling



RQ2: Confidence - Feature Correlation

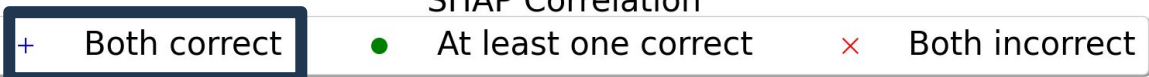
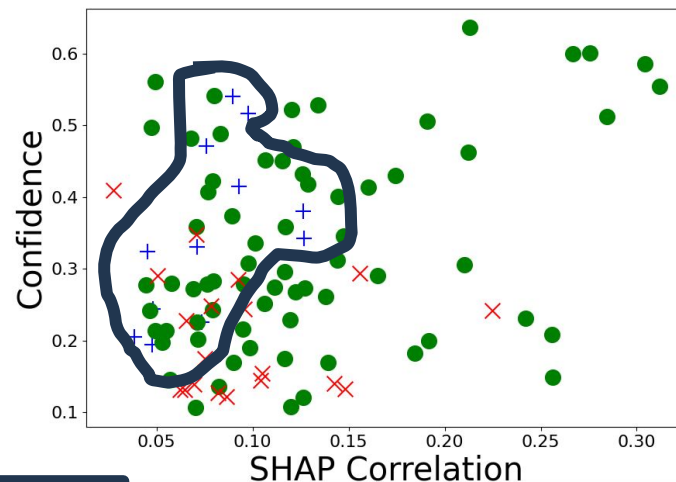
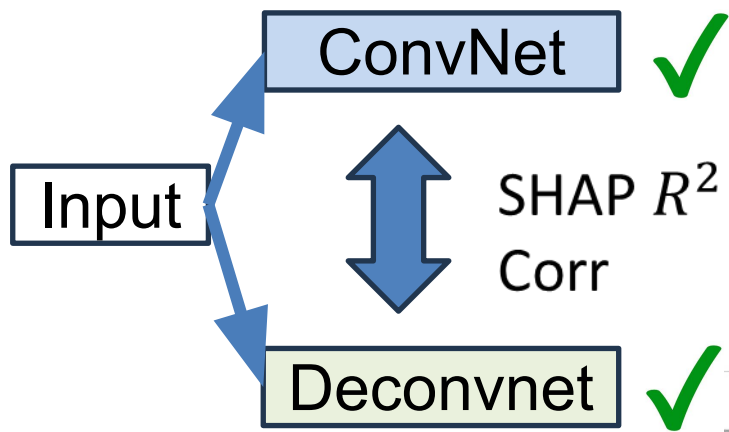
GTSRB, 30% mislabelling



+ Both correct ● At least one correct × Both incorrect

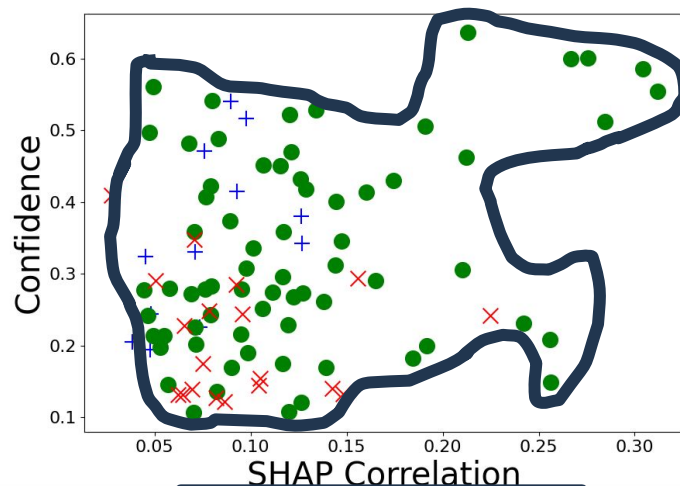
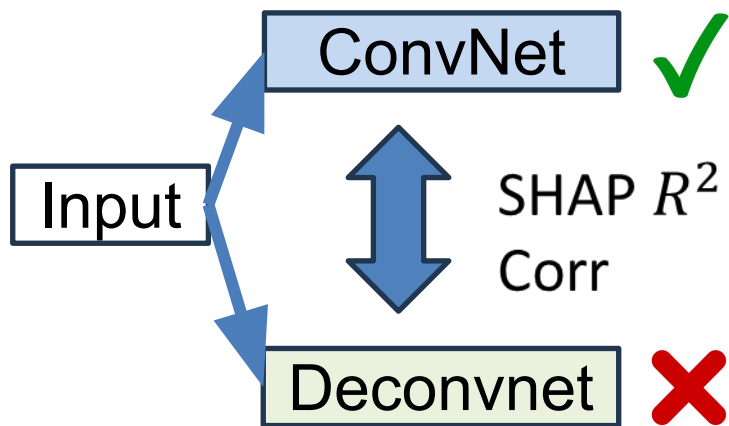
RQ2: Confidence - Feature Correlation

GTSRB, 30% mislabelling



RQ2: Confidence - Feature Correlation

GTSRB, 30% mislabelling



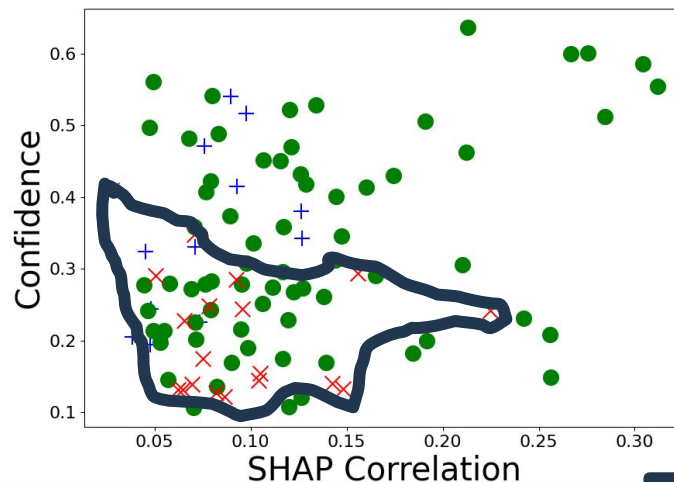
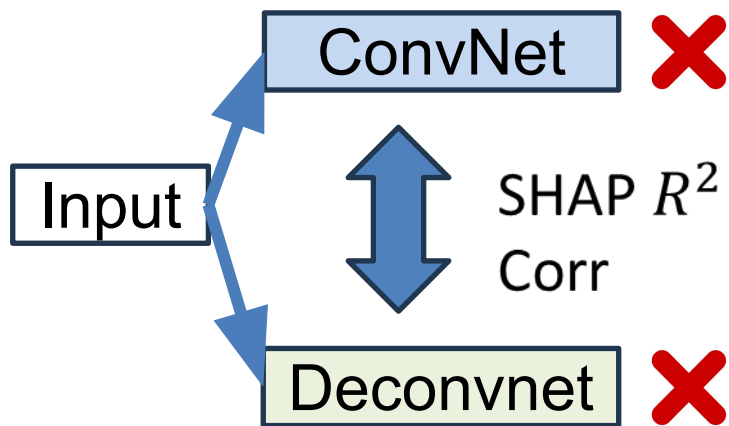
+ Both correct

● At least one correct

✗ Both incorrect

RQ2: Confidence - Feature Correlation

GTSRB, 30% mislabelling



+ Both correct

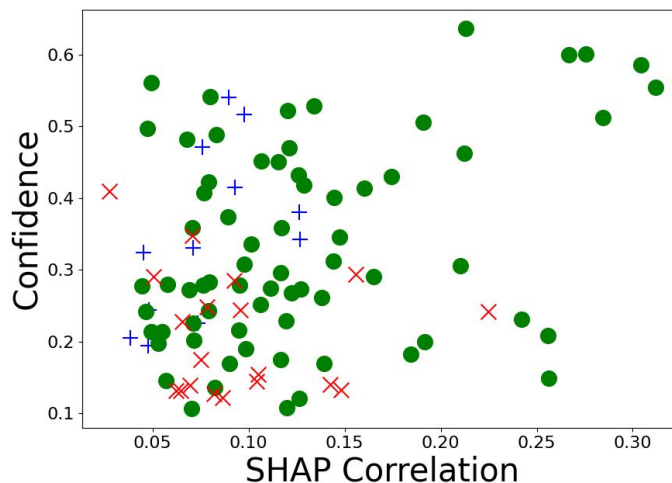
● At least one correct

✗ Both incorrect

RQ2: Confidence - Feature Correlation

Observations:

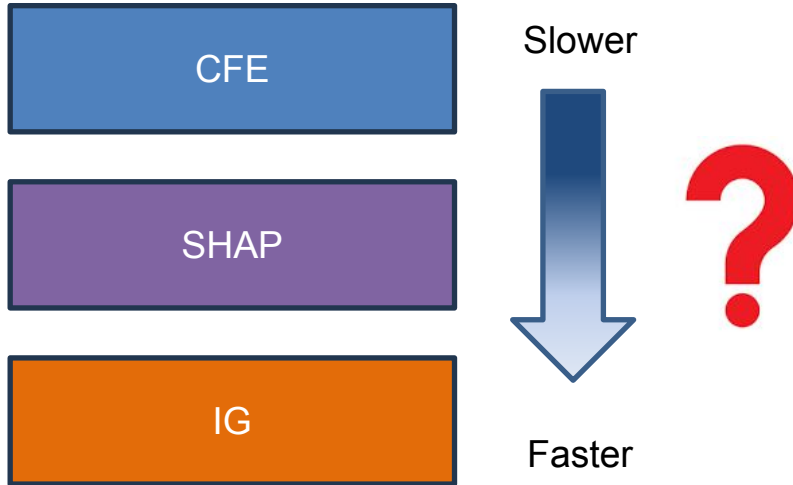
- SHAP correlations are low for both correct and incorrect cases
- Not necessarily true that high confidence have higher SHAP correlation



RQ3: Runtime Overhead

- **Intuition:** Only low confidence inputs needs to be checked by XAI
- 3.3x faster if XAI only applied on low confidence rather than every input

RQ4: Which XAI Technique?



Criteria:

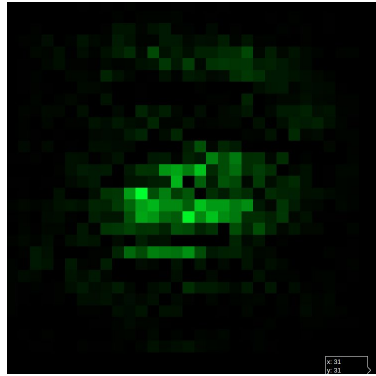
- Consistency
- Contrastivity
- Runtime

RQ5: How to determine weights?

Image

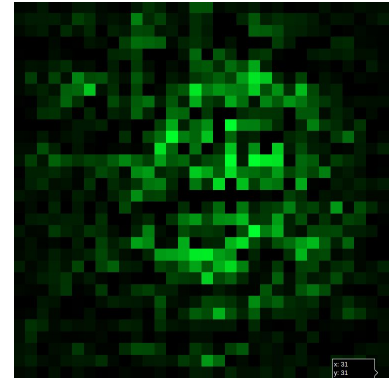


ConvNet



Focused

VGG11



Dispersed

- All models, trained with GTSRB with 30% Mislabelling

Summary

1. Ensembles are resilient, but need dynamic weights
2. Use XAI to determine ensemble weights
3. Combining XAI with prediction confidence

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