Evaluating Machine Learning-Based IoT Device Identification Models for Security Applications

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IMPERIAL

Georgia Institute of Technology

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Images source: https://www.intuz.com/blog/iot-applications-in-smart-warehouse-management

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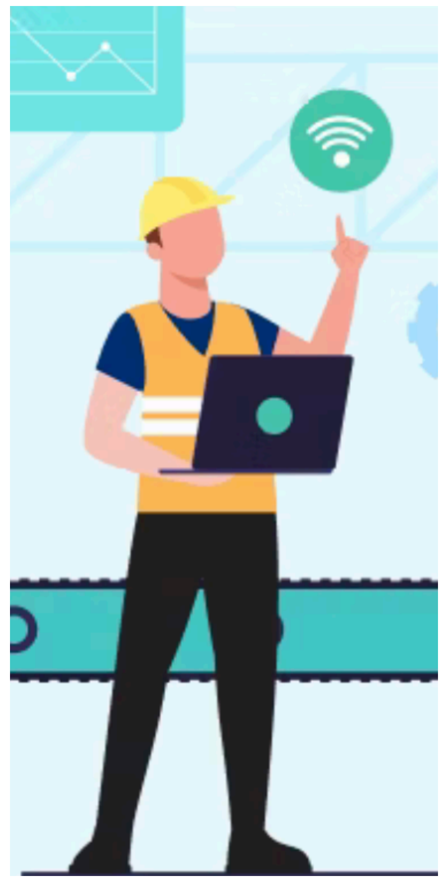

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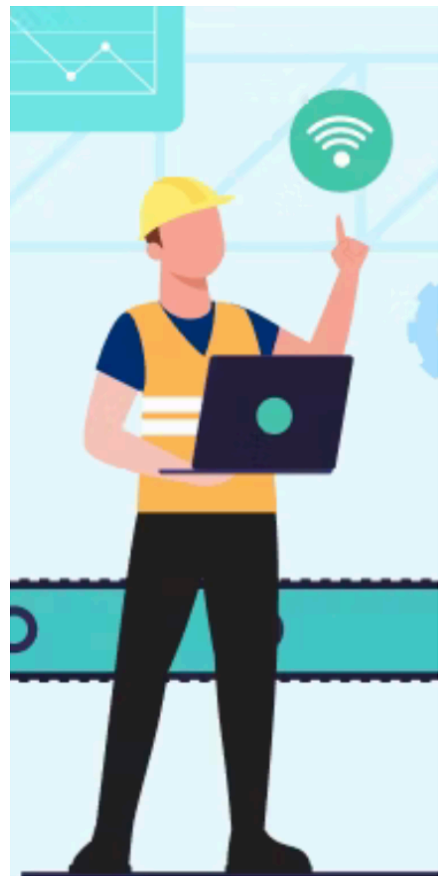

Network Operator

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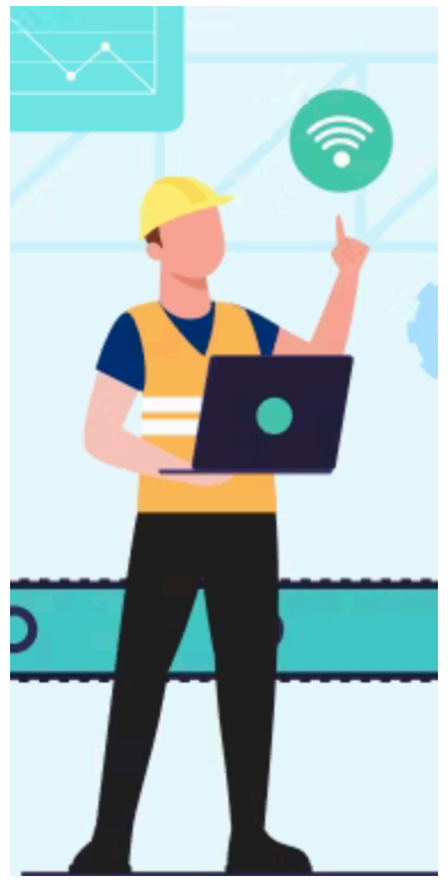

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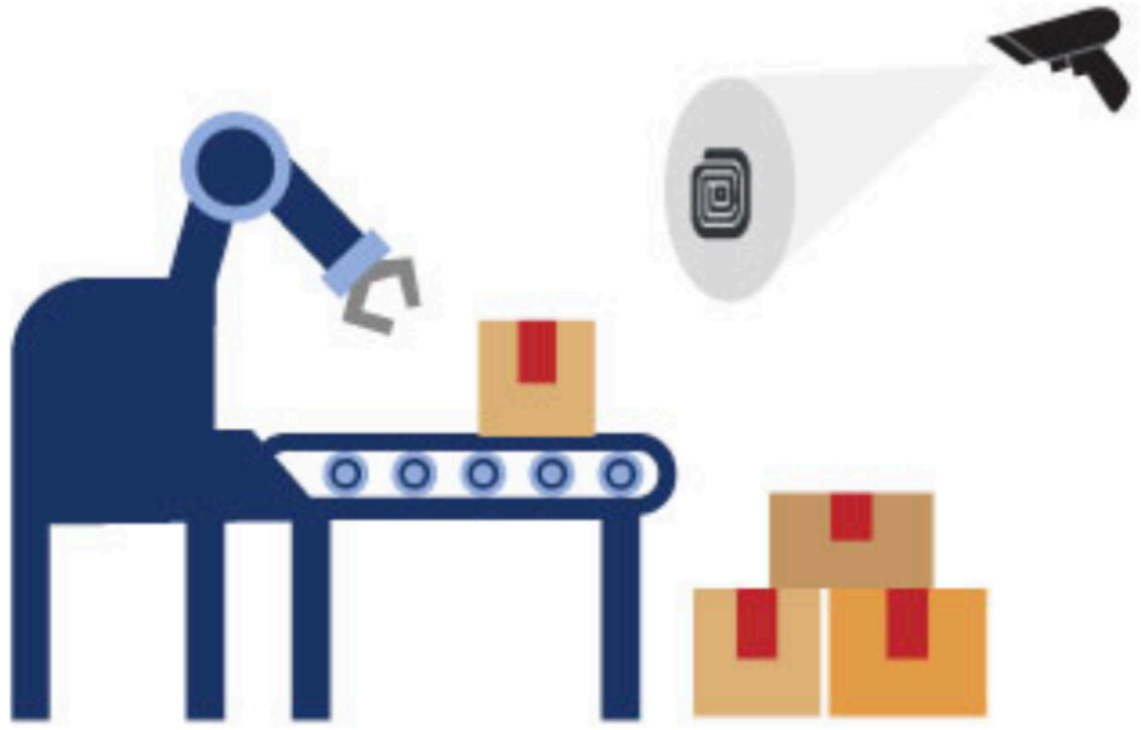
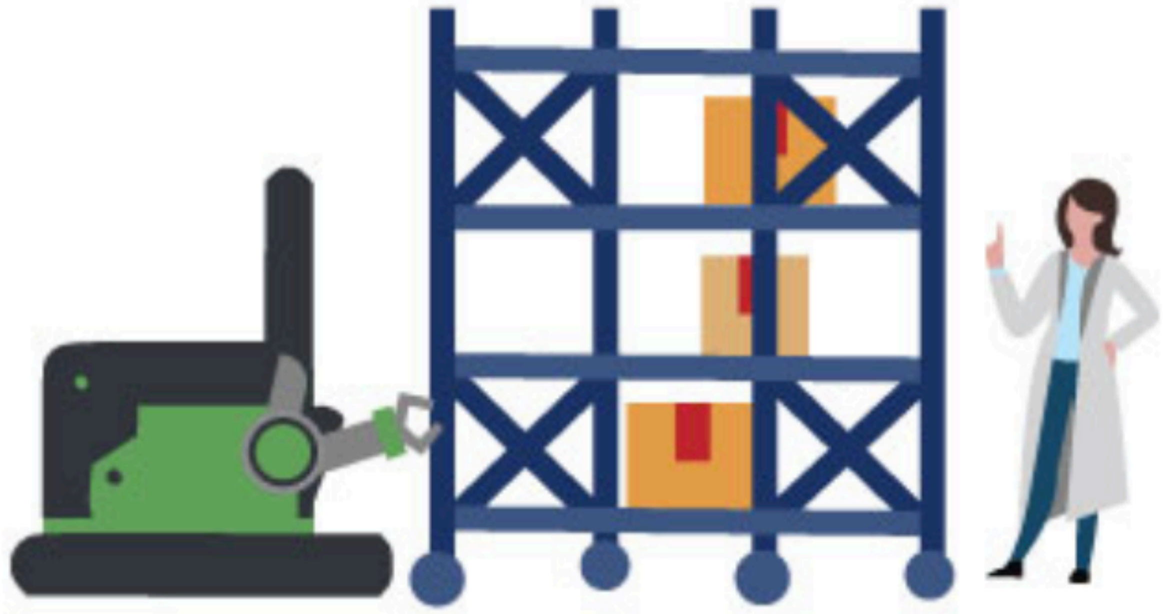
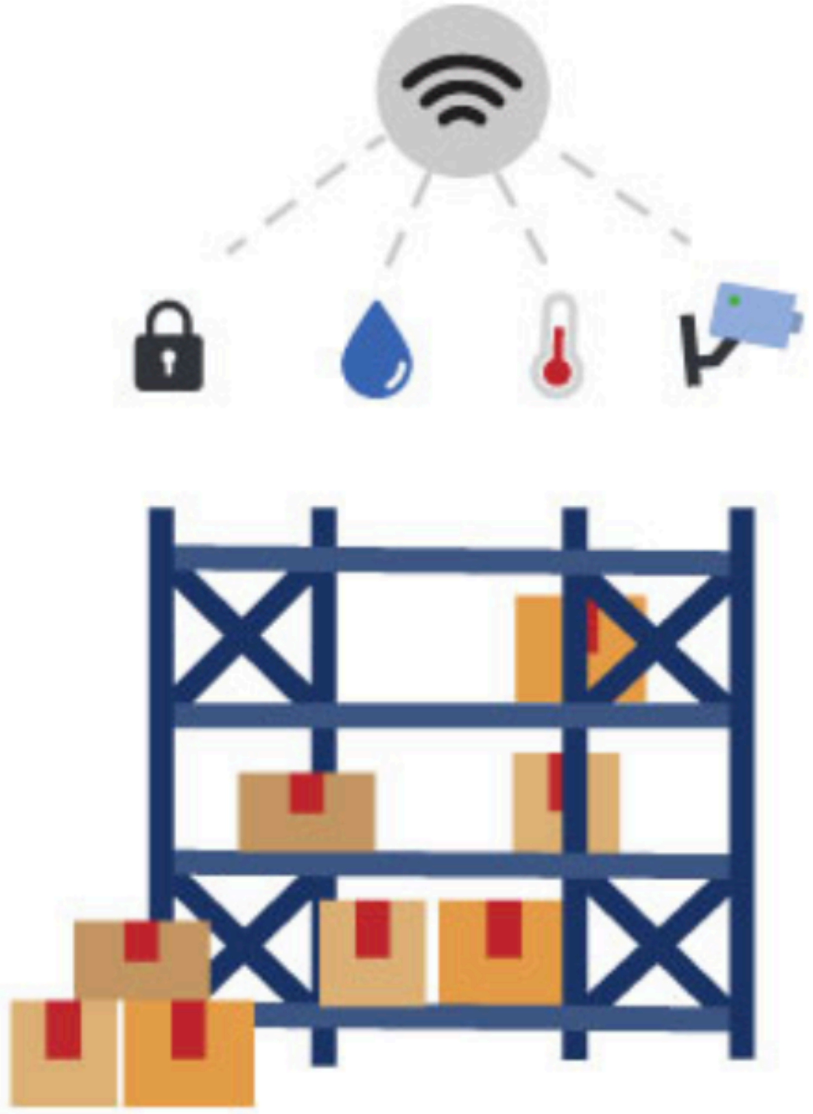


Automated items tracking



Storage racks moved by robots



Smart warehouse maintenance

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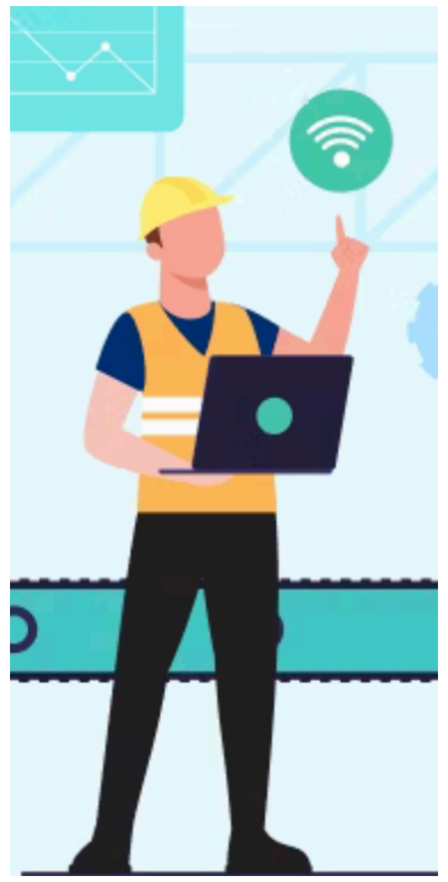

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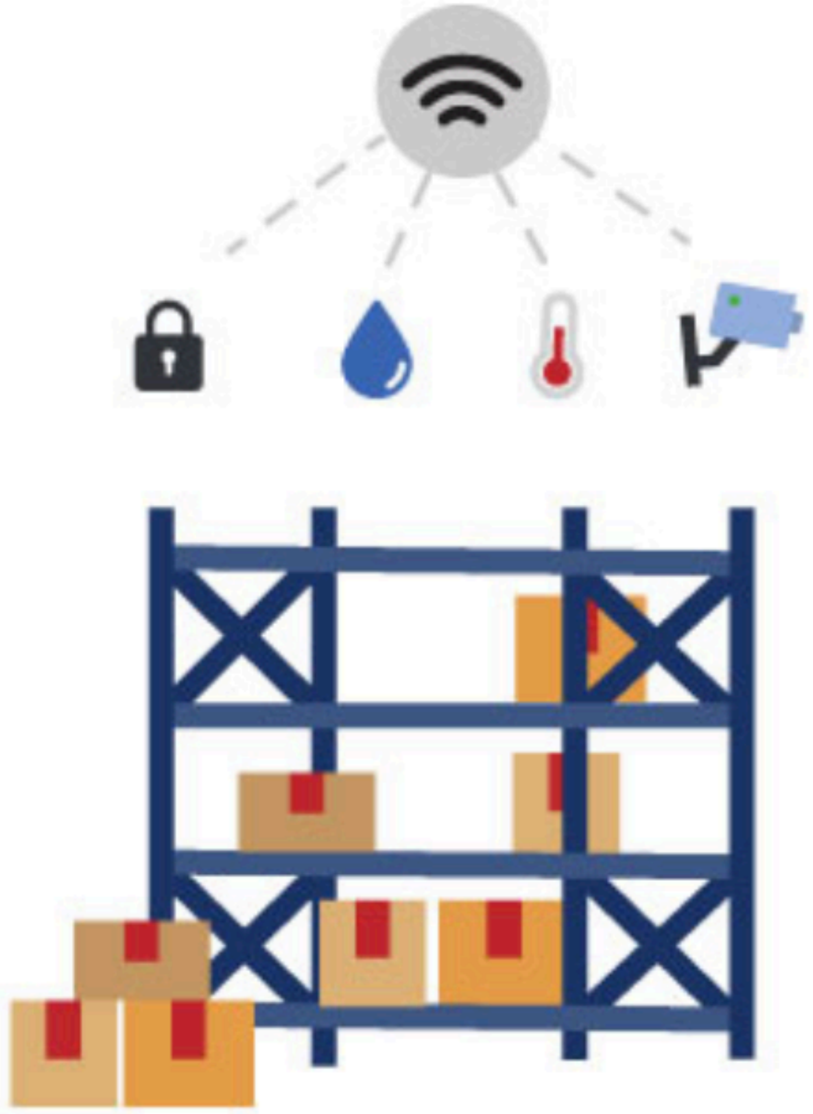

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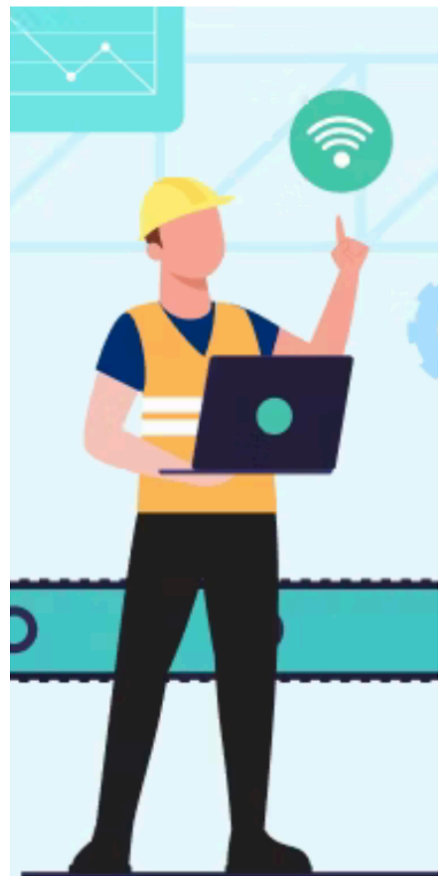

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IoT Identification Solution

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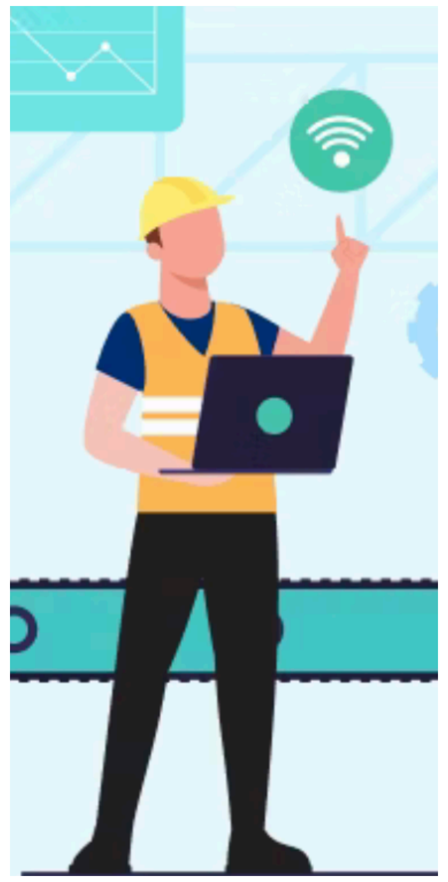

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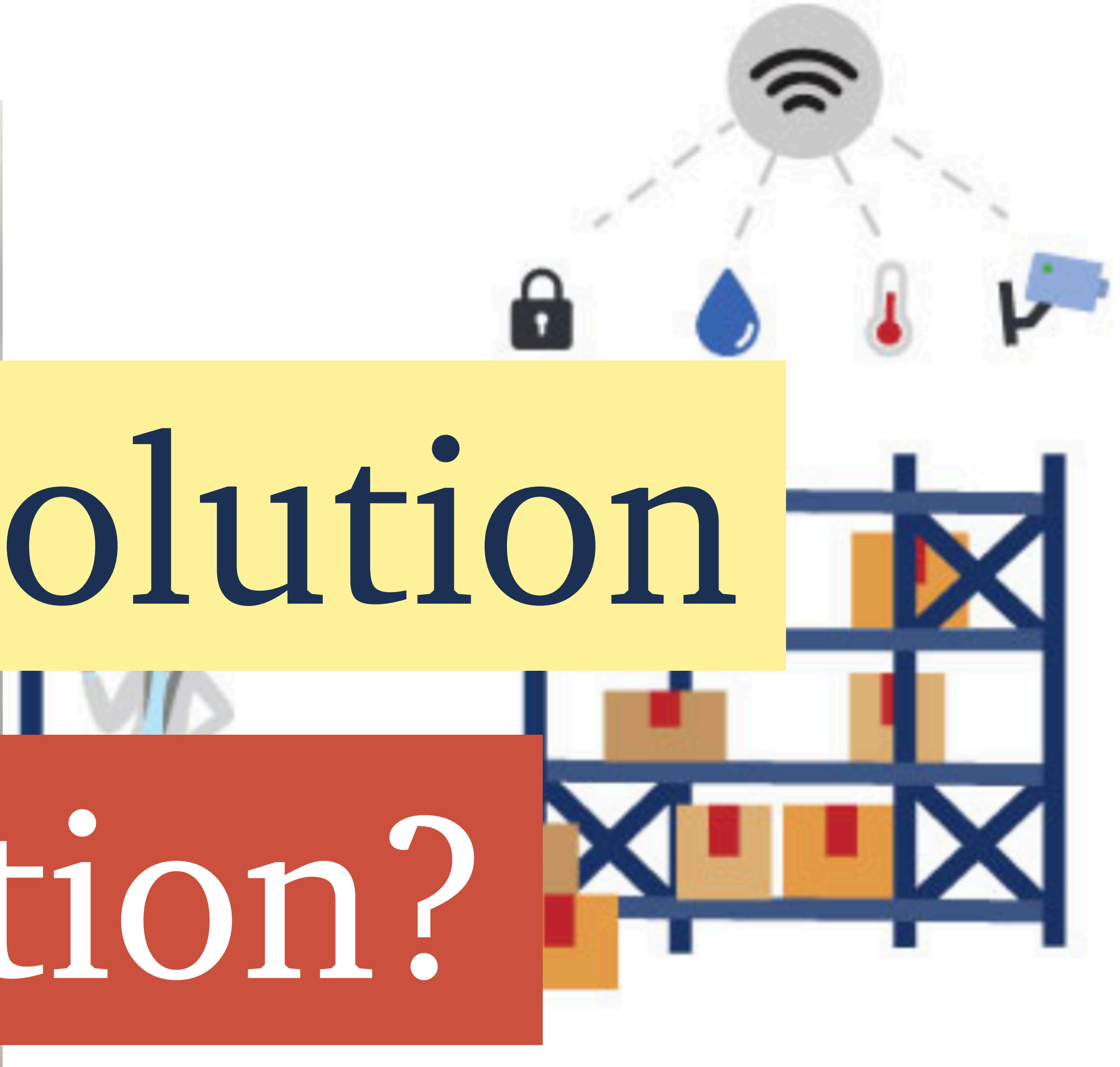

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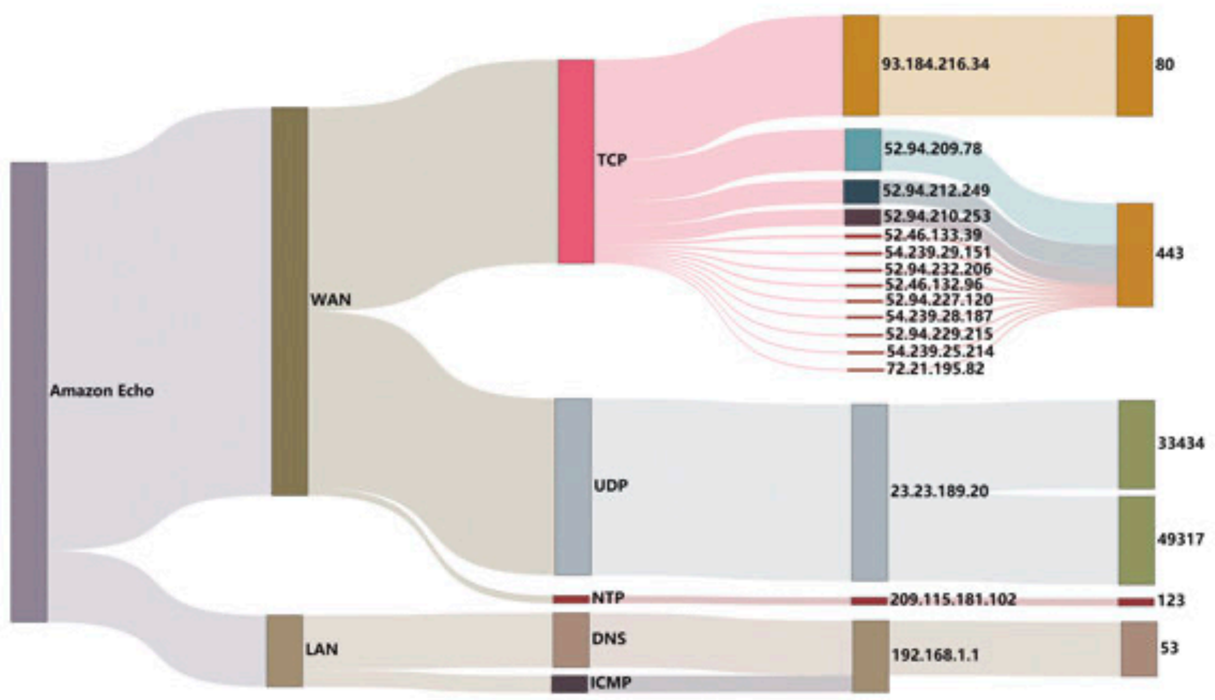
Static/Rule Based

Manufacturer Usage Description (MUD)



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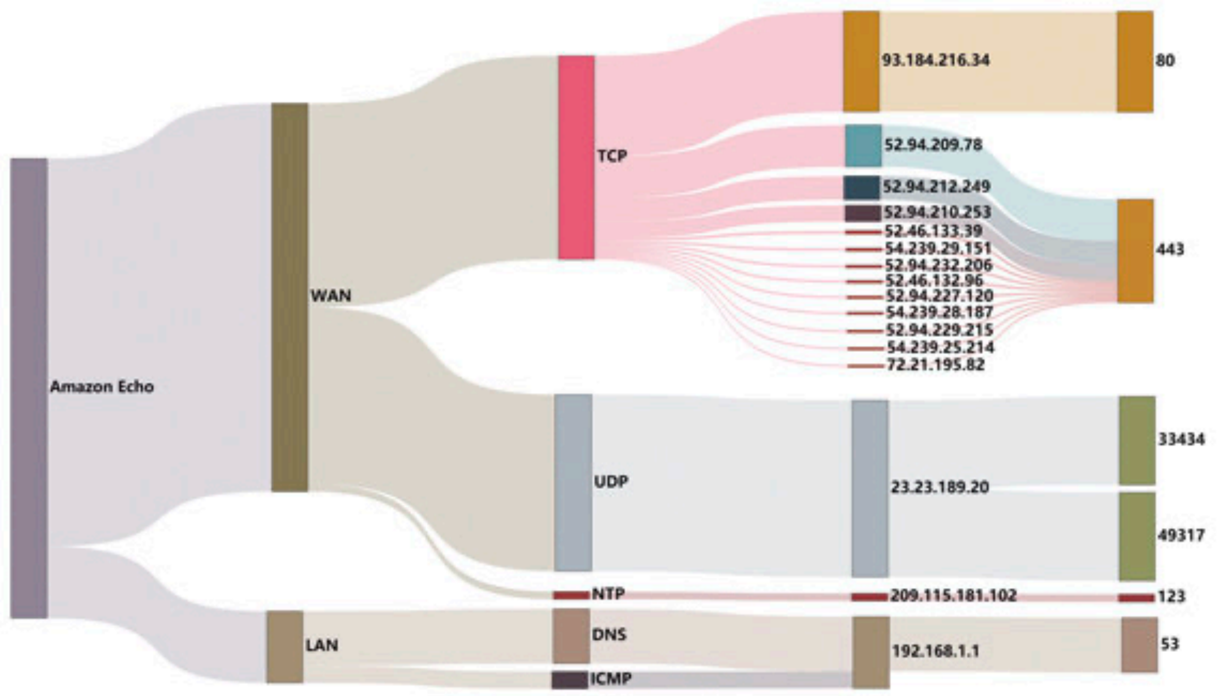

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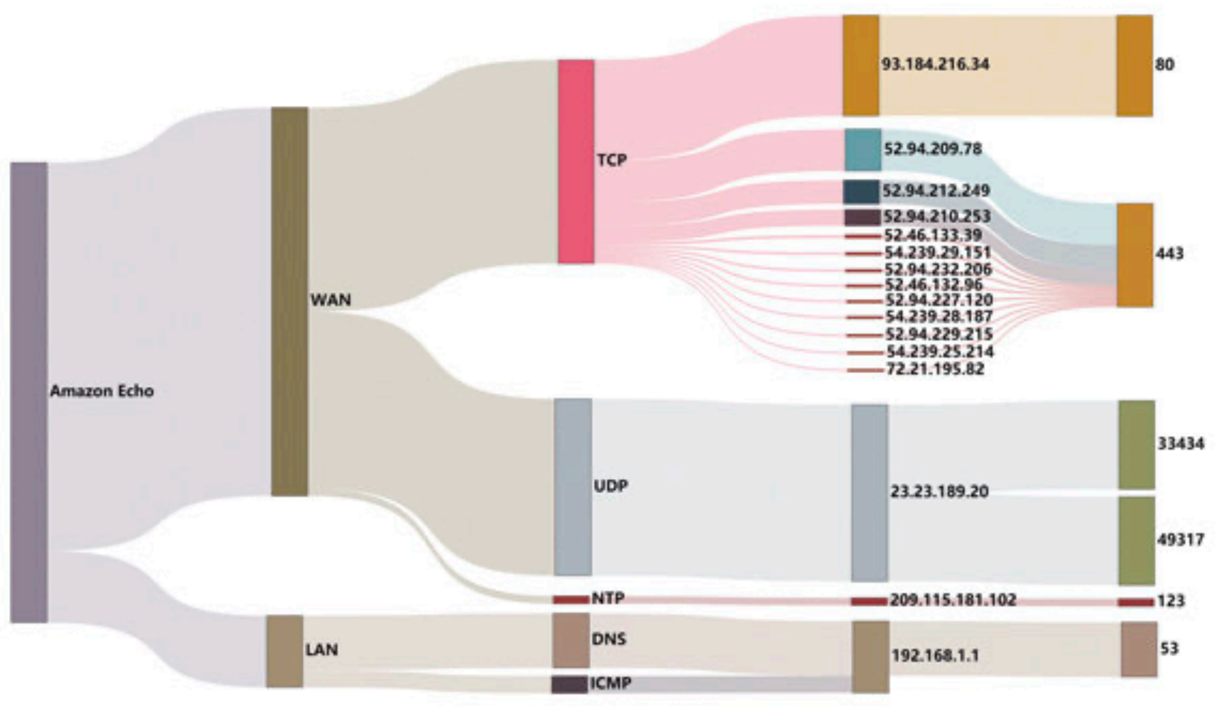

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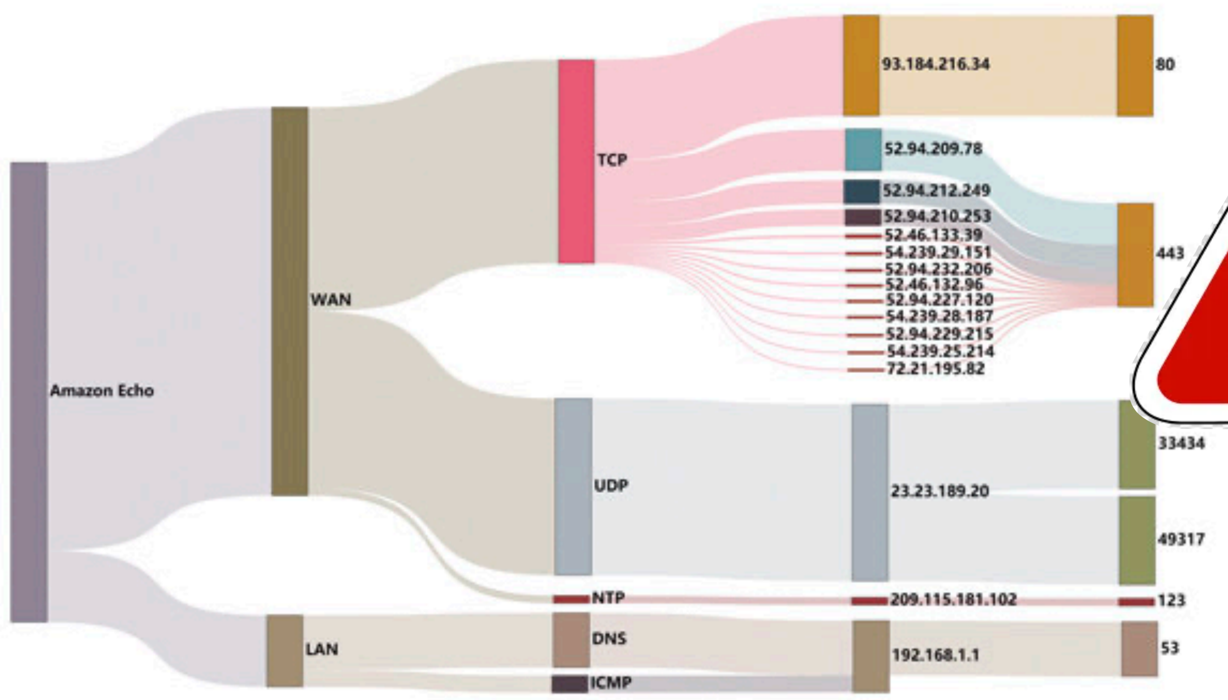

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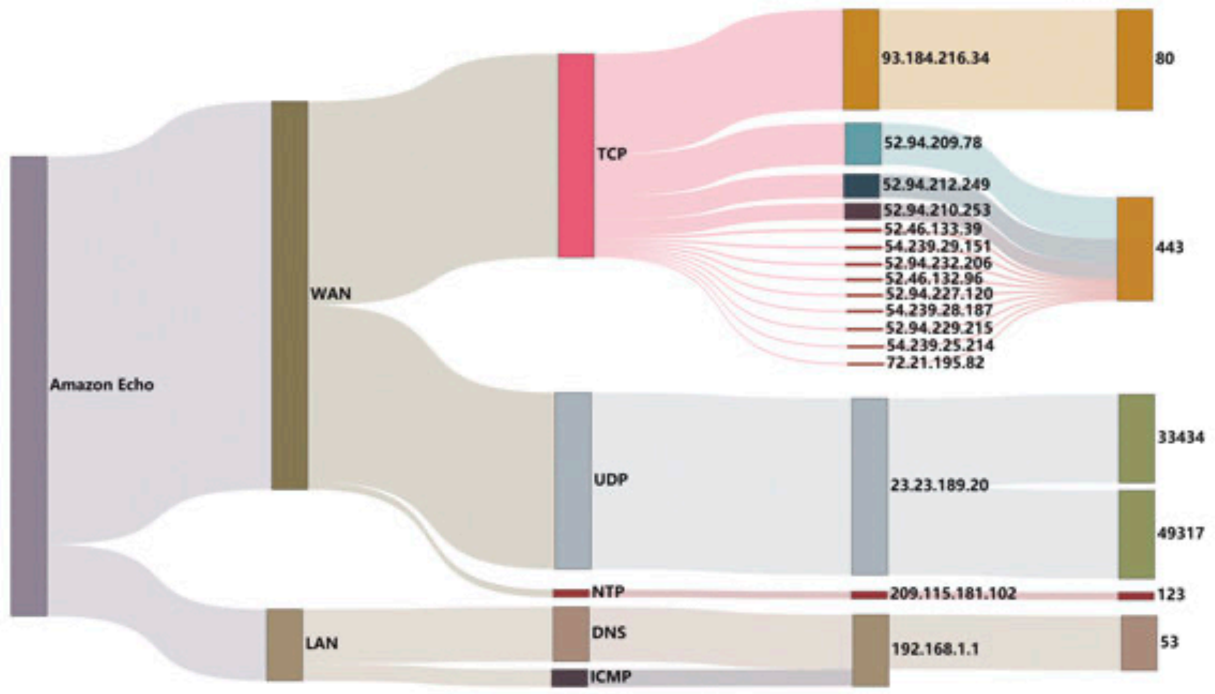

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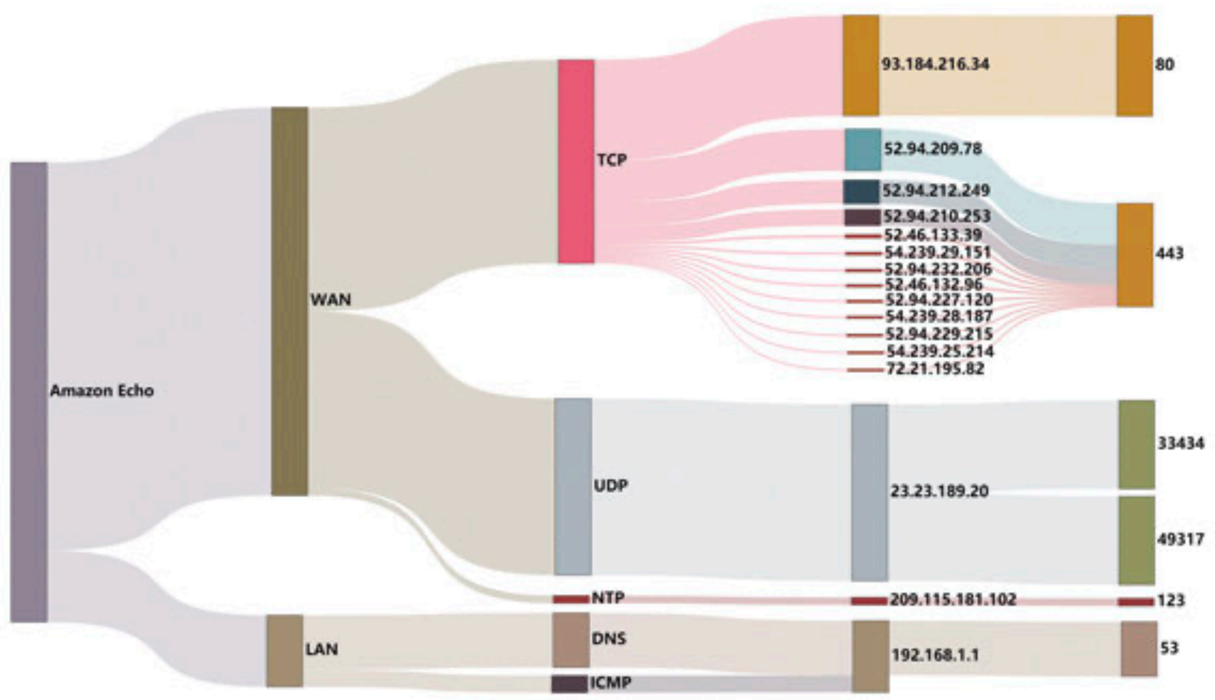

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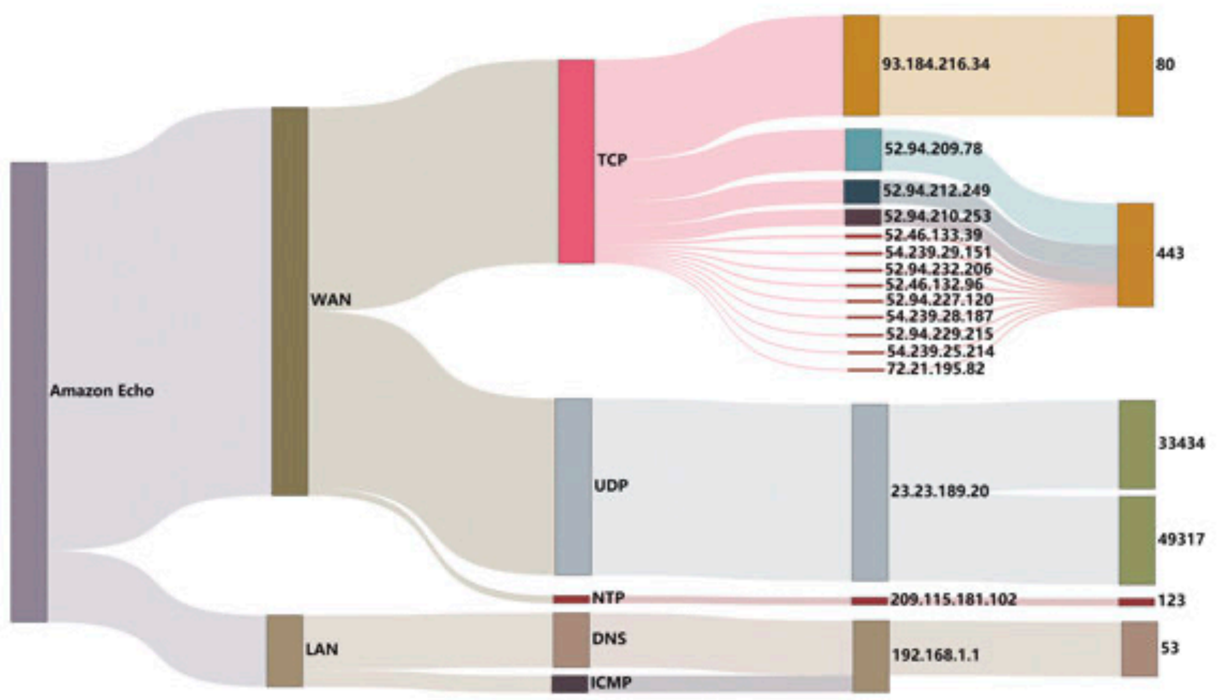

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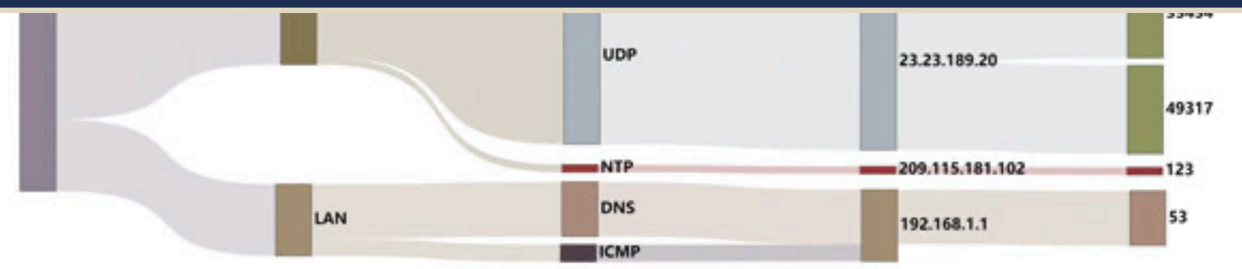

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What defines a practical ML-based device identification model?

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Practicality Definition and Attributes

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The model's capability to ensure robust and reliable IoT device identification across different operational modes, deployment environments, and network conditions.

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3. What network conditions must a solution consider?

What attributes define practicality in ML-based models?

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- Generalisation and Robustness
- Stability Over Time
- Model Scalability
- Data Efficiency
- Deployment Compatibility
- Cost Metric
- Ethics and Societal Impact
- Fairness and Accountability

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Which are relevant to practicality in the context of IoT identification?

Deploying a solution that can be generalised across different environments/configurations simultaneously with robustness in performance and stability over time.

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Mode of Operation

Transferability

Observability

How should current solutions be evaluated against the three attributes?

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Components of ML-based Model

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IoT Identification Problem

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IoT Identification Problem

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Components of ML-based Model

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1. **Dataset** — What data should be collected, and how should the dataset be gathered for evaluation?
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IoT Identification Problem

2

Model

Which model should be used, and how complex should it be?

IoT Identification Problem

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Model

Which model should be used, and how complex should it be?

200

Papers

IoT Identification Problem

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Mode of Operation	Transferability
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Scenarios

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Spatial

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2 *USA vs UK*

Temporal

7 *1 week- 52 weeks Gaps*

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2 *Mix vs active*		2 *USA vs UK*	
3 *Mix vs Mix*	Temporal	7 *1 week- 52 weeks Gaps*	

Scenarios

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Scenarios	1 *Mix (idle & active) vs idle*	Spatial	1 *UK vs USA*	1 *1:100s*
	2 *Mix vs active*		2 *USA vs UK*	
	3 *Mix vs Mix*	Temporal	7 *1 week- 52 weeks Gaps*	

What is the experimental setup for practicality evaluation and attributes?

For each of 10 papers, we have a baseline, and perform the following experimental scenarios:

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In total, we performed 140 practicality evaluation across three attributes.

What are the key findings of the practicality evaluation?

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Mode of Operation	Idle and active modes introduce behavioural shifts that reduce performance.
Transferability	- Spatial degradation drop of 7.5%–74% . - Temporal degradation begins after 1 week (19.32%) and worsens to 85.90% after a year.
Observability	Sampled traffic (e.g., sFlow) reduces performance by an average of 70.09%.

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Mode of Operation. Idle and active modes introduce behavioural shifts that reduce performance.

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Paper

Meid20*

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Paper → ***Setup***

Meid20*

Model: LightGBM

Features: ibytes,

ipackets, TCP flags, Port,
IPv4 address

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Empirical Observation

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Empirical Observation

30% active	70% Idle

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Recommendation

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Empirical Observation 30% active | 70% Idle

Recommendation Training the model in idle mode and then conducting predictions for different periods.

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How can the practicality of ML-based IoT device identification be improved?

Components of ML-based Model

IoT Identification Problem

1. **Dataset** — What data should be collected, and how should the dataset be gathered for evaluation?
2. **Model** — Which model should be used, and how complex should it be?
3. **Features** — What features should be extracted, and how should they be represented?

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IoT Identification Problem

1 Dataset — Privacy and real-world challenges

2 Model — Mode complexities , and how complex

3 Features — Explainable AI and feature importance

How can the practicality of ML-based IoT device identification be improved?

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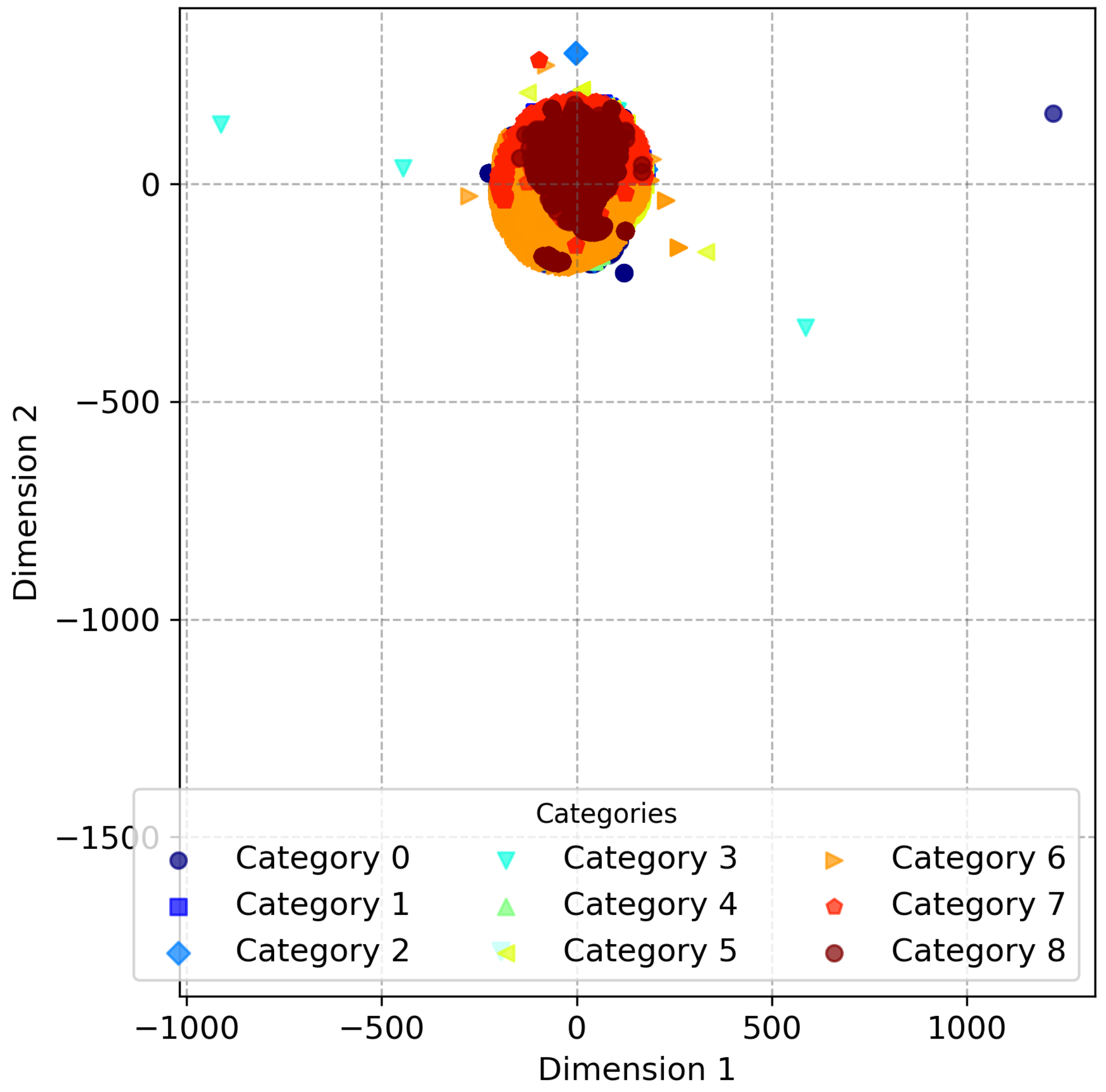
Figure.1: Meid20, LightGBM, incoming bytes, incoming packets, TCP flags, Port, IPv4 add , idle

How can the practicality of ML-based IoT device identification be improved?

t-SNE



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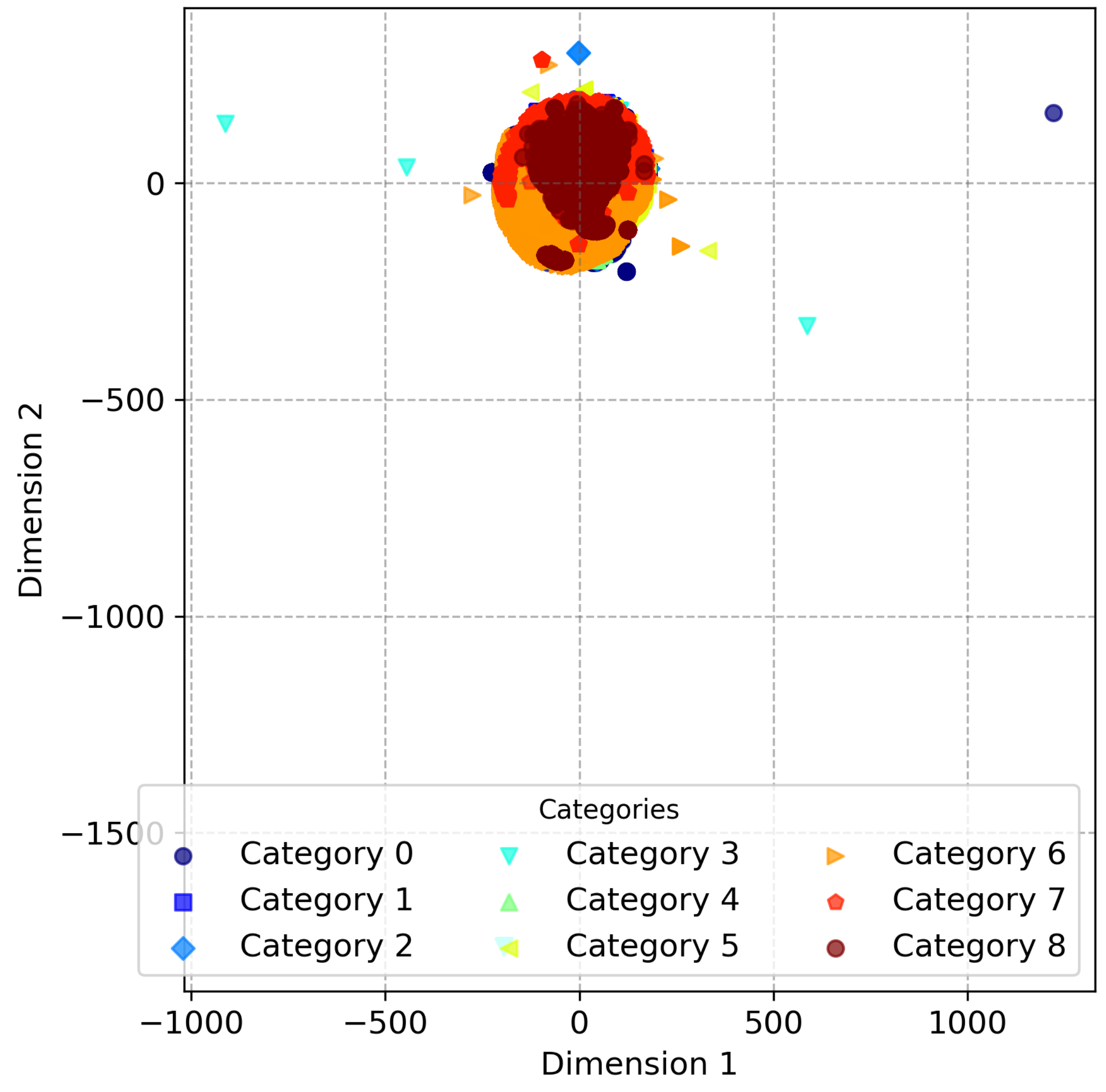
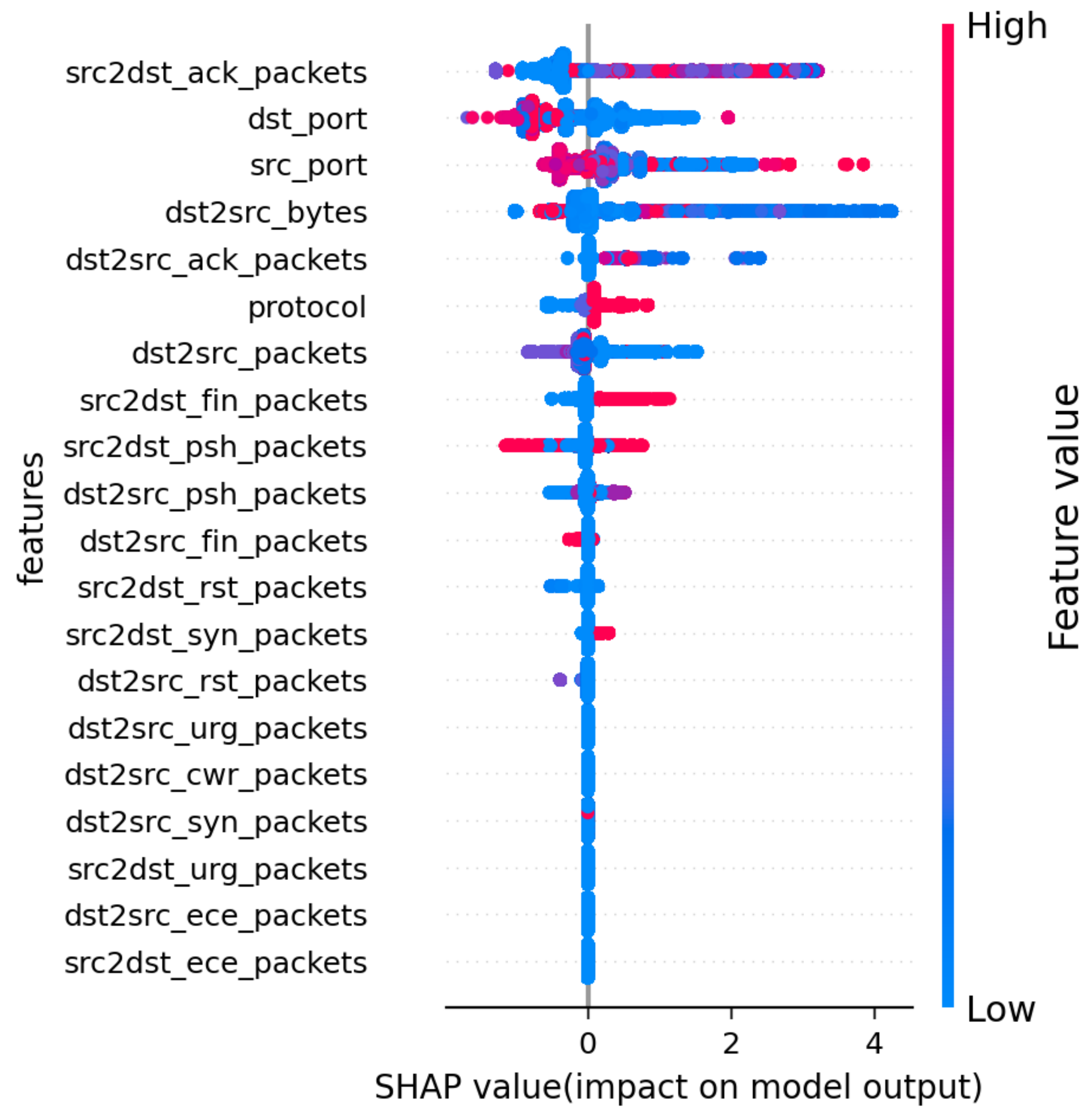


SHAP



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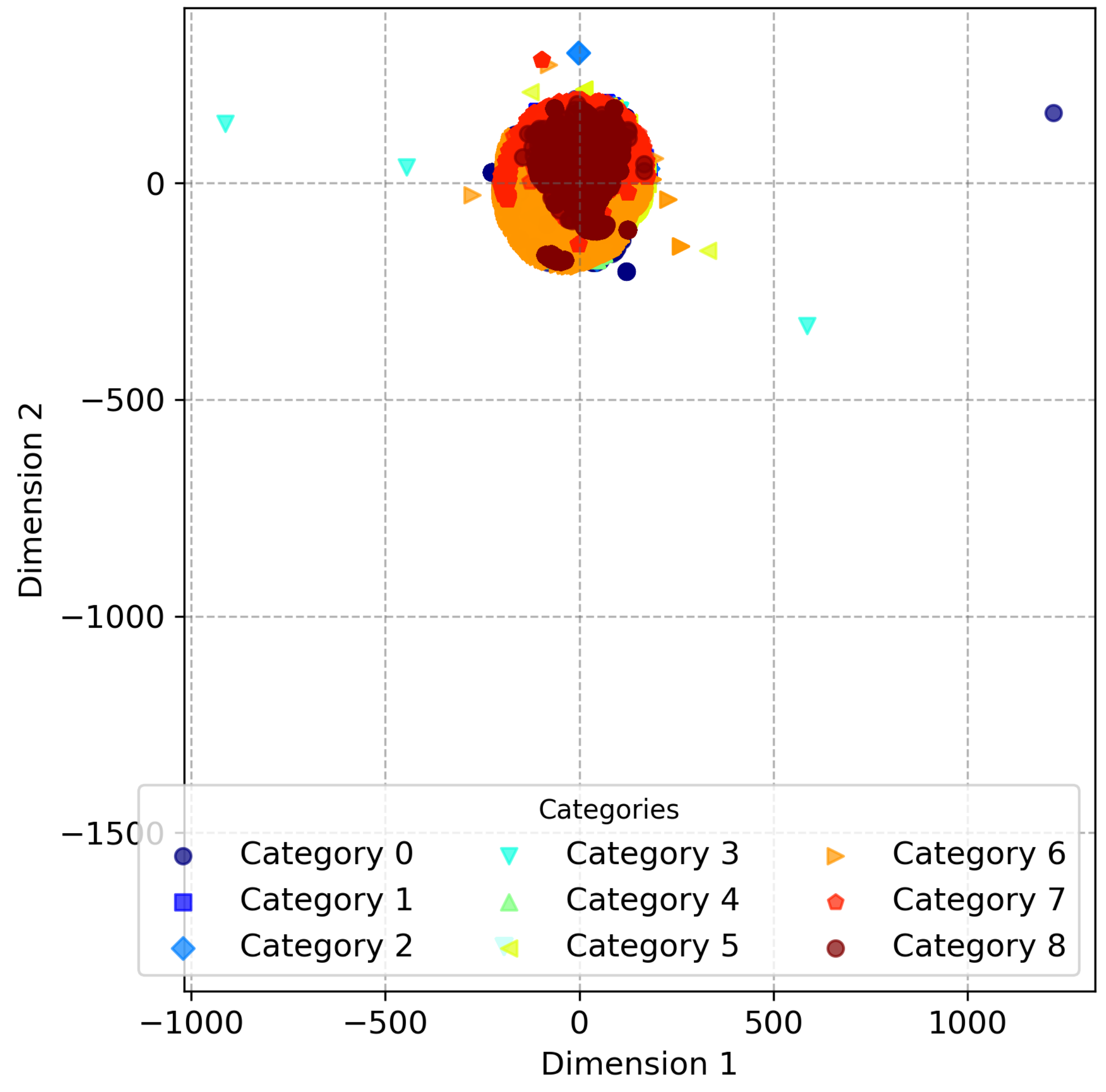

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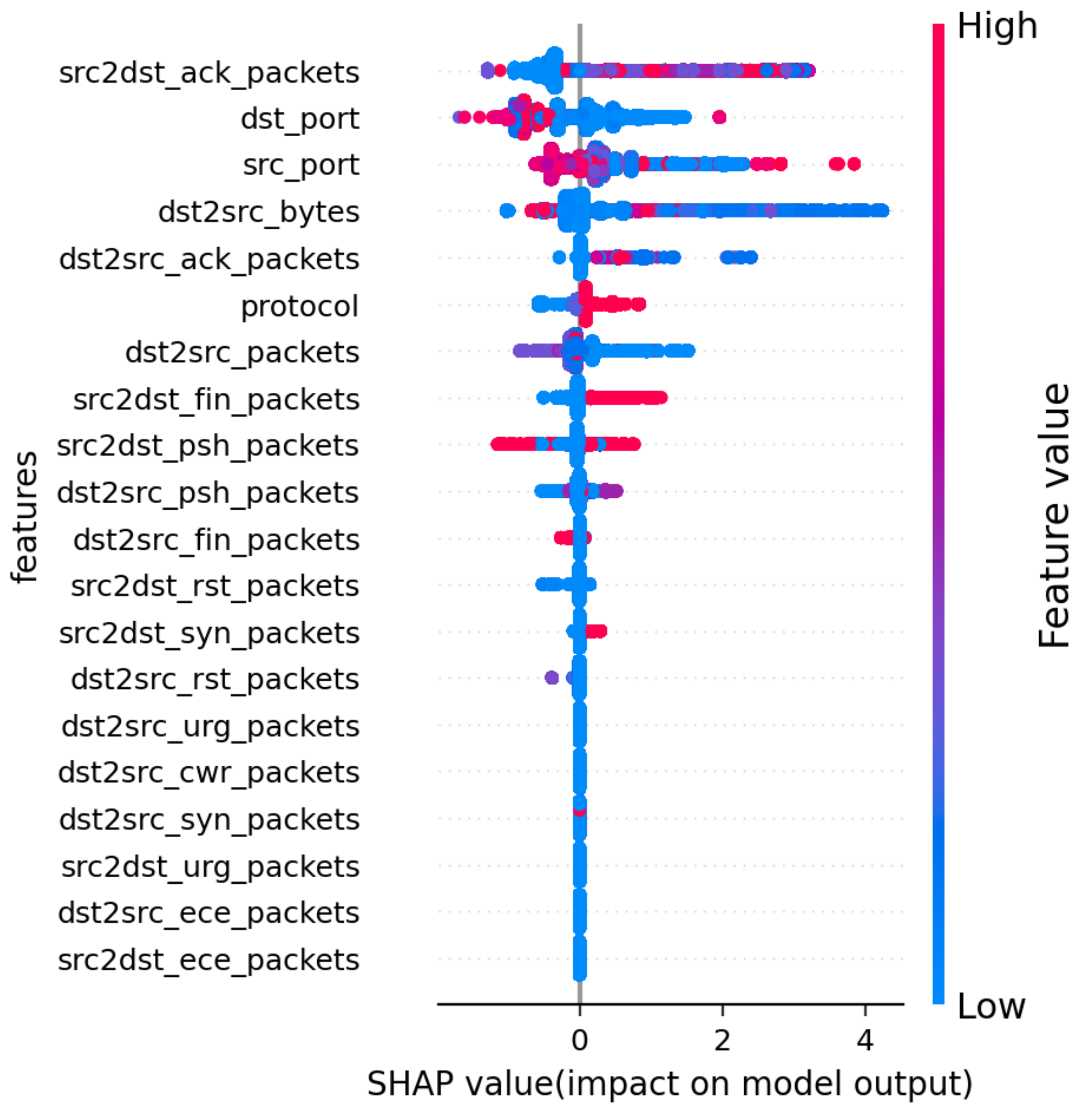

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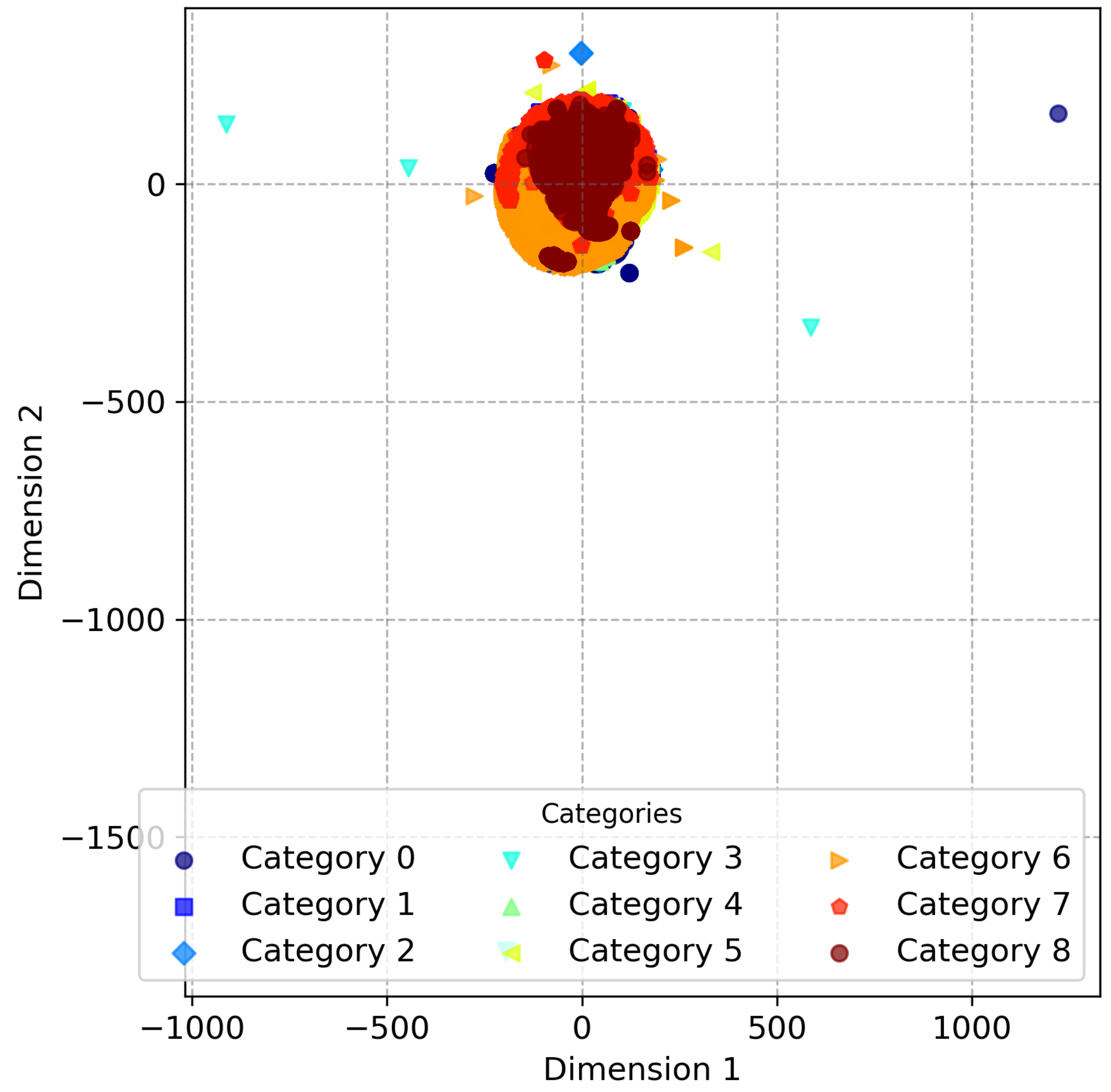

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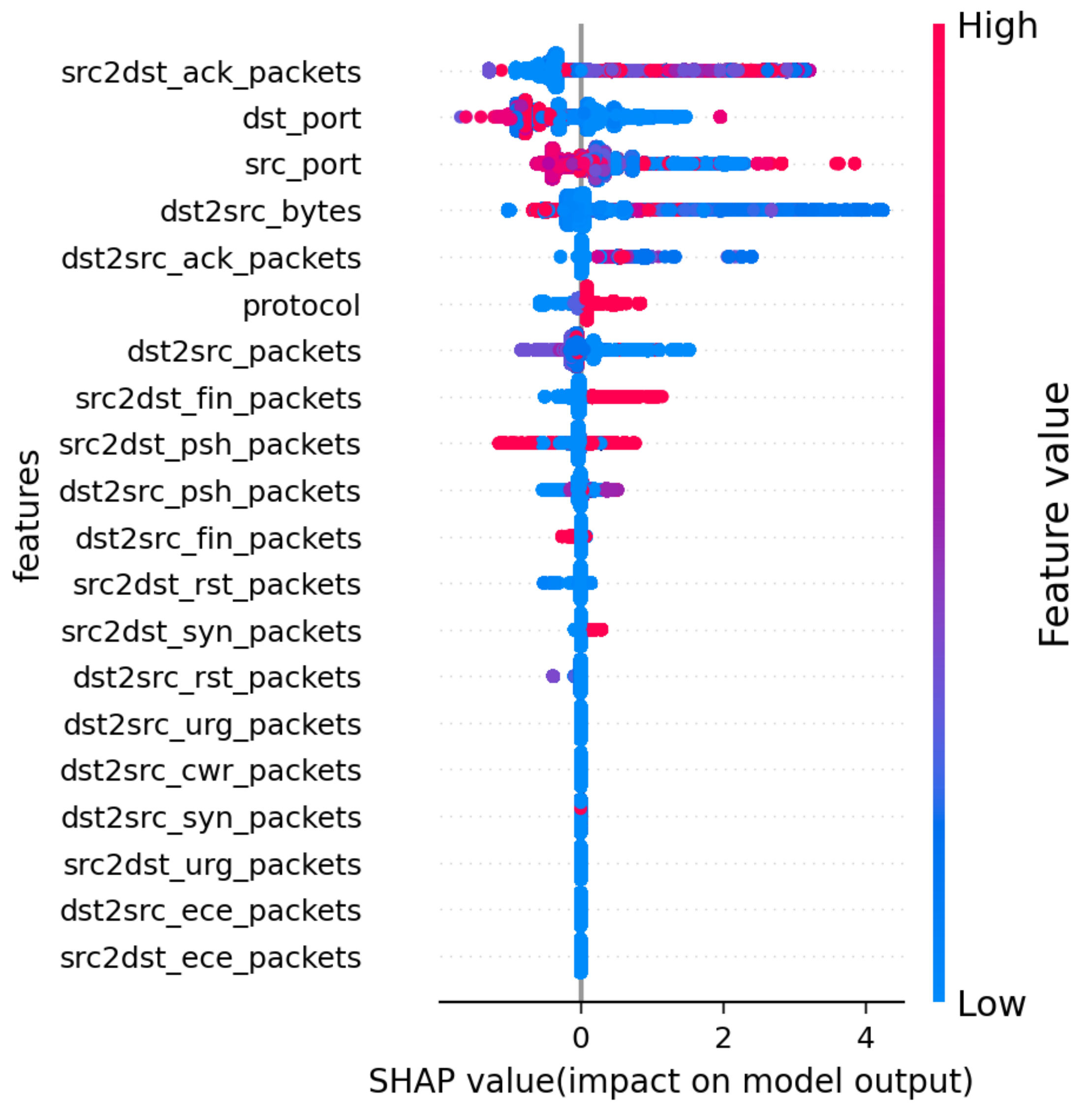

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Key Findings: Simple features used in the training datasets (e.g., mean, variance) fail to capture distributional characteristics effectively.

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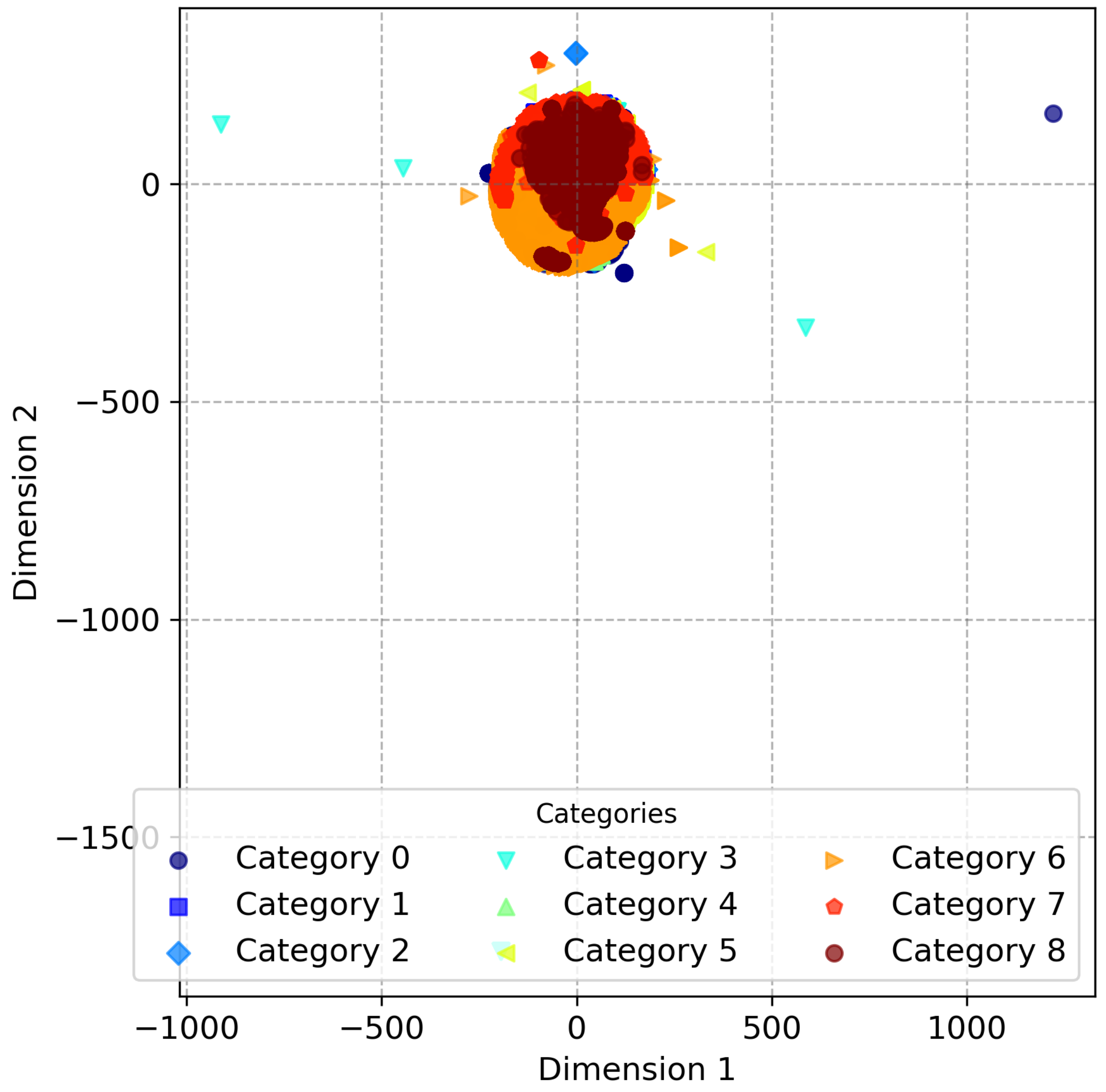

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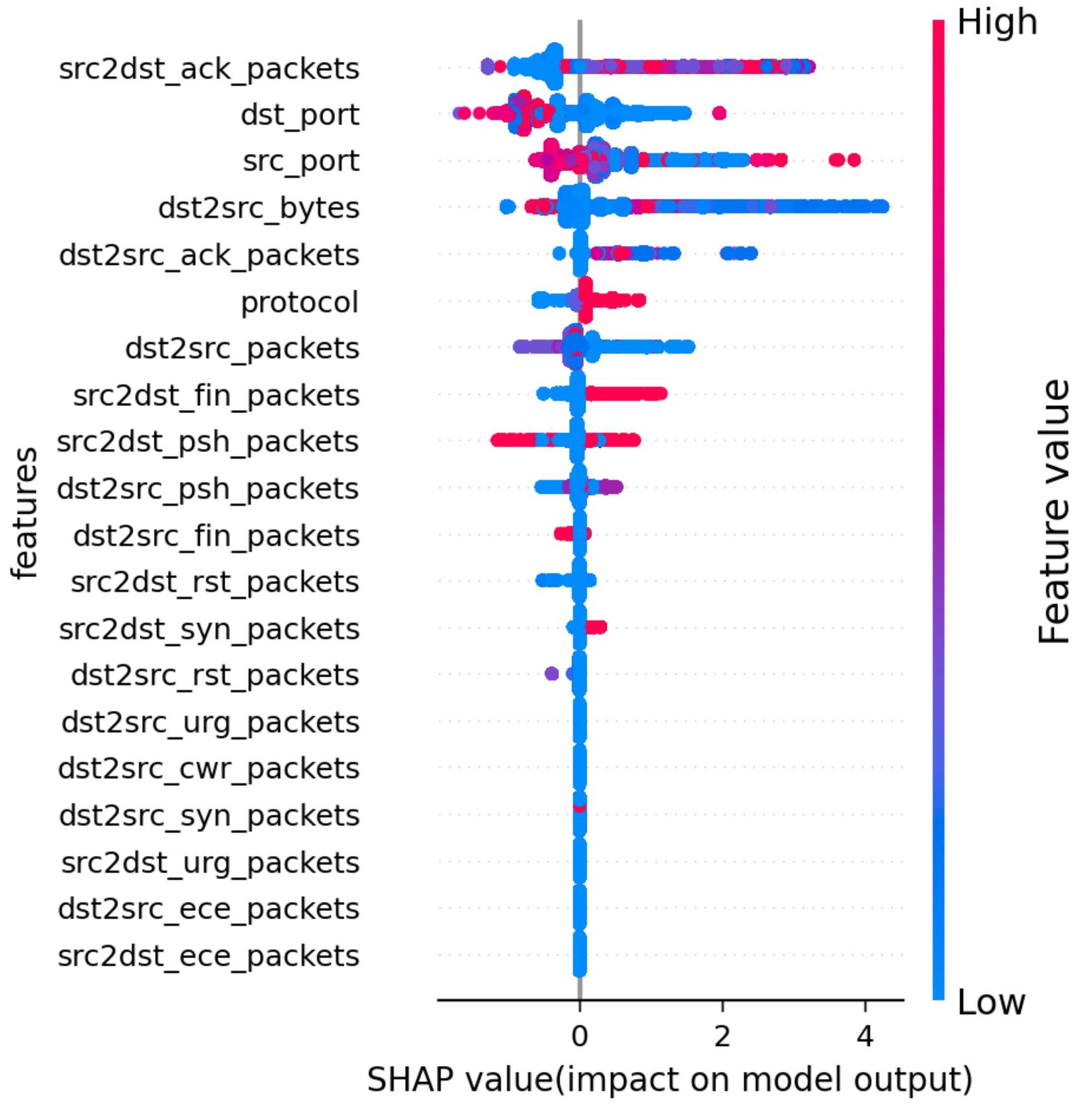

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Key Findings: Simple features used in the training datasets (e.g., mean, variance) fail to capture distributional characteristics effectively.

Recommendation: Avoid simple first-order statistical features (eg., mean, variance), and instead, features such as entropy are more suitable.

Thank You!

Evaluating Machine Learning-Based IoT Device Identification Models for Security Applications

Eman Maali, Omar Alrawi, Julie McCann
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<code>