# Malicious Domain Detection in Real-World Academic DNS Traffic: A Machine-Learning Approach

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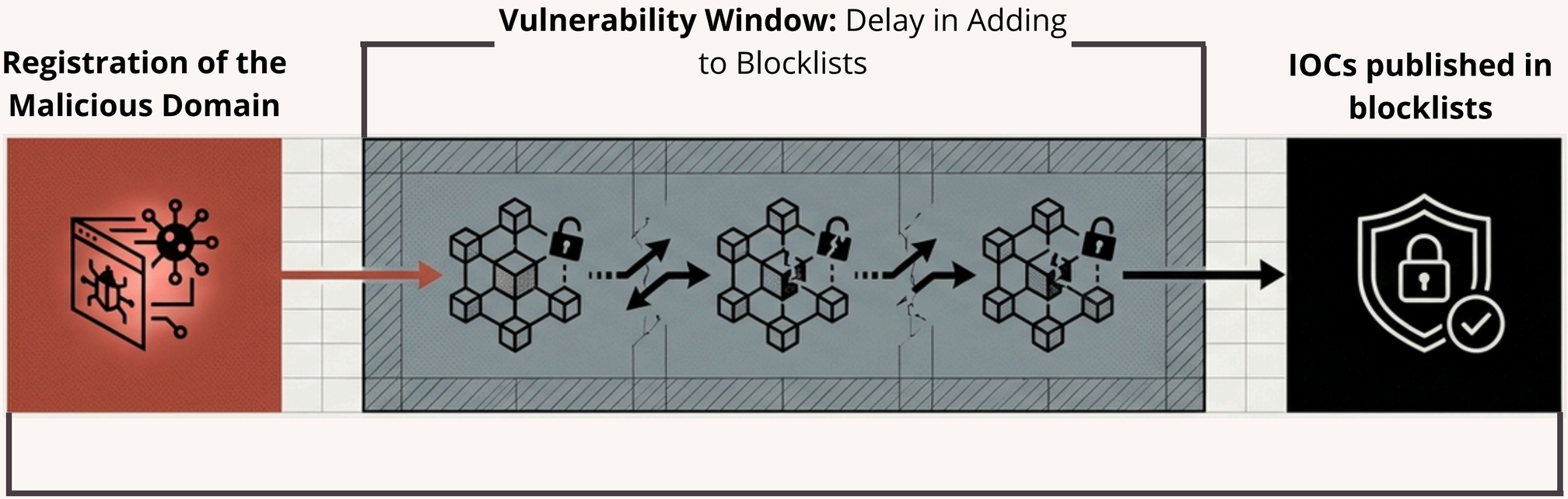
# Problem Context

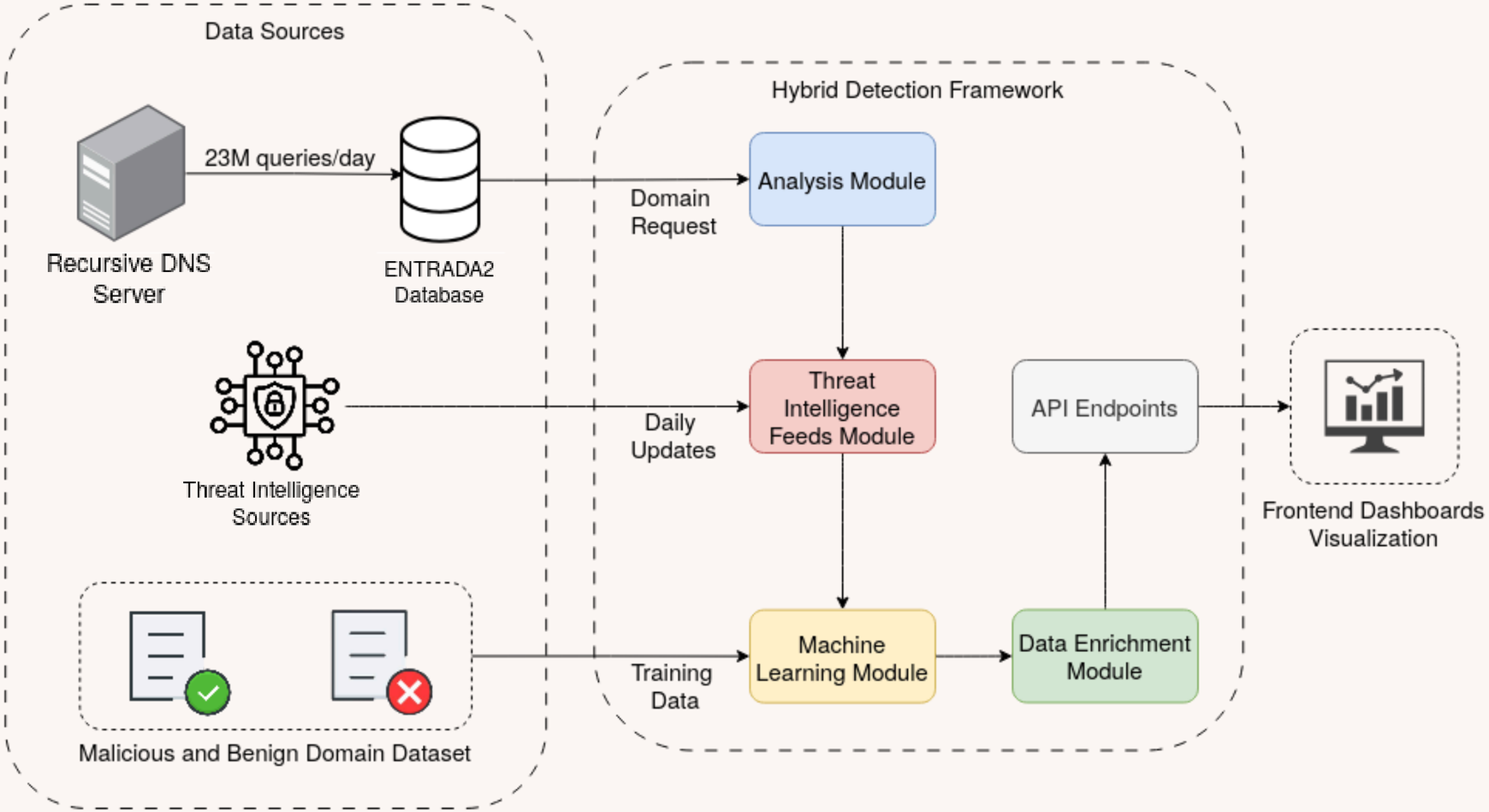



**Timeline of a Malicious Domain**

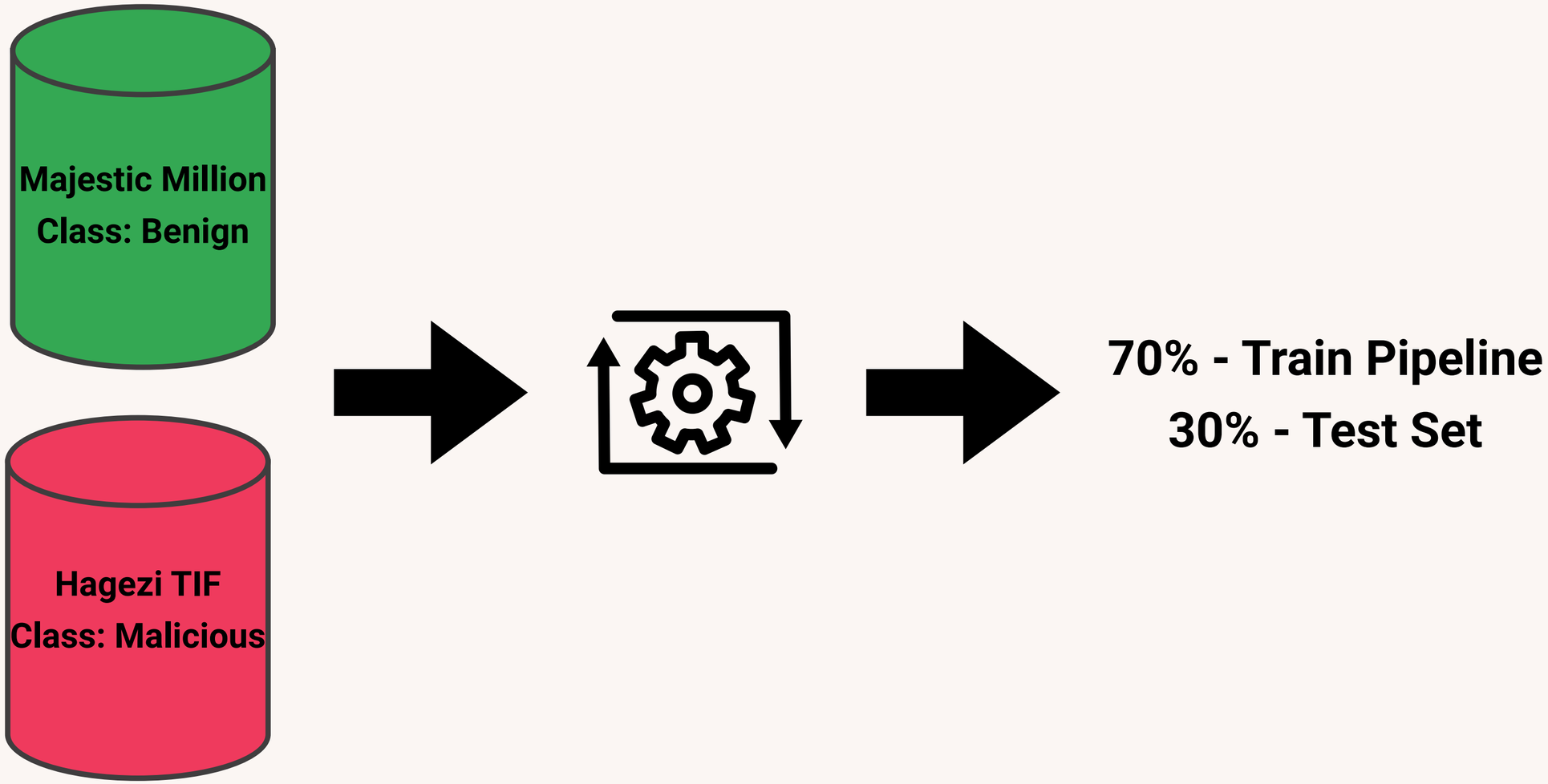
# Objectives

- Verify malicious domain detection with a hybrid combination of threat intelligence feeds and a lightweight Random Forest.
- Evaluate the model using lexical, active DNS and TF-IDF features.
- Analyze system behavior in highly imbalanced real-world traffic, especially regarding early detection and false-positive trade-offs.

# Hybrid Detection Architecuture



# Train Data


Majestic Million
Class: Benign
Hagezi TIF
Class: Malicious
70% - Train Pipeline
30% - Test Set

# Feature Types

## Lexical

Features extracted directly from the syntax and character composition of domain names.

## Active DNS

Live operational metrics collected dynamically through Cloudflare DoH (DNS Over HTTPS).

## TF-IDF

Vectorization metrics specifically mapping textual domain patterns to identify generated anomalies.

# Test-Set Results

| Model State | Precision [1] | Recall [2] | F1 Score [3] | AUC [4] |
|---|---|---|---|---|
| B (Baseline) | 0.7594 | 0.8083 | 0.7831 | 0.8877 |
| F (Fine-tuned) | 0.7688 | 0.8309 | 0.7986 | 0.9028 |
| BT (Base + TF-IDF) | 0.7897 | 0.8211 | 0.8051 | 0.9070 |
| FT (Fine-tuned + TF-IDF) ✓ | 0.7940 | 0.8318 | 0.8125 | 0.9176 |

[1] Measures the proportion of detected malicious domains that are truly malicious

[2] Measures the proportion of actual malicious domains correctly identified by the model

[3] The harmonic mean of precision and recall, providing a balance between both metrics

[4] Measures the model's ability to distinguish between malicious and benign domains across different classification thresholds

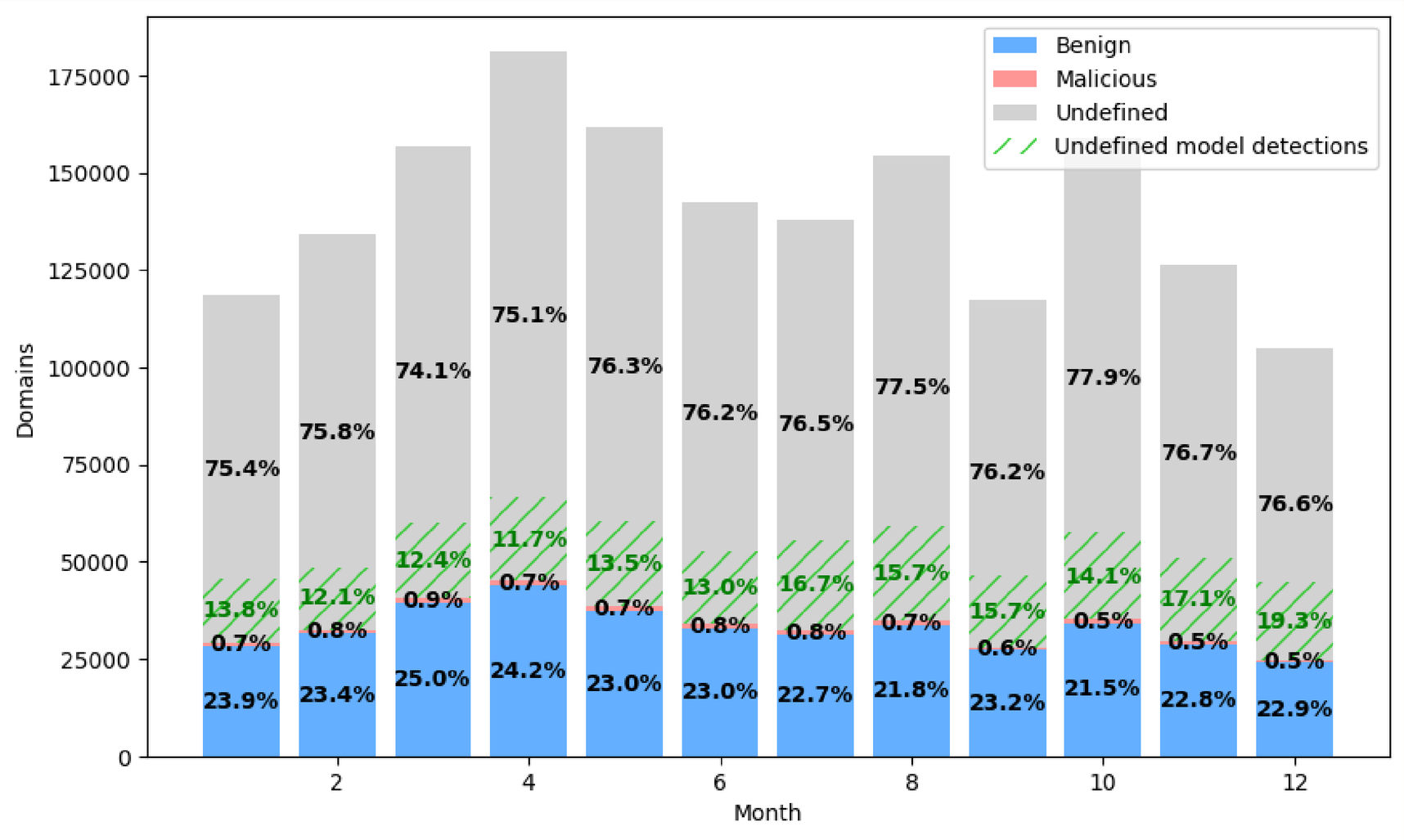
# Real-World Results (1)

- The proposed system was evaluated in a real academic recursive resolver (UNESP) that processes **more than 20 million DNS queries per day**.

- During the one-year deployment, the model identified **between 512 and 1439 malicious domains per month**, all of which were confirmed to be present on public blocklists

- In operational conditions, **precision** ranged from **0.142 to 0.364**, and **recall** ranged from **0.434 to 0.667**.

# Real-World Results (2)



# Threats to Validity

- **Internal validity**: labels depend on external threat intelligence feeds, which may contain noise or delays.
- **External validity**: evaluation was based on a single academic recursive resolver and may differ in corporate environments.
- **Construct validity**: most observed domains were undefined, which may bias the quantitative assessment.
- **Operational validity**: low precision limits the use of the system for fully automatic blocking without human oversight.

# Conclusions

- The hybrid combination is operationally feasible for passive DNS monitoring in a production academic network.
- The tuned model with TF-IDF obtained the best offline performance, reaching AUC = 0.918 and F1 = 0.8125.
- The proposed system should be interpreted as an early-warning and triage component that complements blocklists rather than replaces them.

# Future Work

- Reduce false positives through threshold calibration, ensemble refinement and post-processing rules (fuzzy).
- Explore semi-supervised or unsupervised learning to leverage undefined domains.
- Investigate more robust architectures while preserving real-time feasibility.
- Develop specialized models for phishing, malware and DGA domains instead of a single general-purpose classifier.

# Acknowledgements

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# Thank you!

Any questions?

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