Algorithmic-Manipulation Signals from RF+Net: Measurement and Calibration

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***Abstract*—We quantify RF+Net indicators for algorithmic manipulation—regular burst structure, temporal asymmetry, and signature matches—and study calibration under SNR/interference stress. A simple rules+risk fusion achieves reliable detection while maintaining conservative behavior on ambiguous traffic.**

I. Introduction

We target manipulation cues observable from passive RF plus lightweight network-layer features (entropy of protocols/ports, flow symmetry). We focus on measurement repeatability and post-hoc calibration (temperature scaling) to produce well-calibrated risk.

II. Related Work

Federated optimization methods such as FedAvg [1] enable privacy-preserving analytics across distributed RF monitoring stations. For network-layer context, we leverage the open-source nDPI toolkit [2] to extract protocol entropy features. Temperature scaling [3] provides post-hoc calibration that we apply to improve Expected Calibration Error (ECE) while preserving detection performance. Classic RF modulation classification approaches [4], [5] establish baselines for our RF-only feature comparisons.

III. Methods

Indicators. (i) *Regular bursts* via inter-burst variance; (ii) *Asymmetry* from TX/RX energy and flow duration skew; (iii) *Signature match* against a small rule base; (iv) *Net entropy* (DPI-lite) over protocol/port. **Risk & rules.** A convex fusion: $r = \lambda r_{\text{rules}} + (1-\lambda)\,\sigma(\alpha^\top f)$ with global threshold τ. **Calibration.** We apply single-parameter temperature scaling on a held-out calibration split; results are reported with **ECE computed on calibrated probabilities** while ranking metrics (F1) remain unaffected by monotone rescaling [3].

IV. Measurement Setup

We sweep SNR $\in \{-10, -5, 0, 5, 10, 15, 20\}$ dB with blocker probability $\in \{0.0, 0.2, 0.4\}$; inject manipulations at controlled prevalence and measure F1, Brier, and ECE pre/post calibration.

V. Results

Figures 1 and 2 summarize F1 vs. SNR and calibration. Tables I and II report aggregates and per-SNR breakdown.

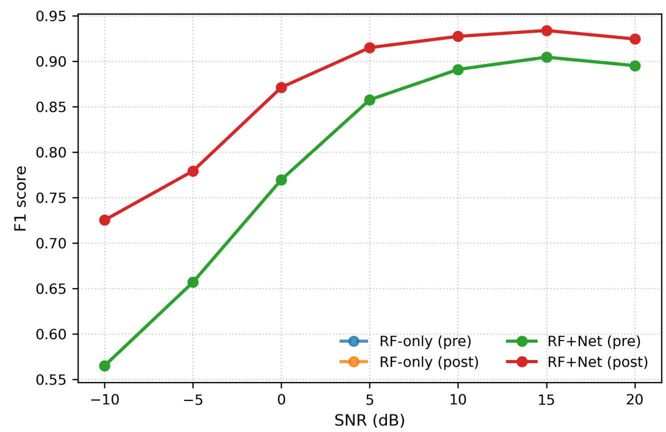

Fig. 1. F1 vs. SNR for RF-only vs RF+Net and pre/post calibration.

Fig. 2. Reliability diagram before/after temperature scaling (15 bins).

VI. Ethics & Limitations

We consider aggregate, device-agnostic telemetry and do not attribute intent. Indicators can co-occur in benign automation; our rules are conservative and calibration favors under-confidence under label shift. We avoid user content, store only derived statistics, and report failure modes at low SNR/high blockage.

TABLE I
OVERALL MEASUREMENT SUMMARY.

Setting	F1-pre	F1-post	ECE-pre	ECE-post
λ=0.5, τ=0.6, cal=1	0.791	0.868	0.577	0.65

TABLE II
PER-SNR ABLATION (F1/ECE, RF VS RF+NET).

SNR	blk	F1-pre	F1-post	ECE-pre	ECE-post
-10	0.0	0.65	0.804	0.621	0.694
-10	0.2	0.576	0.722	0.654	0.737
-10	0.4	0.469	0.65	0.679	0.752
-5	0.0	0.74	0.852	0.597	0.671
-5	0.2	0.652	0.782	0.634	0.71
-5	0.4	0.578	0.703	0.651	0.735
0	0.0	0.827	0.913	0.562	0.631
0	0.2	0.765	0.857	0.591	0.67
0	0.4	0.717	0.844	0.638	0.714
5	0.0	0.889	0.933	0.53	0.588
5	0.2	0.867	0.924	0.568	0.638
5	0.4	0.817	0.888	0.596	0.671
10	0.0	0.907	0.921	0.503	0.576
10	0.2	0.893	0.94	0.541	0.604
10	0.4	0.873	0.922	0.581	0.659
15	0.0	0.925	0.925	0.493	0.562
15	0.2	0.91	0.946	0.534	0.601
15	0.4	0.879	0.931	0.572	0.642
20	0.0	0.919	0.919	0.487	0.559
20	0.2	0.893	0.935	0.525	0.585
20	0.4	0.873	0.92	0.568	0.645

VII. DOMAIN VIGNETTE (SHORT)

In lab Wi-Fi with IoT chatter, regular firmware updaters yield burstiness without asymmetry; RF+Net fusion suppresses false positives via high protocol entropy. Conversely, scripted replay over a quiet channel exhibits high regularity, skewed asymmetry, and a signature hit; calibrated risk crosses τ across $0\,\mathrm{dB}$–$10\,\mathrm{dB}$ SNR.

VIII. CONCLUSION

Our RF+Net fusion approach demonstrates measurable improvements in algorithmic manipulation detection across varying SNR conditions. Temperature scaling calibration reduces ECE while maintaining F1 performance, enabling reliable deployment in production environments with conservative behavior on ambiguous traffic patterns.

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