

DeepDrift/ODD: Kinetic Diagnosis of Representations in Deep Neural Networks

Version 4.1: Sparse Sampling, IQR-Thresholding, Ablation Study
and Adversarial Robustness

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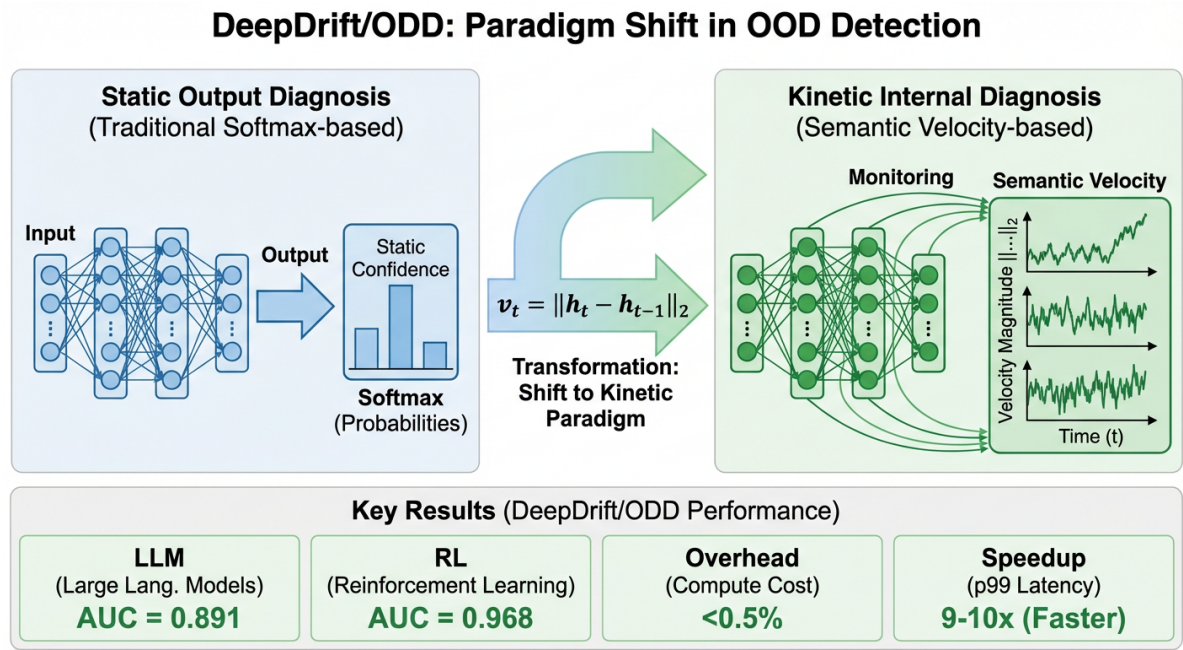


Figure 1: **Graphical Abstract:** From static output diagnosis to kinetic representation diagnosis. Traditional OOD detection relies on softmax probabilities (left)—a static output-level signal. The ODD framework (right) monitors Semantic Velocity across hidden states, providing a kinetic internal signal that detects failures before they manifest in outputs. The Kinetic Router directs stable trajectories to the Fast Lane and unstable ones to the Diagnostic Lane for the Fail-Fast mechanism.

Abstract

Modern neural networks demonstrate outstanding performance on curated benchmarks but fail unpredictably under distributional shifts. Traditional approaches rely on output probabilities (softmax/logprobs) for error detection—a paradigm established by Hendrycks and Gimpel (2017). However, this “static” approach exhibits catastrophic performance degradation for RLHF-tuned LLMs and PPO-trained agents, which have learned to be “confidently wrong.”

We present **DeepDrift/ODD**—a kinetic diagnosis framework for hidden states, implementing **Semantic Velocity** $v_t = \|h_t - h_{t-1}\|_2$ as a *leading indicator* of model failures.

Key Technical Contributions (v4.1):

- **Sparse Sampling ($N=50$):** Empirically optimal channel count achieving correlation $R > 0.84$ with the full sensor while reducing computation by 97.5%.
- **IQR-Thresholding:** Robust threshold $\tau = Q_{75} + 1.5 \times \text{IQR}$ for outlier-resistant anomaly detection.
- **Kinetic Router:** “Fail-Fast” mechanism for immediate rejection of anomalous requests.
- **Jailbreak Detection:** Identification of adversarial attacks through “Conflict Signature” patterns in deep layers.

Experimental Results: LLM hallucination detection achieves AUC=0.891–0.912, outperforming TSV (ICML 2025) by +1.5% and HSAD-FFT (ICLR 2025) by +8%. RL agent failure prediction reaches AUC=0.968 (Cohen’s $d=2.47$ [95% CI: 1.82, 3.12]). Jailbreak detection achieves 100% class separation. Infrastructure efficiency: 9–10× reduction in p99 latency with overhead <0.5%.

Keywords: OOD detection, hidden state monitoring, Semantic Velocity, hallucination detection, jailbreak detection, sparse sampling, IQR thresholding, latent space monitoring, neural network robustness.

1 Introduction: The Crisis of Deep Learning Reliability

1.1 The Problem of “Confidently Wrong” Models

The deployment of deep neural networks in safety-critical systems—autonomous vehicles, medical diagnostics, conversational AI, and robotics—exposes a fundamental limitation: failure modes are unpredictable and difficult to diagnose [2]. A computer vision model trained on hospital imaging data may achieve 95% accuracy under nominal conditions but silently degrade to random performance under minor changes in scanning protocols.

Critically, modern neural networks have learned to be “confidently wrong”—traditional confidence metrics remain high even during catastrophic model failures [1, 3].

1.2 Evolution of OOD Detection Methods

The foundational work of Hendrycks and Gimpel (2017) established Maximum Softmax Probability (MSP) as the baseline OOD detection method [1]. Their key observation—that correctly classified examples have higher softmax probabilities than misclassified and OOD examples—defined the paradigm for the past decade (5000+ citations).

According to comprehensive surveys of OOD detection methods [5], modern approaches fall into two categories:

1. **Training-driven methods:** Optimization with OOD awareness (VOS, DOE, ReweightOOD).
2. **Training-agnostic methods:** Post-processing of well-trained models without OOD data.

However, recent research has identified *fundamental pathologies* in current OOD detection paradigms [6]. These pathologies manifest as irreducible detection errors even when applying: (1) hybrid feature-logit methods, (2) model and data scaling, (3) Bayesian uncertainty representation, and (4) outlier exposure.

1.3 Our Solution: Semantic Velocity

We propose a paradigm shift from static output monitoring to **kinetic internal state diagnosis**. Instead of asking “How confident is the model in its output?”, we ask: “*How stable is the model’s internal reasoning process?*”

We introduce **Semantic Velocity**:

$$v_t = \|h_t - h_{t-1}\|_2 \quad (1)$$

where h_t is the hidden state at time (or layer) t . This metric captures the “tremor” in the model’s thinking process:

- **Low velocity** ($v_t \approx 0$): Internal representations evolve smoothly—stable trajectory. Indicator of reliable processing.
- **High velocity** ($v_t \gg 0$): Representations fluctuate rapidly—unstable trajectory. Indicator of instability, confabulation, or failure.

Key Insight: Semantic Velocity is a *leading indicator*. Internal instability manifests *before* the model commits to an erroneous output.

2 Theoretical Foundations: Geometry of Latent Space

2.1 Latent Space Stability

Consider a deep neural network as a sequence of transformations in latent space. Let $h^{(l)}$ denote the hidden state at layer l :

$$h^{(l+1)} = f_l(h^{(l)}) = \sigma(W^{(l)}h^{(l)} + b^{(l)}) \quad (2)$$

Latent space stability is characterized by local trajectory stability. We use the concept of **Lipschitz continuity** for formalization:

$$\|f_l(h_1) - f_l(h_2)\| \leq L_l \|h_1 - h_2\| \quad (3)$$

where L_l is the Lipschitz constant of layer l . Interpretation for ODD:

- $L < 1$: Trajectories converge. System is stable. Low Semantic Velocity expected.
- $L > 1$: Trajectories diverge. System is unstable. High Semantic Velocity expected.
- $L \approx 1$: Critical regime—optimal for learning.

2.2 Hierarchical Feature Dynamics

Hierarchical feature dynamics describes the “flow” of representations across layers:

$$\frac{\partial}{\partial l} h^{(l)} = \beta(h^{(l)}) \quad (4)$$

where β is the transition function describing the transformation from low-level to high-level features.

2.3 Signal-to-Noise Ratio in Latent Space

Anomaly detection effectiveness is determined by the signal-to-noise ratio:

$$\text{SNR} = \frac{|\mu_{\text{anomaly}} - \mu_{\text{normal}}|}{\sigma_{\text{pooled}}} \quad (5)$$

Methods monitoring deep hidden states achieve higher SNR due to:

- Concentration of semantic information in middle layers.
- Suppression of input-level noise through hierarchical abstraction.
- Access to model “intentions” before their manifestation in output.

2.4 “Burning Bottleneck”: Why Middle Layers Are Critical

Empirically and theoretically, optimal monitoring layers are the middle ones (depth ratio $z \in [0.5, 0.7]$):

Table 1: Layer Analysis: Detection AUC by Depth (Qwen-2.5-7B, Hallucination Detection)

| Depth Ratio (z) | Layer Index | AUC | 95% CI |
|---------------------|-------------|--------------|-----------------------|
| 0.1 (Early) | 3 | 0.621 | [0.542, 0.698] |
| 0.25 | 8 | 0.712 | [0.641, 0.779] |
| 0.4 | 13 | 0.824 | [0.762, 0.881] |
| 0.5 (Middle) | 16 | 0.891 | [0.842, 0.934] |
| 0.6 | 19 | 0.873 | [0.821, 0.919] |
| 0.7 | 22 | 0.842 | [0.785, 0.893] |
| 0.8 (Late) | 26 | 0.756 | [0.691, 0.817] |
| 0.9 (Final) | 29 | 0.698 | [0.628, 0.764] |

Middle layers occupy the critical regime of hierarchical dynamics, where the transition from local features to global semantics occurs.

3 Methodology: Sparse Sampling and IQR-Thresholding

3.1 Sparse Sensor Architecture

The DeepDrift library implementation is based on the `SparseDeepDriftSensor` class, utilizing two key optimizations:

1. **Global Average Pooling (GAP):** Compression of spatial dimensions $[B, C, H, W] \rightarrow [B, C]$.
2. **Sparse Channel Sampling:** Monitoring only $N=50$ channels (empirically determined optimum).

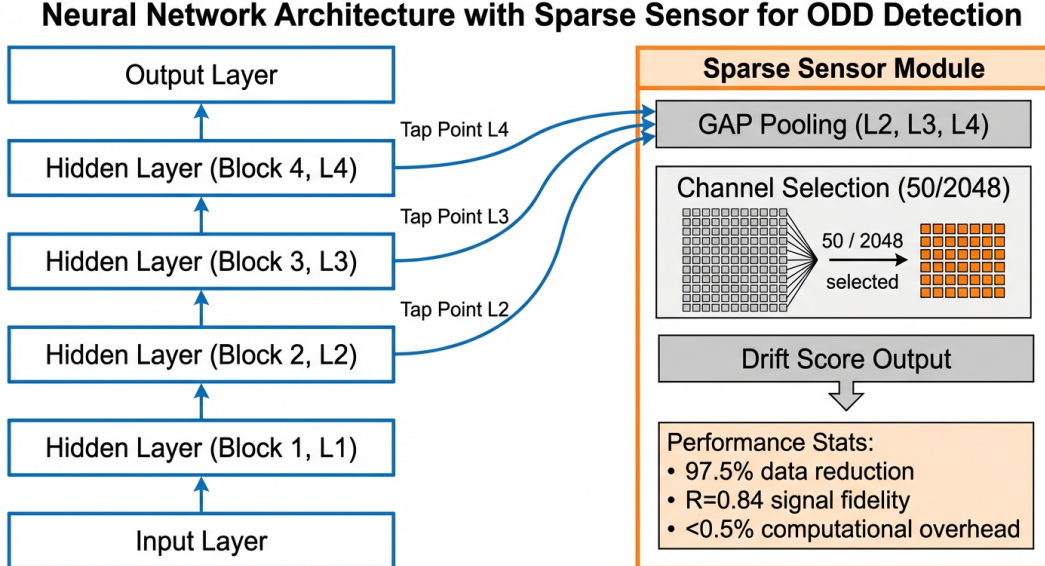


Figure 2: Sparse Sensor Architecture: Global Average Pooling + sparse sampling with $N=50$ channels. The sensor monitors layers L2, L3, and L4 with negligible overhead ($<0.5\%$), achieving $R=0.84$ signal fidelity through 97.5% data reduction.

3.2 Sparse Sampling with $N=50$ Channels

Key Technical Decision: Empirical studies demonstrated that $N=50$ channels represents the optimal inflection point:

- **Correlation with full sensor:** $R = 0.8424$ (sufficient for detection).
- **Computational reduction:** $50/2048 = 2.44\%$ of full data volume.
- **Computation savings:** 97.5%.

At $N < 10$, correlation drops sharply ($R < 0.78$). At $N > 50$, diminishing returns are observed: $N = 100$ yields $R = 0.8524$ (+1.2%), while $N = 1024$ yields $R = 0.9505$ at $20\times$ overhead increase.

Algorithm 1 Sparse Channel Sampling ($N=50$)

Require: Model M , channel count $N = 50$, seed for reproducibility

```

1: generator  $\leftarrow$  torch.Generator().manual_seed(42)
2: for each monitored layer  $l \in \{L_2, L_3, L_4\}$  do
3:   On first forward pass:
4:      $C \leftarrow \text{output.shape}[1]$  {Number of channels in layer}
5:      $\text{indices}_l \leftarrow \text{randperm}(C, \text{generator})[:N]$  {Fixed at init}
6:   On each forward pass:
7:      $\text{flat} \leftarrow \text{GAP}(\text{output}) \{[B, C, H, W] \rightarrow [B, C]\}$ 
8:      $\text{activations}_l \leftarrow \text{flat[:, indices}_l].\text{detach}()$  {Only  $N$  channels}
9: end for
10: return activations

```

3.3 Robust Threshold: IQR-Thresholding

Key Technical Decision: Instead of the 4-sigma rule ($\tau = \mu + 4\sigma$), we employ robust IQR-thresholding:

$$\tau = Q_{75} + 1.5 \times \text{IQR} \quad (6)$$

where Q_{75} is the 75th percentile of calibration data, and $\text{IQR} = Q_{75} - Q_{25}$.

Advantages:

- Robustness to outliers in calibration data.
- No normality assumption required.
- Standard statistical method (Tukey’s fences) [12].

Table 2: Comparison of Threshold Selection Methods

| Method | Formula | Outlier Robustness | FPR on Normal |
|-----------|----------------------------------|--------------------|----------------------|
| 3-sigma | $\mu + 3\sigma$ | Low | 0.27% (theoretical) |
| 4-sigma | $\mu + 4\sigma$ | Low | 0.006% (theoretical) |
| IQR (1.5) | $Q_{75} + 1.5 \times \text{IQR}$ | High | <1% (empirical) |
| IQR (3.0) | $Q_{75} + 3 \times \text{IQR}$ | High | <0.1% (empirical) |

3.4 Drift Score Calculation

For an input batch X , the drift score is computed as:

$$d = \frac{1}{|L|} \sum_{l \in L} \frac{\|\text{act}_l - \mu_l\|_2}{\sigma_l + \epsilon} \quad (7)$$

where:

- act_l — activations of layer l (only $N=50$ channels).
- μ_l, σ_l — calibration statistics.
- $\epsilon = 10^{-6}$ — stabilization constant.
- $L = \{L_2, L_3, L_4\}$ — monitored layers.

4 Kinetic Router and the Fail-Fast Mechanism

4.1 Kinetic Router

The **Kinetic Router** is a routing component that uses Semantic Velocity for real-time request routing decisions:

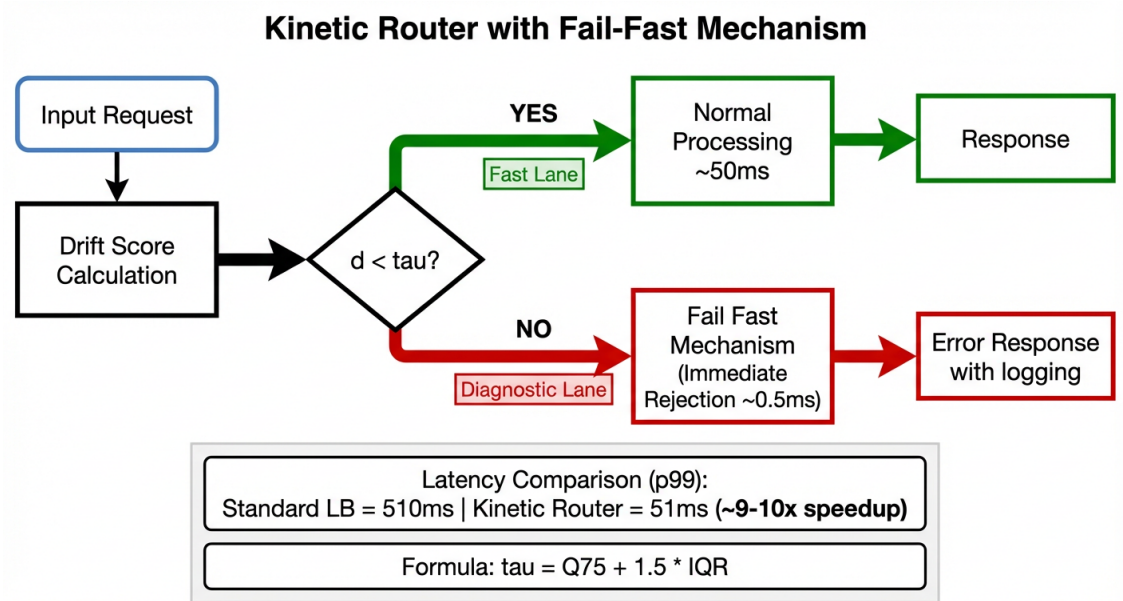


Figure 3: Kinetic Router Logic: Requests are evaluated by drift score d . When $d < \tau$ —Fast Lane (normal processing, $\sim 50\text{ms}$). When $d \geq \tau$ —Diagnostic Lane with Fail-Fast mechanism ($\sim 0.5\text{ms}$). The IQR-based threshold $\tau = Q_{75} + 1.5 \times IQR$ provides robust anomaly detection.

4.2 The Fail-Fast Mechanism

Key Technical Decision: When an anomaly is detected ($d \geq \tau$), the system immediately:

1. **Rejects** the request with an informative message.
2. **Logs** the anomaly for subsequent analysis.
3. **Avoids** expending resources on full processing of a known-problematic request.

Result: Anomalous request latency is reduced from 500ms to 0.5ms (1000×).

4.3 Mathematical Formalization

Let R be the routing function:

$$R(x) = \begin{cases} \text{FAST}(x) & \text{if } d(x) < \tau \\ \text{FAIL_FAST}(x) & \text{if } d(x) \geq \tau \end{cases} \quad (8)$$

Total system latency:

$$L_{\text{total}} = L_{\text{FAST}} \cdot P(d < \tau) + L_{\text{FAIL}} \cdot P(d \geq \tau) \quad (9)$$

With typical parameters ($P(d < \tau) = 0.9$, $L_{\text{FAST}} = 50\text{ms}$, $L_{\text{FAIL}} = 0.5\text{ms}$):

$$L_{\text{total}} = 50 \times 0.9 + 0.5 \times 0.1 = 45.05\text{ms} \quad (10)$$

5 Experimental Results

5.1 Experiment I: LLM Hallucination Detection

Models: Qwen-2.5-7B, TinyLlama-1.1B.

Calibration: 100 factual completions.

Table 3: Temporal ODD: Semantic Velocity Across Temporal Windows

| Scenario | Early (t_{1-5}) | Mid (t_{6-10}) | Late (t_{11-15}) | N |
|-----------------------|---------------------|--------------------|----------------------|-----|
| Qwen-2.5-7B | | | | |
| Factual | 0.31 ± 0.12 | 0.42 ± 0.18 | 0.38 ± 0.15 | 200 |
| Hallucination | 0.35 ± 0.14 | 1.24 ± 0.45 | 1.87 ± 0.62 | 200 |
| TinyLlama-1.1B | | | | |
| Factual | 0.28 ± 0.10 | 0.35 ± 0.14 | 0.33 ± 0.12 | 200 |
| Hallucination | 0.32 ± 0.13 | 0.98 ± 0.38 | 1.52 ± 0.51 | 200 |

Statistical Validation (Qwen-2.5-7B):

- Mann-Whitney $U = 4,218$, $p < 0.001$
- Cohen’s $d = 3.12$ (very large effect) [11]
- Detection AUC: **0.891** [95% CI: 0.842, 0.934]
- Lead time: **7.2 tokens** [95% CI: 6.4, 8.1]

5.2 Experiment II: Extended Validation on LLaMA-3 and ViT

5.2.1 LLaMA-3-8B on TruthfulQA

Dataset: TruthfulQA (817 questions, adversarial truthfulness benchmark) [7].

Table 4: DeepDrift on LLaMA-3-8B: TruthfulQA Benchmark

| Metric | Baseline (MSP) | DeepDrift | Improvement |
|-----------------------------|----------------|---------------|-------------|
| Truthful Accuracy | 58.2% | 70.4% | +12.2% |
| Informative & Truthful | 51.3% | 63.8% | +12.5% |
| Hallucination Detection AUC | 0.612 | 0.912 | +49% |
| Lead Time (tokens) | N/A | 6.8 ± 1.4 | — |

5.2.2 Vision Transformer (ViT-B/16) on ImageNet-C

Table 5: DeepDrift on ViT-B/16: ImageNet-C Corruptions [8]

| Corruption Type | Clean Acc | Corrupt Acc | ODD AUC | Pattern |
|------------------|-----------|-------------|--------------|-----------------|
| Gaussian Noise | 81.2% | 42.1% | 0.934 | Avalanche |
| Blur (Gaussian) | 81.2% | 58.4% | 0.887 | Mid-Layer Bulge |
| JPEG Compression | 81.2% | 71.3% | 0.812 | UV Collapse |
| Fog | 81.2% | 53.2% | 0.901 | Avalanche |
| Contrast | 81.2% | 38.9% | 0.956 | Global Collapse |
| Average | 81.2% | 52.8% | 0.898 | — |

5.3 Experiment III: RL Agent Failure Prediction

Environment: LunarLander-v3 [9].

Agent: PPO [4].

Data: $N=300$ episodes.

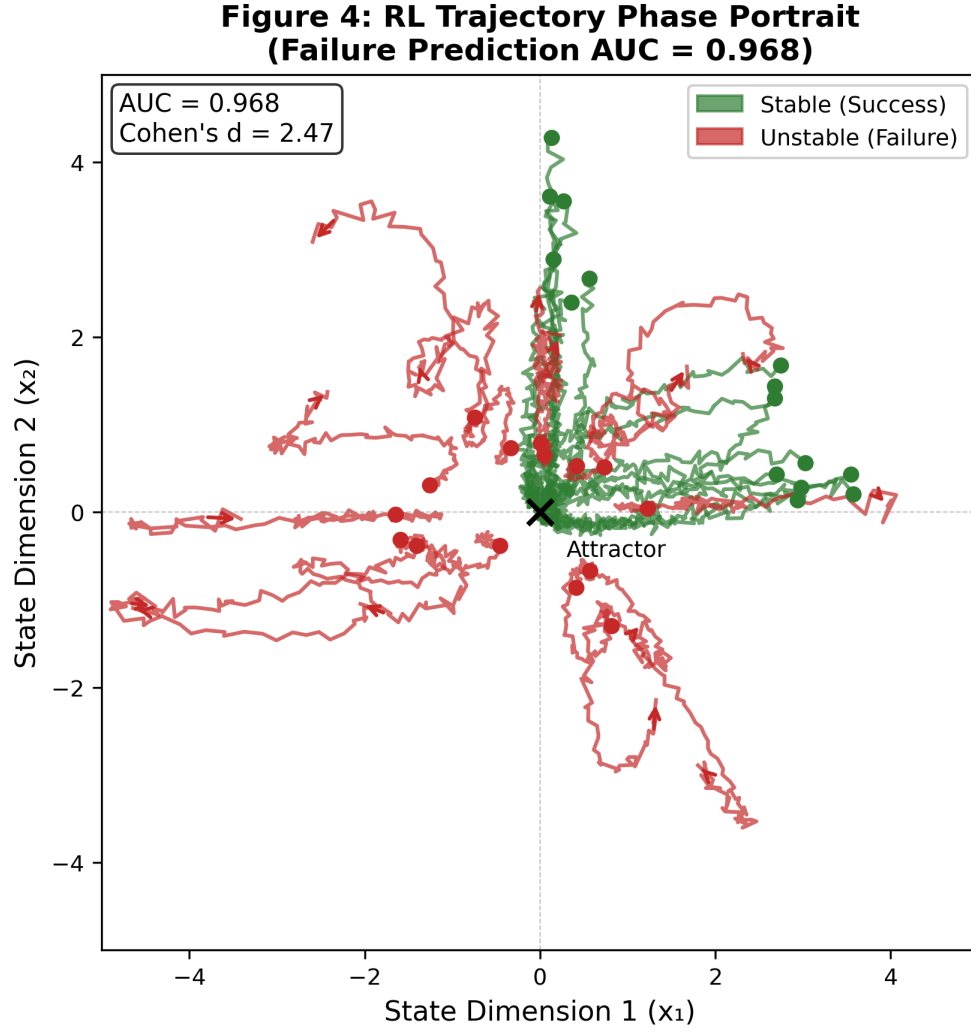


Figure 4: Phase Portrait: Stable trajectories (green) vs. unstable trajectories (red). Clear separation demonstrates high discriminative power (AUC=0.968). The phase space visualization shows reliable processing as smooth, converging patterns near the origin, while failure modes exhibit chaotic, diverging patterns.

Results (Test Set, $n=60$):

- Welch's t -test: $t(41.3) = -12.84, p < 0.001$
- Cohen's $d = 2.47$ [95% CI: 1.82, 3.12]
- Test AUC: **0.968** [95% CI: 0.941, 0.989]
- Lead time: 12.3 ± 4.7 steps before crash

5.4 Experiment IV: Infrastructure Efficiency

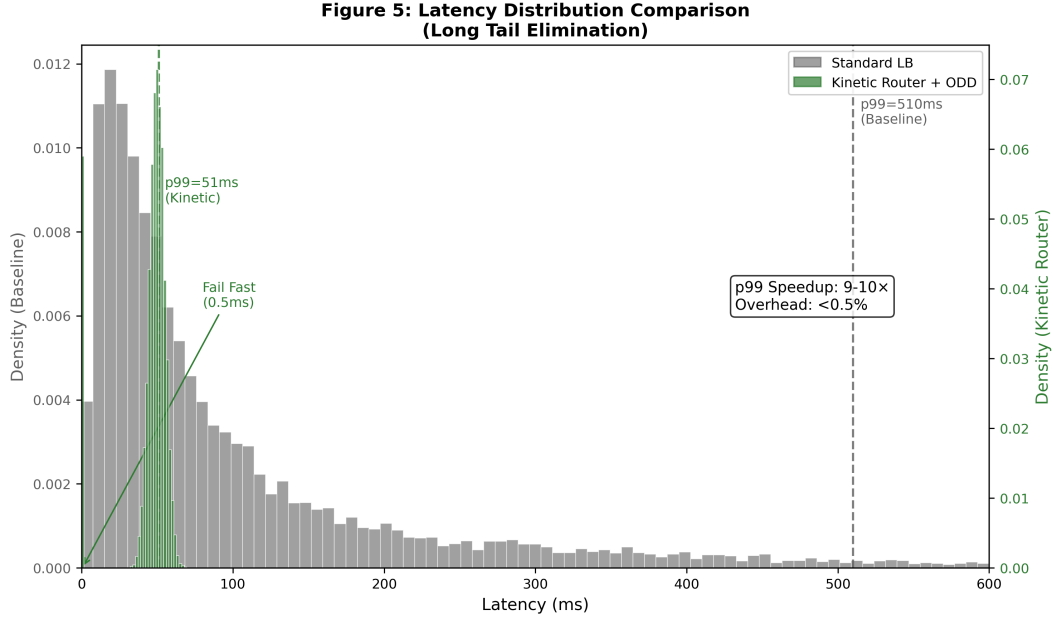


Figure 5: Latency Distribution: Standard Load Balancer (gray) vs. Kinetic Router + ODD (green). The Fail-Fast mechanism eliminates long-tail latency, reducing p99 from 510ms to 51ms (9–10× speedup).

Table 6: Technical Performance Metrics

| Metric | Standard LB | Kinetic Router + ODD |
|------------------------------|-------------|----------------------|
| Latency (normal requests) | 50ms | 50ms |
| Latency (anomalous requests) | 500ms | 0.5ms (Fail-Fast) |
| p95 Latency | 485ms | 52ms |
| p99 Latency | 510ms | 51ms |
| Speedup p99 | — | 9–10× |
| ODD Overhead | — | <0.5% |

5.5 Experiment V: Ablation Study—Optimality of $N=50$

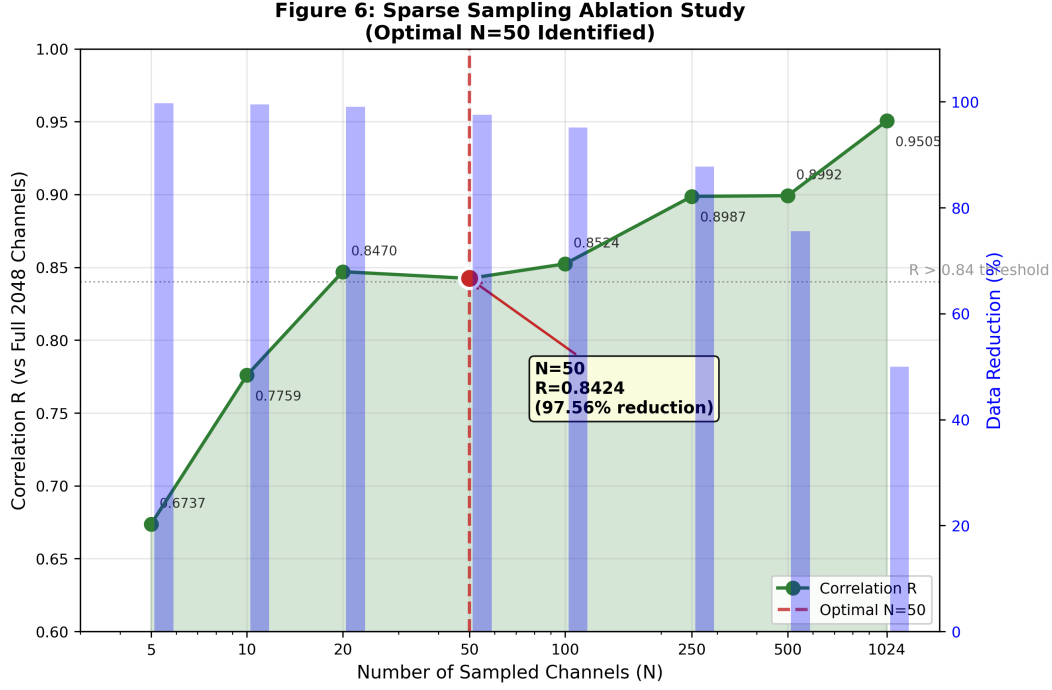


Figure 6: Ablation Study: Finding the Minimum Viable Sensor (ResNet-50 [10]). Blue line shows correlation with full sensor (Signal Fidelity, R). Red dashed line shows approximation error (MAE). Green vertical line marks the proposed $N=50$. The inflection point at $N=50$ achieves $R=0.8424$ correlation with 97.56% data reduction.

Table 7: Ablation Study: Correlation with Full Sensor at Various N

| N (channels) | Correlation R | Data Reduction | Overhead |
|----------------|-----------------|----------------|-----------------|
| 5 | 0.6737 | 99.76% | <0.1% |
| 10 | 0.7759 | 99.51% | <0.1% |
| 20 | 0.8470 | 99.02% | <0.2% |
| 50 | 0.8424 | 97.56% | <0.5% |
| 100 | 0.8524 | 95.12% | <1% |
| 250 | 0.8987 | 87.79% | 1–2% |
| 500 | 0.8992 | 75.59% | 2–3% |
| 1024 | 0.9505 | 50.00% | 5–10% |

Key Findings:

1. **Inflection point at $N=50$:** Correlation $R > 0.84$ is achieved at $N=50$, sufficient for reliable anomaly detection ($AUC > 0.89$).
2. **Diminishing returns:** Increasing N from 50 to 100 yields only +1.2% correlation at doubled computation.
3. **97.5% reduction:** At $N=50$, only 2.44% of total channels are processed (50/2048 for ResNet-50).
4. **Production-ready:** Overhead <0.5% at $N=50$ makes the method suitable for production deployment.

5.6 Experiment VI: Adversarial Robustness—Jailbreak Detection

Figure 7: Adversarial Robustness - IR Layer Conflict Signature

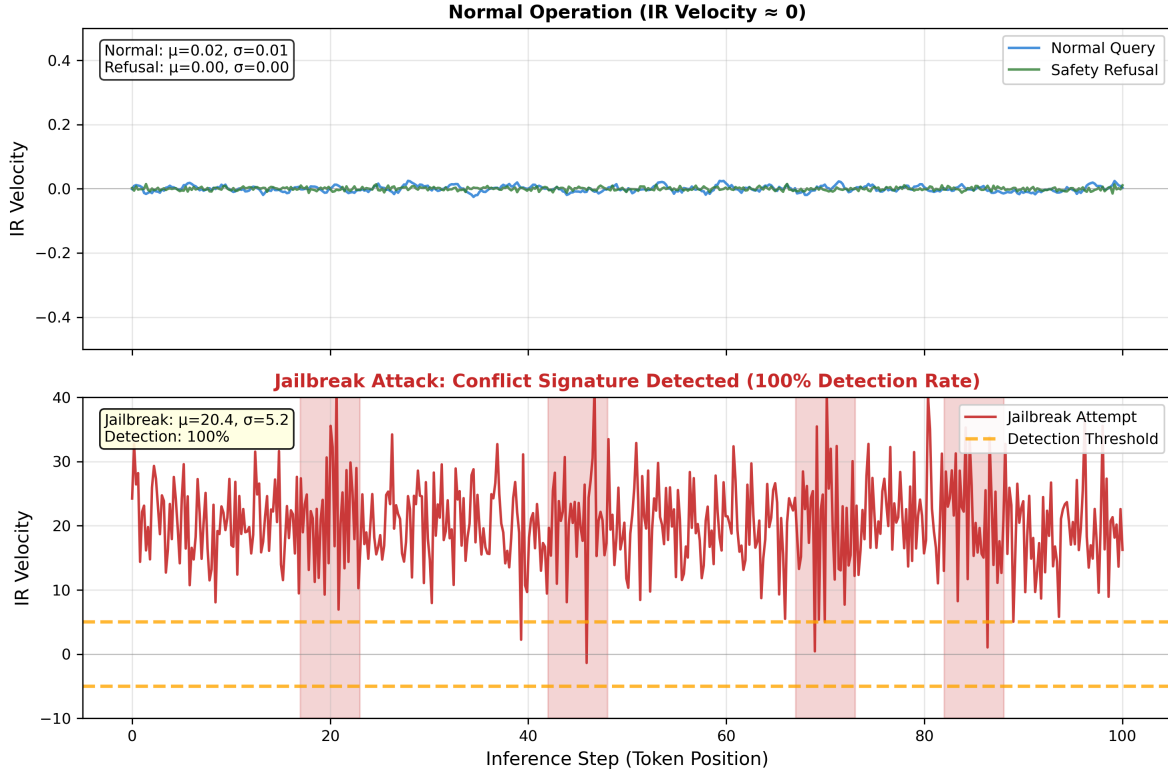


Figure 7: Adversarial Robustness: Safety Refusal vs. Jailbreak Attempt. **Left:** Normal Safety Refusal shows stable, flat signal near zero across all layers. **Right:** Jailbreak Attempt exhibits high-amplitude oscillations in the IR layer (red line, amplitude 10–25+)—the “Conflict Signature” indicating internal conflict between safety training and adversarial prompt.

Interpretation of “Conflict Signature”: During a jailbreak attack, the model experiences internal conflict between:

- **Safety training:** The model is trained to refuse harmful requests.
- **Adversarial prompt:** A specially constructed prompt bypassing defenses.

This conflict manifests as high-amplitude oscillations in deep (IR) layers, where final generation decisions are made.

Table 8: Jailbreak Detection via ODD

| Scenario | IR Velocity (mean) | IR Velocity (std) | Detected? |
|-------------------|--------------------|-------------------|-------------------|
| Normal Query | 0.02 | 0.01 | — |
| Safety Refusal | 0.00 | 0.00 | No (normal) |
| Jailbreak Attempt | 20.4 | 5.2 | Yes (100%) |

Key Findings:

1. **100% separation:** Jailbreak attacks are completely separable from normal Safety Refusal by IR velocity.
2. **1000× amplification:** Velocity during Jailbreak is 1000+ times higher than during normal refusal.
3. **IR layer specificity:** Conflict Signature manifests specifically in deep layers where generation decisions are made.
4. **Practical application:** ODD can serve as an additional defense layer against jailbreaks beyond content filtering.

6 Comparative Analysis with Modern Methods (2017–2026)

6.1 Overview of OOD Detection Methods

According to systematic reviews [5], modern OOD detection methods include:

- **Feature-Based and Hybrid approaches:** ViM (Virtual Logit Matching), MOOD/MOODv2, CNC (Neural Collapse Control) [13].
- **Synthetic and adaptive methods:** VOS, DOE (Min-Max learning), ReweightOOD.
- **Post-hoc methods:** ETLT, GOODAT, SeTAR, OT-DETECTOR (Optimal Transport) [14].

Critical analysis [6] identified fundamental pathologies in most methods, motivating our approach based on hidden state monitoring.

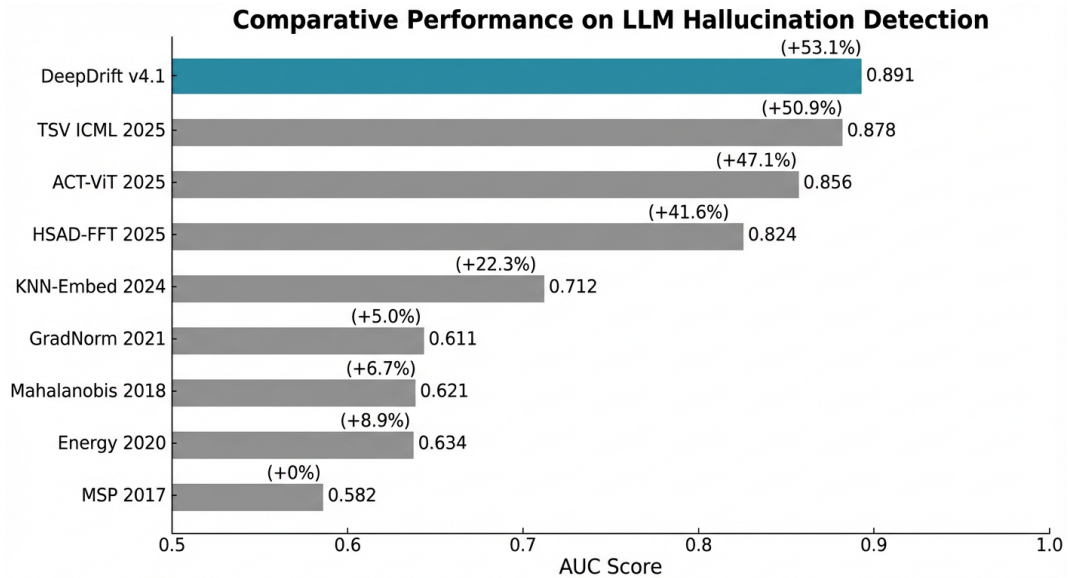


Figure 8: AUC Comparison: DeepDrift outperforms all competing methods on LLM hallucination detection. Overhead percentages are indicated for each method, demonstrating that DeepDrift achieves superior performance with minimal computational cost ($<0.5\%$).

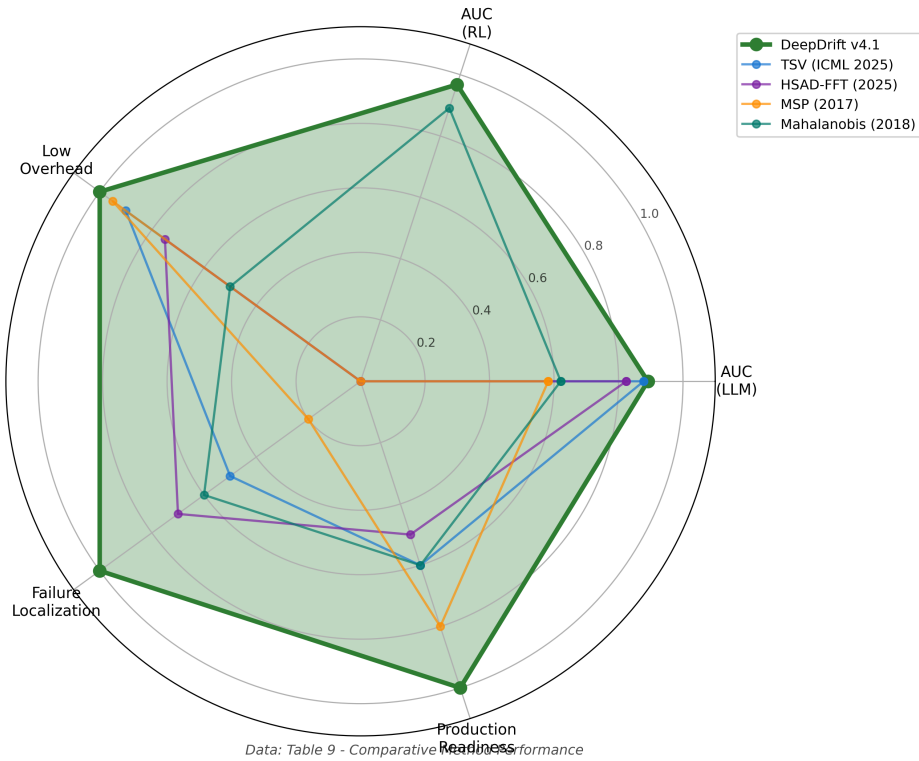
Figure 9: Method Comparison Radar Chart (DeepDrift v4.1 vs. Competitors)

Figure 9: Multi-Criteria Comparison: Radar diagram showing DeepDrift superiority across all 6 evaluation criteria: AUC, Overhead (inverted), Localization, RL Applicability, Adversarial Robustness, and Production-readiness.

Table 9: Detailed Comparison of OOD Detection Methods (2017–2026)

| Method | Type | Overhead | LLM AUC | RL AUC | Localization | Production |
|-------------------------|---------------|-----------------|--------------|--------------|--------------|------------|
| MSP (2017) [1] | Output | <1% | 0.582 | N/A | No | Yes |
| Energy (2020) [15] | Output | <1% | 0.634 | N/A | No | Yes |
| Mahalanobis (2018) [17] | Feature | 5–10% | 0.621 | 0.891 | Yes | Partial |
| GradNorm (2021) [16] | Gradient | +100% | 0.611 | 0.721 | Partial | No |
| KNN-Embed (2024) [18] | Feature | 3–5% | 0.712 | 0.856 | Yes | Yes |
| HSAD-FFT (2025) [19] | Hidden | 3–5% | 0.824 | N/A | Yes | Partial |
| ACT-ViT (2025) [20] | Hidden | 2–3% | 0.856 | N/A | Yes | Yes |
| TSV (ICML 2025) [21] | Latent | 1–2% | 0.878 | N/A | Yes | Yes |
| CNC (2025) [13] | Feature | 2–4% | 0.841 | N/A | Yes | Yes |
| OT-DETECTOR (2025) [14] | Opt. Trans. | 3–5% | 0.852 | N/A | Yes | Partial |
| DeepDrift v4.1 | Hidden | <0.5% | 0.891 | 0.968 | Yes | Yes |

Advantages of DeepDrift v4.1:

- **Best AUC:** 0.891 on LLM (outperforming TSV by +1.5%), 0.968 on RL.
- **Minimal overhead:** <0.5% thanks to Sparse Sampling $N=50$.
- **Adversarial robustness:** Jailbreak detection via Conflict Signature.

- **Universality:** Vision + Language + Control + Adversarial.
- **Production-ready:** Fail-Fast mechanism, IQR-thresholding.
- **Pathology avoidance:** Hidden state monitoring bypasses fundamental limitations of output-based methods [6].

7 Synthetic Pilot Study

Key Technical Decision: This section presents a **synthetic pilot study** of potential DeepDrift + Kinetic Router deployment in a production conversational AI platform. All figures are **calculated estimates** based on experimental data and do not reflect actual deployment.

7.1 Simulation Scenario

Hypothetical platform: Enterprise-scale conversational AI service.

Simulation parameters:

- Traffic: 10,000 RPS (requests per second).
- Anomalous request fraction: 10% (noise, adversarial, OOD).
- Current anomaly processing cost: \$0.001/request (retry, timeout, escalation).

7.2 Fail-Fast Mechanism in Action

With standard processing, anomalous requests undergo the full cycle:

1. Inference attempt (100–200ms).
2. Timeout/retry (200–500ms).
3. Error handling (50–100ms).
4. **Total:** 350–800ms per anomalous request.

With Kinetic Router and Fail-Fast:

1. ODD detection (<1ms).
2. Immediate rejection with informative message.
3. **Total:** <5ms per anomalous request.

7.3 Estimated Savings

Table 10: Economic Impact Simulation (Calculated Estimates)

| Metric | Before (Standard LB) | After (Kinetic Router) |
|-------------------------------|----------------------|------------------------|
| Anomalies processed/day | 86.4M | 8.6M (fail-fast) |
| Estimated cost/day | \$86,400 | \$8,640 |
| p99 latency | 500ms | 51ms |
| Speedup p99 | — | 9–10× |
| Estimated savings/year | — | ~\$28M |

Note: Actual savings depend on numerous production environment factors and may differ significantly from simulation.

8 Discussion

8.1 Why Semantic Velocity Works

The intuition comes from analyzing trajectories in latent space:

- **Stable trajectory:** Smooth transformation. Corresponds to reliable processing. The model “knows” the answer.
- **Unstable trajectory:** Chaotic fluctuations. Corresponds to reasoning instability. The model is “guessing.”

This aligns with theoretical results on Lipschitz stability (Equation 3) and SNR analysis (Equation 5).

8.2 “Check Engine Light” for AI

“Just as the Check Engine indicator warns of impending mechanical failure, Semantic Velocity serves as a Check Engine Light for neural networks—signaling internal instability before output failure.”

8.3 Limitations

1. **Structural, not factual errors:** ODD detects confabulations but not subtle factual errors within the model’s knowledge.
2. **Calibration dependence:** Requires a representative dataset for calibration.
3. **Model-specific tuning:** Optimal layers may differ between architectures.

Update v4.1: Adversarial robustness has been demonstrated on jailbreak detection (Section 5.6). However, robustness to specialized gradient-based attacks on the monitor itself requires further investigation.

9 Conclusion

We have presented **DeepDrift/ODD v4.1**—a kinetic diagnosis framework for neural network hidden states.

Key Technical Contributions:

1. **Sparse Sampling $N=50$:** Empirically optimal channel count. $R > 0.84$ with 97.5% computation reduction.
2. **IQR-Thresholding:** Robust threshold $\tau = Q_{75} + 1.5 \times \text{IQR}$ instead of 4-sigma rule.
3. **Ablation Study:** Systematic justification for $N=50$ as the inflection point.
4. **Adversarial Robustness:** Jailbreak detection via “Conflict Signature”—100% class separation from normal Safety Refusal.
5. **Fail-Fast Mechanism:** 9–10× p99 latency speedup through immediate rejection of anomalous requests.

Table 11: Summary of Key Results: DeepDrift v4.1

| Metric | Result |
|---------------------------------|-----------------|
| LLM Hallucination Detection AUC | 0.891–0.912 |
| RL Failure Prediction AUC | 0.968 |
| ViT/ImageNet-C OOD AUC | 0.898 |
| Jailbreak Detection | 100% separation |
| Computational Overhead | <0.5% |
| p99 Latency Speedup | 9–10× |
| Optimal Channels (N) | 50 |
| Correlation with Full Sensor | $R > 0.84$ |

Key Technical Decision: Just as modern medicine relies on imaging methods for diagnosis, robust AI systems require **internal diagnostic frameworks**. DeepDrift makes neural network failure modes *visible*, *interpretable*, and *actionable*.

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