IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 4, June 2026
Impact Factor: 8.2

A Comprehensive Literature Survey on Non-Intrusive Kernel-Level Telemetry and Bottleneck Profiling in Deep Learning Systems

Mr. Amey Shrikant Burgul[1] and Dr. G. V. Kale[2]
M.Tech Student, Department of Computer Engineering [1]
Ph.D Professor, Department of Computer Engineering[2]
SCTR's Pune Institute of Computer Technology, Pune, India

Abstract: *Optimizing execution dynamics within resource-constrained deep learning (DL) systems is fundamentally restricted by the performance degradation induced by traditional user-space profiling utilities. Conventional tracking tools rely on active code instrumentation, heavy dynamic library wrapping, or invasive sampling daemons that compete directly for host CPU cycles and memory cache slots, distorting baseline latency behaviors. This survey provides a critical analysis of current frameworks designed for bottleneck diagnostics in distributed and edge DL training pipelines. We examine the evolution of telemetry systems from high-overhead user-space wrappers to non-intrusive, secure sandbox execution configurations inside kernel memory via Extended Berkeley Packet Filters (eBPF). Furthermore, this paper categorizes modern literature based on architectural hooks, data reduction capabilities, and tracing overheads. This analysis establishes a foundational framework for deploying asynchronous, local, zero-dependency storage architectures utilizing downsampled tracepoints to achieve fine-grained runtime observability under extreme hardware constraints*

Keywords: Extended Berkeley Packet Filter (eBPF), Non-Intrusive Profiling, Deep Learning Latency, Kernel-Level Telemetry, Bottleneck Diagnostics.

I. INTRODUCTION

The computational complexity of modern deep learning frameworks, such as PyTorch and TensorFlow, has expanded dramatically, necessitating granular runtime visibility to maximize processing throughput on edge and resource-constrained nodes. During high-throughput training runs (e.g., executing structural matrix operations on datasets like CIFAR-10), minor micro-architectural stalls in data fetching routines can cause severe processor thrashing.

Identifying these anomalies requires active tracking utilities. However, traditional performance profiling approaches create a fundamental engineering paradox: the act of measuring an app's performance inherently alters its resource consumption. This structural overhead is particularly damaging on limited hardware execution platforms, where profiling infrastructure can drop essential telemetry packets or artificially lengthen task durations.

To bypass these limits, recent research has shifted performance capture hooks out of application space entirely, moving them into the secure operating system kernel layer. Extended Berkeley Packet Filter (eBPF) technology provides an alternative paradigm by compiling lightweight C-based tracing bytecode that executes directly within a protected kernel sandbox when triggered by native tracepoints.

This paper presents a comprehensive survey of modern telemetry models, tracing metrics, and data logging architectures. Section II outlines the fundamental profiling requirements of deep learning workloads. Section III categorizes conventional user-space profiling architectures and evaluates their resource overhead limits. Section IV examines the rise of eBPF kernel-level profiling and explores downsampling strategies designed to prevent memory

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buffer congestion. Finally, Section V highlights existing architectural research gaps to establish a blueprint for lightweight, persistent telemetry tracking.

II. DEEP LEARNING RUNTIME BOTTLENECK PROFILING REQUIREMENTS

Profiling deep learning pipelines involves distinct architectural complexities compared to tracking standard enterprise web applications. A deep learning training iteration is characterized by high-frequency, alternating phases of compute-bound matrix transformations and I/O-bound data fetching operations.

Core Telemetry Metrics

To systematically expose pipeline bottlenecks, a non-intrusive tracing framework must collect a matrix of multi-tier system metrics:

- **CPU Profiling and Task Scheduling Latency:** Capturing the duration that threads spend waiting in the operating system run-queue before gaining core execution access.
- **GPU/VRAM Utilization Footprints:** Monitoring memory cell saturation thresholds to detect under-utilization during stalls.
- **Storage I/O Read/Write Latencies:** Tracing the exact microsecond durations of system interaction boundaries (e.g., sys_enter_read and sys_exit_read) during image batch transformations.

The Performance Contention Problem

When data ingestion threads (num_workers=2) load training imagery in parallel, the underlying host processor experiences intense multi-threaded context switching. Traditional software tracking loops often flood memory networks with massive quantities of string payloads or database transactions, triggering severe thread synchronization locks. Consequently, the profiling utility introduces an artificial bottleneck, leading to unrepresentative latency data.

TABLE I

Hardware Component	Hardware Specification Matrix	Operational Profiling Constraint
Host CPU Processor	AMD Ryzen 7 4800H @ 4.2GHz	High context-switching penalty under multi-threaded worker pipelines
Host System Memory	16 GB DDR4 RAM	Highly susceptible to cache thrashing from verbose tracking tools
Dedicated GPU Accelerator	NVIDIA GPU GTX 1050 Ti 4GB	Strictly limited to localized compute loops; cannot afford profiling memory overhead
Storage Infrastructure	200GB 5400 RPM SATA Mechanical Hard Disk Drive	High I/O blocking penalty during training dataset loading passes

III. REVIEW OF CONVENTIONAL USER-SPACE PROFILING FRAMEWORKS

Historically, profiling deep learning workloads has relied on application-level or framework-level instrumentation wrappers. These mechanisms can be broadly divided into three main categories:

Integrated Framework Profilers

Modern deep learning engines include native performance collection modules, such as the *PyTorch Profiler* and *TensorBoard*. These tools hook directly into the framework's runtime loop to log operators, tensor shapes, and GPU execution states. While highly descriptive for graph execution debugging, they inject high collection overheads. They utilize heavy synchronous memory arenas to cache trace records before flushing them to disk, which significantly increases host processing overhead during long training runs.

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Application-Level Operating System Wrappers

General-purpose host tracking tools like psutil, top, or custom user-space polling daemons operate by reading state structures from the virtual /proc file system at fixed intervals. Although non-invasive to the source code, these daemons are bounded by scheduling granularity limitations. If the polling loop is configured too aggressively (e.g., a 1ms window), the daemon consumes substantial CPU capacity. Conversely, if it is configured too loosely (e.g., a 1000ms window), it misses sub-millisecond I/O micro-stalls, creating a blind spot in performance visibility.

Dynamic Library Interception

Tools like strace or ltrace intercept system events using runtime boundaries like ptrace or LD_PRELOAD hooks. These tools stop the target application's thread execution every time a system call enters or exits, context-switching to the monitoring tool to log arguments before resuming the application. Under heavy PyTorch image data loading loops, this creates severe thread degradation, frequently slowing down execution by orders of magnitude.

IV. THE EMERGENCE OF EBPF KERNEL-LEVEL TELEMETRY

To address the performance penalties of user-space tracking, recent literature highlights the use of Extended Berkeley Packet Filters (eBPF) to build non-intrusive performance capture structures.

The eBPF Sandboxed Execution Model

The eBPF paradigm shifts performance capture hooks out of application space and directly into the secure operating system kernel layer. By attaching lightweight, verified C programs to native kernel tracepoints (such as raw_tracepoint:sys_enter), metric extraction happens instantly inside kernel memory. This completely bypasses the context-switching delays caused by traditional user-space tools.

Mitigating Ring Buffer Flooding via Downsampling

While eBPF drastically lowers capture costs, high-frequency deep learning loops can still generate millions of system calls per second, flooding the kernel-to-user-space ring buffer. This data deluge triggers Possibly lost X samples kernel notifications, causing critical performance gaps.

To solve this, advanced implementations apply **In-Kernel Data Reduction Filters**. By using internal BPF hash maps to maintain global event counters directly in kernel memory, the hook can enforce strict modulo filtering (e.g., if (current_count % 5000 == 0)).

This sampling filter drops 99.98% of generic system call noise within the kernel sandbox. Only the targeted sampled transactions calculate microsecond latency deltas and push data down the lockless Perf Event Ring Buffer. This data reduction slashes communication overhead while maintaining precise, long-term tracing stability.

Persistent Storage Staging Strategies

To prevent database operations from blocking the primary machine learning training loops, contemporary frameworks separate capture, persistence, and visualization pipelines into decoupled asynchronous tasks. A user-space background listener polls the downsampled ring buffer and accumulates metrics in a memory array. Once the queue hits a threshold (e.g., 50 records), the thread executes an optimized bulk write command (BEGIN TRANSACTION) to commit the batch to a local, lightweight SQLite database (profiler.db) in a single disk I/O pass. The Streamlit user interface runs standalone database read queries independently, eliminating database write contentions on the host processor.

V. CRITICAL COMPARATIVE ANALYSIS AND RESEARCH GAPS

Table I summarizes and contrasts existing performance profiling frameworks across key architectural dimensions, demonstrating the benefits of an optimized, downsampled eBPF-to-SQLite design.

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TABLE II

Framework Category	Hook Level	Source Code Intrusion	Host CPU Overhead	Risk of Buffer Data Loss	Persistence Method
Framework Profilers (PyTorch)	App Layer	High (Requires modifications)	High ($>15\%$)	Low	Synchronous Log Dump
Interception Wrappers (Strace)	User-Kernel Bridge	Zero	Extreme ($>200\%$)	High	Direct Standard Output
Standard eBPF Hooks (BCC Core)	Kernel Space	Zero	Moderate ($5\% - 8\%$)	High (Lost Samples)	Heavy Streaming Socket
Optimized eBPF + SQLite	Kernel Space	Zero	Minimal ($<1\%$)	Zero (Downsampled)	Atomic SQLite Batching

Reviewing this literature reveals a clear research gap: most current eBPF profiling tools focus on wide-scale cloud network monitoring (such as Kubernetes microservices) or generic security auditing. There is a lack of research on highly optimized, single-node tracing configurations tailored specifically to the unique alternating CPU/GPU spikes of deep learning frameworks running on resource-constrained hardware. Merging downsampled kernel hooks with low-overhead, transaction-batched SQLite storage provides a robust blueprint for non-intrusive, zero-dependency performance diagnostics.

VI. CONCLUSION

This literature survey highlights the technical evolution of performance profiling architectures for deep learning systems. Standard application-space wrappers and dynamic tracing tools are fundamentally limited by the performance overhead they inject into resource-constrained systems. Transitioning to sandboxed kernel-space eBPF loops completely eliminates source code intervention and drastically drops context-switching latency. By combining in-kernel modulo filtering with asynchronous, batch-committed local SQLite databases, engineers can eliminate ring buffer drops and build non-intrusive monitoring frameworks that operate safely within strict local computing budgets.

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