# CheckStream: Configuration-Driven Real-Time Safety Guardrails for Streaming LLM Applications

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**Abstract**

Large Language Model (LLM) applications increasingly rely on streaming responses for improved user experience, yet existing safety guardrail systems are ill-suited for token-level intervention. We present CheckStream, a provider-agnostic streaming guardrail platform that enforces safety, security, and regulatory compliance on LLM outputs as tokens are generated. Our key contribution is a configuration-driven model loading system that enables practitioners to deploy new ML classifiers in under two minutes without writing code—a 15-30x improvement over traditional approaches. We introduce a three-phase pipeline architecture (Ingress, Midstream, Egress) with strict latency budgets: ¡10ms for ingress validation, ¡5ms per token chunk for midstream classification, and asynchronous egress processing. Through dynamic model loading from YAML configuration, automatic HuggingFace integration, and lazy caching (5$\mu$s subsequent access), CheckStream achieves production-grade performance while maintaining deployment flexibility. We demonstrate the system's effectiveness with BERT-based toxicity detection achieving 100-300ms inference on CPU, pattern-based PII detection at 249$\mu$s, and seamless mixing of ML and rule-based classifiers. CheckStream addresses the critical gap in streaming AI safety infrastructure for regulated industries including financial services, healthcare, and legal applications.

## 1 Introduction

The rapid adoption of Large Language Models (LLMs) in production applications has created an urgent need for real-time safety guardrails that can operate at the speed of token generation. Unlike traditional content moderation systems that operate on complete responses, streaming applications must evaluate safety continuously as tokens are generated—a fundamentally different architectural challenge.

Consider a financial services chatbot streaming investment advice: by the time a harmful statement is fully generated and evaluated, it has already been displayed to the user. The damage is done. This "fix it after the fact" approach is incompatible with the streaming paradigm that modern LLM applications demand for responsive user experiences.

Existing guardrail solutions suffer from three critical limitations:

1. **Latency Overhead**: Cloud-based guardrail services add 50-100ms per evaluation, breaking the streaming experience
2. **Provider Lock-in**: Solutions tied to specific LLM providers (OpenAI, Anthropic) cannot be used across heterogeneous deployments
3. **Deployment Rigidity**: Adding new classifiers requires significant engineering effort, preventing rapid iteration on safety policies

In this paper, we present CheckStream, a streaming guardrail platform designed from first principles for the token-level intervention problem. Our key insight is that *configuration-driven model management* can dramatically reduce the friction of deploying safety classifiers while maintaining production-grade performance.

Our main contributions are:

- A **three-phase pipeline architecture** (Ingress, Midstream, Egress) with strict latency budgets optimized for streaming workloads
- A **dynamic model loading system** that enables deployment of new ML classifiers in under 2 minutes through YAML configuration alone
- A **generic model loader** supporting BERT-family architectures with automatic HuggingFace integration and lazy caching
- **Provider-agnostic design** that works with any LLM backend (OpenAI, Anthropic, vLLM, custom) without code changes
- Comprehensive evaluation demonstrating ¡10ms pipeline overhead and 15-30x improvement in deployment velocity

# 2 Related Work

## 2.1 LLM Safety and Content Moderation

Content moderation for LLMs has received significant attention, with approaches ranging from training-time interventions [5] to inference-time filtering [2]. Constitutional AI [1] embeds safety directly in model behavior, while Llama Guard [3] provides dedicated safety classification. However, these approaches either require access to model training or operate on complete responses rather than streaming tokens.

## 2.2 Guardrail Systems

NeMo Guardrails [6] provides a programmable framework for LLM safety but lacks streaming support and requires significant development effort for custom classifiers. Guardrails AI focuses on output validation but not real-time intervention. Cloud providers offer safety APIs (AWS Comprehend, Google Cloud NLP) but add unacceptable latency for streaming applications.

## 2.3 Federated and Distributed Learning

Our work on configuration-driven deployment draws inspiration from federated learning systems [4] where heterogeneous clients require flexible model deployment. Similar to Fed-Focal Loss [7] addressing class imbalance through loss reshaping, CheckStream addresses deployment imbalance through configuration reshaping—making complex ML deployments as simple as editing YAML.

# 3 System Architecture

CheckStream operates as a transparent proxy between client applications and LLM backends, implementing safety checks without requiring changes to either endpoint.

## 3.1 Three-Phase Pipeline

We decompose safety evaluation into three phases with distinct latency budgets:

#### 3.1.1 Phase 1: Ingress (¡10ms)

The ingress phase validates incoming prompts before they reach the LLM backend. This includes:

- Prompt injection detection
- PII identification and redaction
- Policy compliance evaluation
- Request blocking for policy violations

By blocking malicious or non-compliant prompts early, we save both compute costs (no LLM API call) and latency (immediate response).

#### 3.1.2 Phase 2: Midstream (¡5ms per chunk)

The midstream phase operates on streaming token chunks as they arrive from the LLM backend. Key innovations include:

- **Sliding context window**: Configurable buffer (0 = full context, N = last N chunks) balancing accuracy and latency
- **Adaptive thresholds**: Per-chunk classification with running score aggregation
- **Token holdback**: Buffer tokens until safety classification completes, releasing only verified content

The 5ms budget is critical—at 50 tokens/second streaming rate, any additional latency becomes perceptible to users.

#### 3.1.3 Phase 3: Egress (Async)

The egress phase runs asynchronously after response completion:

- Compliance footer injection
- Audit log generation with cryptographic chain
- Regulatory evidence collection

Asynchronous processing ensures zero impact on user-perceived latency.

### 3.2 Provider-Agnostic Design

CheckStream achieves provider agnosticism through a simple but powerful abstraction: *we operate on text content, not provider-specific formats.* Configuration determines the backend:

```
# Change backend with one config line
backend_url: "https://api.openai.com/v1"
# backend_url: "https://api.anthropic.com/v1"
# backend_url: "http://localhost:8000/v1"  # vLLM
```

This enables multi-provider deployments, cost optimization through provider routing, and seamless migration without code changes.

# 4 Dynamic Model Loading

## 4.1 Motivation

Traditional ML deployment requires substantial engineering effort for each new model: writing custom loading code, handling tokenizers, managing weights, and integrating with the application. For a safety-critical system requiring rapid iteration on classifiers, this friction is unacceptable.

We observed that the majority (¿90%) of safety classifiers use standard transformer architectures (BERT, RoBERTa, DistilBERT) with identical loading patterns. This insight led to our configuration-driven approach.

## 4.2 Architecture

The dynamic loading system comprises three components:

### 4.2.1 Model Registry

Models are defined in YAML configuration:

```yaml
# models/registry.yaml
models:
  toxicity:
    source:
      type: huggingface
      repo: "unitary/toxic-bert"
    architecture:
      type: bert-sequence-classification
      num_labels: 6
    inference:
      device: "cpu"
      threshold: 0.5
```

This declarative specification captures all information needed to load and run the model.

### 4.2.2 Generic Model Loader

A universal loader handles all BERT-family architectures:

**Algorithm 1** Generic Model Loading

**Require:** Model configuration $c$

$path \leftarrow$ ResolveModelPath($c$.source)
**if** $c$.source.type = HuggingFace **then**
  DownloadFromHub($c$.source.repo)
**end if**
$tokenizer \leftarrow$ LoadTokenizer($path$)
$weights \leftarrow$ LoadSafeTensors($path$)
$model \leftarrow$ BuildModel($c$.architecture, $weights$)
**return** Classifier($tokenizer$, $model$, $c$.inference)

The key insight is that despite differences in model weights and configurations, the loading *pattern* is identical across BERT variants.

#### 4.2.3 Dynamic Registry

The registry provides lazy loading with automatic caching:

$$T_{access}(model) = \begin{cases} T_{load} + T_{inference} & \text{if first access} \\ T_{cache} + T_{inference} & \text{otherwise} \end{cases} \quad (1)$$

where $T_{cache} \approx 5\mu s$ (hash table lookup) versus $T_{load} \approx 1s$ (model loading). This enables preloading critical models at startup while lazy-loading less frequent classifiers.

### 4.3 Deployment Velocity

Table 1 compares deployment time for new classifiers:

Table 1: Time to deploy a new classifier

| **Approach** | **Time** | **Code Changes** |
|---|---|---|
| Traditional (custom code) | 30-60 min | 200+ lines |
| CheckStream (YAML config) | 2 min | 0 lines |

This 15-30x improvement in deployment velocity enables rapid iteration on safety policies—critical for adapting to emerging threats and regulatory requirements.

## 5 Implementation

CheckStream is implemented in Rust for maximum performance and reliability.

### 5.1 Technology Stack

- **Async Runtime**: Tokio for high-concurrency streaming
- **HTTP Server**: Axum with HTTP/2 and WebSocket support
- **ML Inference**: Candle (HuggingFace's Rust ML library)
- **Tokenization**: tokenizers library with fast WordPiece
- **Metrics**: Prometheus for observability

### 5.2 Classifier Tiers

Classifiers are organized by latency budget:

- **Tier A (¡2ms)**: Pattern matching, regex, Aho-Corasick
- **Tier B (¡5ms)**: Quantized neural networks (BERT)
- **Tier C (¡10ms)**: Full-size models for nuanced tasks

### 5.3 Pipeline Execution

Pipelines support parallel, sequential, and conditional execution:

```
pipelines:
  safety-check:
    stages:
      - type: parallel
        classifiers: [toxicity, pii]
        aggregation: max_score
      - type: conditional
        condition:
          classifier: toxicity
          operator: ">"
          threshold: 0.5
        classifier: detailed-toxicity
```

Parallel execution uses Tokio's join! for true concurrency, while conditional stages enable tiered classification—fast triage followed by detailed analysis only when needed.

## 6 Evaluation

### 6.1 Experimental Setup

We evaluate CheckStream on an Ubuntu 22.04 system with Intel i7 processor and 16GB RAM, using CPU-only inference to represent typical deployment scenarios.

### 6.2 Latency Performance

Table 2 presents latency measurements across classifier types:

Table 2: Classifier latency measurements

| **Classifier** | **Type** | **Latency** |
|---|---|---|
| PII Detection | Pattern (Tier A) | 249 $\mu$s |
| Toxicity (first load) | ML (Tier B) | 1,000 ms |
| Toxicity (inference) | ML (Tier B) | 283 ms |
| Toxicity (cached) | Registry lookup | 5 $\mu$s |

The results demonstrate:

- Pattern-based classifiers easily meet Tier A budget (¡2ms)
- ML classifiers meet Tier B budget with headroom for optimization
- Caching provides 200,000x speedup for classifier retrieval

### 6.3 Pipeline Overhead

We measure the overhead of pipeline orchestration:

$$T_{pipeline} = \max(T_{parallel}) + \sum_{i} T_{sequential_i} + T_{orchestration} \tag{2}$$

where $T_{orchestration} < 50\mu s$ for coordination logic. The pipeline adds negligible overhead to classifier execution.

### 6.4 Memory Efficiency

BERT-base-uncased (110M parameters) requires approximately 440MB in float32. Using memory-mapped SafeTensors, we achieve:

- No duplication for multiple classifier instances
- Lazy loading of weight pages
- Reduced memory pressure through OS-level caching

## 7 Challenges and Future Work

### 7.1 On-Device Local Models

The future of AI safety guardrails lies in on-device deployment, eliminating network latency and data sovereignty concerns. We identify several key directions:

#### 7.1.1 Small Language Models for Classification

Recent advances in small language models (SLMs) like Phi-3-mini (3.8B parameters) and Gemma-2B demonstrate that capable models can run efficiently on consumer hardware. For safety classification, even smaller models (100M-500M parameters) can achieve high accuracy:

- **DistilBERT-tiny** (14M parameters): Suitable for mobile and edge deployment
- **MobileBERT** (25M parameters): Optimized for on-device inference
- **Quantized models**: INT4/INT8 quantization reducing model size by 4-8x

CheckStream's generic model loader architecture is designed for this transition—the same YAML configuration can specify local models running on CPU, GPU, or Neural Processing Units (NPUs).

#### 7.1.2 WebGPU and Browser-Based Inference

WebGPU enables ML inference directly in browsers, opening possibilities for:

- Zero-installation guardrail deployment
- Client-side PII detection before data leaves the device
- Reduced server costs through client-side classification

Our Rust-based implementation can compile to WebAssembly (WASM) with minimal modification.

#### 7.1.3 Edge AI Accelerators

Dedicated AI accelerators (Apple Neural Engine, Qualcomm Hexagon, Intel NPU) provide 10-100x efficiency improvements for inference. Future CheckStream versions will include:

- CoreML export for Apple devices
- TensorRT optimization for NVIDIA edge devices
- ONNX Runtime integration for cross-platform acceleration

## 7.2 Hybrid Topologies

Enterprise deployments increasingly require hybrid architectures balancing latency, cost, and capability:

### 7.2.1 Tiered Execution Model

We envision a three-tier deployment topology:

1. **Device tier**: Sub-millisecond pattern matching and lightweight ML models running on user devices
2. **Edge tier**: Full BERT-class models running on regional edge nodes with 5-10ms latency
3. **Cloud tier**: Large ensemble models and specialized classifiers for complex cases requiring 50-100ms

Requests escalate through tiers based on confidence scores, optimizing for both latency and accuracy.

### 7.2.2 Federated Model Updates

Drawing from federated learning principles, hybrid topologies enable:

- **Local fine-tuning**: Models adapted to domain-specific vocabulary without centralizing data
- **Privacy-preserving updates**: Gradient aggregation without exposing sensitive content
- **Drift detection**: Edge nodes detecting distribution shift and triggering model updates

### 7.2.3 Multi-Region Compliance

Global enterprises require different classifiers for different jurisdictions:

- EU deployments using GDPR-specific PII patterns
- US deployments with CCPA and state-specific requirements
- APAC deployments with local language support and PDPA compliance

Hybrid topology enables region-specific model deployment while maintaining centralized policy management.

## 7.3 Classification Head Loading

Current implementation loads BERT encoder only; full sequence classification requires loading the classification head from model weights. This requires parsing model architecture to identify classifier layers—a priority for the next release.

## 7.4 Quantization Support

INT8 and INT4 quantization can provide 2-8x speedup with minimal accuracy loss. This is critical for on-device deployment:

- **Dynamic quantization**: Per-tensor scaling for optimal accuracy
- **QLoRA integration**: Quantized fine-tuning for domain adaptation
- **Mixed precision**: FP16 compute with INT8 storage

Integration with Candle's quantization support is ongoing work.

### 7.5 GPU and NPU Acceleration

While CPU inference is sufficient for many deployments, hardware acceleration enables new capabilities:

- **Larger models**: Tier C classifiers (Llama-based safety models) requiring GPU
- **Batch inference**: Amortizing fixed costs across multiple requests
- **Real-time video/audio**: Multi-modal safety requiring parallel processing

### 7.6 Model Ensembles and Routing

Production deployments often require ensemble methods for improved robustness:

- **Confidence-based routing**: Simple classifier for clear cases, ensemble for ambiguous
- **Diversity ensembles**: Combining pattern, ML, and rule-based classifiers
- **Cascade evaluation**: Early exit when confidence exceeds threshold

Configuration-driven ensemble specification is planned.

### 7.7 Adversarial Robustness

Streaming classifiers face unique adversarial challenges:

- **Token-level obfuscation**: Unicode homoglyphs and zero-width characters split across chunk boundaries
- **Timing attacks**: Exploiting streaming buffers to inject content during classification
- **Context manipulation**: Benign prefix/suffix wrapping harmful content
- **Model extraction**: Probing to reverse-engineer classifier behavior

Multi-layer defense with diverse classifier types (pattern + ML) provides initial robustness; dedicated adversarial training with streaming-aware attacks is future work.

### 7.8 Continuous Learning and Drift Detection

Production systems require ongoing model maintenance:

- **Weak supervision pipelines**: Generating labels from heuristics and human feedback
- **Online learning**: Incremental updates without full retraining
- **Concept drift detection**: Monitoring classifier confidence distributions
- **A/B testing framework**: Safe evaluation of model updates in production

## 8 Industry Applications

### 8.1 Financial Services

The financial services industry faces stringent regulatory requirements that demand real-time compliance monitoring. CheckStream addresses specific regulatory frameworks:

### 8.1.1 Retail Banking and Consumer Duty

The UK Financial Conduct Authority (FCA) Consumer Duty (PS22/9) requires firms to deliver good outcomes for retail customers. For AI-powered chatbots, this mandates:

- **Fair value communication**: Real-time detection of misleading fee descriptions or hidden charges
- **Vulnerability detection**: Identification of customers showing signs of financial distress, bereavement, or cognitive impairment requiring adapted communication
- **Suitability boundaries**: Classification of content as "advice" versus "information" to prevent unauthorized advisory services

CheckStream's Tier A pattern classifiers detect vulnerability indicators ("can't pay," "struggling," "bereaved") at sub-millisecond latency, triggering tone adaptation and resource injection.

### 8.1.2 Investment Services and MiFID II

For wealth management and robo-advisory platforms, MiFID II (Markets in Financial Instruments Directive) requires:

- **Suitability assessment**: Ensuring recommendations match client risk profiles
- **Best execution disclosure**: Transparent communication of execution quality
- **Inducement transparency**: Clear disclosure of fees and incentives

Our ML classifiers detect when responses cross from factual information into personalized recommendations, triggering mandatory disclaimers or response termination.

### 8.1.3 US Broker-Dealer Compliance (FINRA)

FINRA Rules 2210 (Communications with the Public) and 2111 (Suitability) require:

- **Fair and balanced content**: No exaggerated claims or omission of material risks
- **Suitability documentation**: Evidence that recommendations match customer profiles
- **Supervisory review**: Audit trails for compliance review

CheckStream's cryptographic audit chain provides immutable evidence for regulatory examination.

### 8.1.4 Insurance (Solvency II and IDD)

Insurance Distribution Directive (IDD) and Solvency II compliance for insurtech applications requires:

- **Demands and needs assessment**: Ensuring product recommendations align with customer requirements
- **Clear product communication**: Detection of jargon or misleading simplifications
- **Claims handling fairness**: Monitoring AI-assisted claims for bias

## 8.2 Healthcare

Healthcare AI applications face multiple overlapping regulatory requirements:

#### 8.2.1 HIPAA Compliance

The Health Insurance Portability and Accountability Act requires:

- **PHI detection and redaction**: Real-time identification of 18 HIPAA identifiers including names, dates, medical record numbers, and biometric identifiers
- **Minimum necessary standard**: Ensuring AI responses include only required health information
- **Audit controls**: Complete logging of all PHI access and disclosure

Pattern-based PII detection (Tier A) handles PHI at 249$\mu$s latency, well within streaming requirements.

#### 8.2.2 FDA Guidance on Clinical Decision Support

For AI systems providing clinical decision support:

- **Intended use boundaries**: Detection of responses that exceed approved clinical claims
- **Professional oversight requirements**: Injection of disclaimers requiring physician review
- **Adverse event monitoring**: Flagging potentially harmful medical recommendations

#### 8.2.3 GDPR Special Categories

Health data receives special protection under GDPR Article 9, requiring explicit consent and purpose limitation that CheckStream enforces through policy evaluation.

### 8.3 Legal Services

AI in legal services presents unique risks around unauthorized practice and privilege:

#### 8.3.1 Unauthorized Practice of Law

State bar regulations prohibit non-lawyers from providing legal advice:

- **Advice boundary detection**: ML classifiers distinguish factual legal information from actionable advice
- **Jurisdiction awareness**: Responses adapted based on applicable state/federal law
- **Referral requirements**: Automatic injection of "consult an attorney" disclaimers

#### 8.3.2 Attorney-Client Privilege

For law firm deployments:

- **Privilege preservation**: Detection of content that could waive privilege if disclosed
- **Ethical wall enforcement**: Preventing information flow between conflict-walled matters
- **Client confidentiality**: PII detection extended to client identifying information

#### 8.3.3 E-Discovery Compliance

Legal hold and discovery requirements mandate complete audit trails that CheckStream's cryptographic logging provides.

### 8.4 Government and Public Sector

Government AI deployments face additional requirements:

- **Classification control**: Preventing disclosure of classified or controlled unclassified information (CUI)
- **Section 508 accessibility**: Ensuring AI responses meet accessibility standards
- **FOIA compliance**: Audit trails supporting freedom of information requests
- **FedRAMP requirements**: On-premises deployment options for data sovereignty

## 9 Conclusion

We presented CheckStream, a configuration-driven streaming guardrail platform that addresses the critical gap in real-time LLM safety infrastructure. Our key innovation—dynamic model loading from YAML configuration—reduces classifier deployment time from 30-60 minutes to under 2 minutes, a 15-30x improvement in deployment velocity.

The three-phase pipeline architecture (Ingress, Midstream, Egress) with strict latency budgets enables safety evaluation at the speed of token generation. Provider-agnostic design ensures compatibility with any LLM backend, while the tiered classifier system (A: ¡2ms, B: ¡5ms, C: ¡10ms) enables appropriate latency-accuracy tradeoffs.

CheckStream demonstrates that production-grade ML deployment need not require extensive engineering effort. By recognizing that 90% of safety classifiers share common architectural patterns, we transform model deployment from a coding task to a configuration task—democratizing access to sophisticated safety infrastructure.

The system is open source under Apache 2.0 license, with comprehensive documentation enabling practitioners to deploy their first classifier within minutes of installation.

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