Rakshak

ENTERPRISE LOG ANOMALY DETECTION SYSTEM

log-anomaly-frontend.vercel.app

Krishna Sharma
AP22110010128

Introduction

Enterprise Log Anomaly Detection Platform: Production-grade AI system that identifies anomalies across diverse enterprise logs with real-time, high-precision detection.

Key Outcomes

- 88.5% F1-Score | 0.94 AUROC | 91.2% Balanced Accuracy
- <200ms inference latency across 16 log sources
- Handles extreme imbalance up to 249:1
- 32,000+ logs processed with cross-source generalization

Core Intelligence

- 848-dimensional hybrid features (BERT + templates + stats)
- 22 trained models (ML, DL, BERT, Meta, Federated)
- LOSO evaluation → robust cross-domain performance

Deployment Ready

- REST API (Django) + React UI + HuggingFace models
- Cloud-hosted (Render + Vercel) with real-time anomaly preview

Problem & Motivation

The Enterprise Log Challenge: Modern distributed systems generate millions of logs per day, across multiple sources, formats, and platforms. Hidden within them are rare but critical anomalies: breaches, failures, outages, misuse.

Core Pain Points

- Extreme class imbalance (as high as 249:1)
- Multi-source heterogeneity
- High-volume, real-time ingestion
- Unstructured & semi-structured patterns
- Evolving system behavior

Why Traditional Methods Fail

- Rule-based SIEMs require constant tuning and still miss novel events
- Standard ML assumes balanced data → overfits to “normal”
- Many systems cannot transfer learn across log sources
- Deep models without imbalance awareness spike false negatives

Motivation

To build a resilient, interpretable, real-time anomaly detection engine that:

- Handles severe imbalance without collapsing recall
- Generalizes across 16 distinct log environments
- Detects never-seen-before behaviors
- Delivers predictions within <200ms

Solution Overview

What This System Delivers: A production-grade anomaly detection platform that automates log intelligence, handles extreme imbalance, and scales to multi-source enterprise environments.

Core Capabilities

- Detects anomalies across 16 independent log ecosystems
- Learns semantic + structural patterns via BERT + templates + statistics
- <200ms real-time inference for streaming operational reliability

End-to-End Architecture

Raw Logs → Labeling → Processing → Feature Engineering → Models → Inference → UI

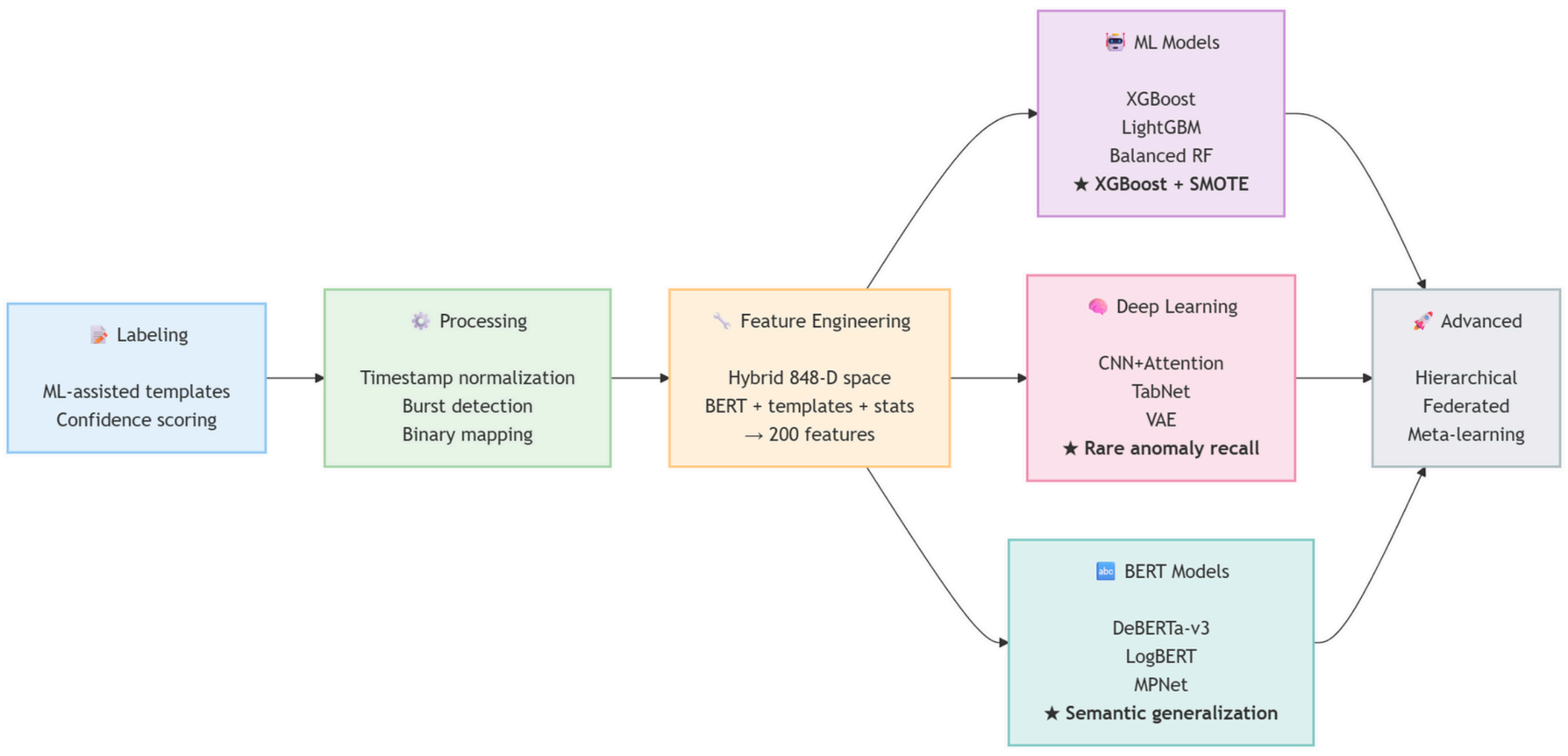
- Labeling: Smart ML-assisted template labeling
- Processing: Temporal & burst normalization for 16 sources
- Feature Engineering: 848-D hybrid representations (BERT, Drain, stats)
- Modeling: ML, DL, BERT, Federated, Hierarchical
- Deployment: Django REST API + React UI + Cloud serving

What Makes It Effective

- Cross-source generalization (LOSO): learns beyond single dataset boundaries
- Multi-level imbalance strategy: SMOTE + Focal Loss + threshold tuning
- Hybrid feature stack: semantic + structural + temporal insights
- Model ensemble strategy: choose best model per environment

Complete Pipeline Flow

Transforms raw logs into real-time anomaly decisions



Data Landscape

True anomalies are rare, hidden, and format-dependent—demanding a cross-source, imbalance-aware approach.

Multi-Source Enterprise Logs

- 32,000+ logs collected across 16 heterogeneous sources
- Formats include: Apache, Linux, Android, HDFS, OpenSSH, Hadoop, Spark, HealthApp, Cloud services

Diversity & Variability

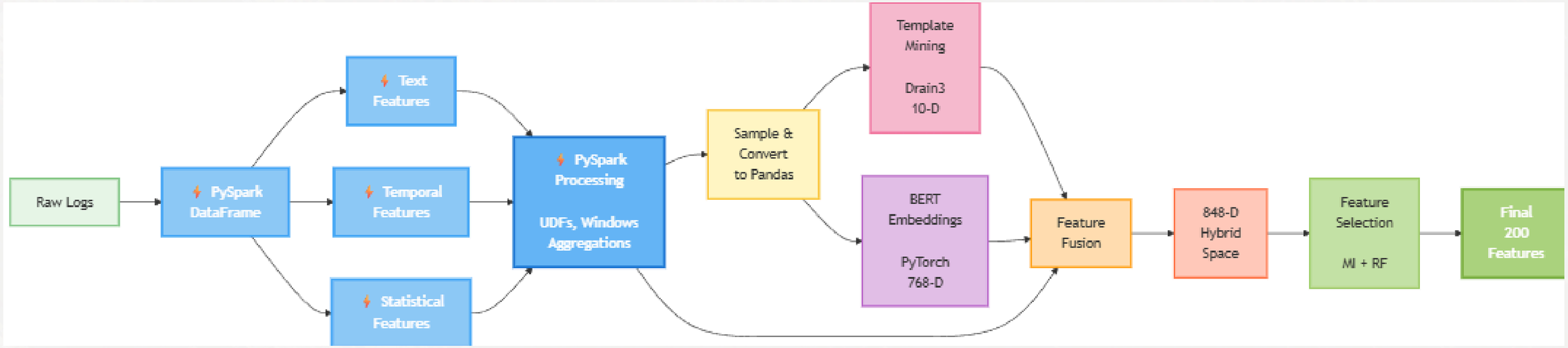
- Structured + semi-structured + free-text logs
- Varying grammar, templates, verbosity, timestamp styles
- Frequent out-of-vocabulary tokens (IP, UUID, HEX, PATH)

Severe Class Imbalance

- Anomalies often <1% of total
- Worst-case ratio: 249 : 1 (Spark, HealthApp)
- Standard classifiers collapse to “all normal” without correction

Feature Engineering

Distributed Feature Pipeline (PySpark + BERT): A scalable feature workflow transforming raw logs into a 200-feature anomaly-ready vector.



PySpark's Role

Parallel log processing + temporal bursts + statistical windows using UDFs & Window functions.

- Drain3 Templates (10-D) → structure patterns
- BERT Embeddings (768-D) → semantic meaning
- PySpark Features (~70+ signals) → bursts, entropy, frequency, off-hours
- MI + RF Selection → final 200 best features

Model Architecture Overview

Multi-stack system evaluated across 16 log sources for cross-domain robustness.

Category	Models	Purpose
ML	XGBoost, LightGBM, RF, SVM, Balanced RF, Easy Ensemble	Fast, production-grade baseline
DL	CNN+Attention, VAE, TabNet, FLNN	Handles imbalance, hidden patterns
BERT	LogBERT, DeBERTa-v3, MPNet, DAPT-BERT	Deep semantic log understanding
Advanced	Hierarchical Transformer, Federated Contrastive, Meta-Learner	Cross-source & few-shot generalization

Why Multi-Model?

- Diverse logs require both structural + semantic learners
- BERT captures intent, ML handles speed, DL absorbs imbalance
- Advanced models extend to new unseen log sources

Deployment Architecture

End-to-end real-time anomaly detection delivered through a modular web stack.

Frontend

React + Tailwind

- Live anomaly feed
- Confidence scoring
- Source auto-identification

Backend

Django REST API + HuggingFace Model Serving

- Fast inference routing
- JSON prediction endpoints
- Stateless microservice design

Cloud Hosting

- UI: Vercel
- API: Render
- Models: HuggingFace Inference Hub

Vercel

Render

Hugging Face

The End

THANK YOU FOR LISTENING

Krishna Sharma
AP22110010128