Log Analysis Leveraging Vector Database

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***Abstract*— Log data generated by distributed systems and applications contain critical insights for monitoring, debugging, and security auditing. Traditional log analysis approaches often rely on keyword matching or statistical summaries, which struggle to capture the semantic relationships and high-dimensional patterns inherent in large-scale, heterogeneous logs. In this work, we propose a general framework for log analysis that leverages vector databases to encode log entries into dense embeddings, enabling efficient similarity search, clustering, and anomaly detection. We first preprocess raw logs through tokenization and normalization before transforming them into embeddings using a pre-trained language model fine-tuned on domain-agnostic log corpora. These embeddings are indexed in a vector database optimized for low-latency nearest-neighbor queries. We demonstrate how this architecture supports real-time detection of anomalous sequences, root-cause investigation via semantic clustering, and adaptive alerting thresholds. Experimental evaluations on synthetic and public benchmark datasets show that our method achieves over 90% detection accuracy while reducing query latency by up to 70% compared to inverted-index alternatives. Finally, we discuss scalability considerations, integration strategies with existing observability pipelines, and directions for extending the framework to multimodal telemetry analysis.**

***Keywords*— Log Analysis; Vector Database; Embeddings; Anomaly Detection; Similarity Search; Semantic Clustering.**

I. Introduction

The rapid adoption of distributed architectures, microservices, and cloud-native platforms has resulted in a dramatic increase in the volume, velocity, and variety of log data, which are indispensable for observability, debugging, and security analysis [1], [2]. Conventional approaches—rooted in keyword searches, regular expressions, or inverted‑index mechanisms—often fail to capture the nuanced semantic relationships among log entries and cannot scale efficiently under real‑time constraints [3]. Meanwhile, advances in representation learning have enabled the encoding of textual logs into dense vector embeddings that preserve semantic similarity in high-dimensional spaces [4], [5]. When paired with vector databases optimized for approximate nearest-neighbor searches, these embeddings facilitate low-latency retrieval, enabling more effective anomaly detection, similarity-based grouping, and root-cause exploration [6], [7]. In this paper, we propose a general, extensible framework that (i) preprocesses and normalizes raw log streams, (ii) leverages a pre trained language model for embedding generation, and (iii) indexes embeddings in a vector database to support real-time similarity search, clustering, and anomaly detection. We validate our approach on multiple public benchmark datasets, demonstrating improvements of up to 15% in detection accuracy and reductions of up to 70% in query latency compared to traditional methods.

II. Related Work

In [1], Guan *et al.* introduce LogLLM, a novel approach to log-based anomaly detection leveraging large language models fine-tuned on extensive, domain-agnostic log corpora. They preprocess raw logs via tokenization and normalization before feeding them into a transformer-based model that learns contextual embeddings of log events. The system then employs semantic similarity measures to distinguish normal from anomalous patterns. Their evaluation on multiple benchmark datasets demonstrates that LogLLM achieves high recall and precision, outperforming traditional keyword‑based detectors by over 12%. The work highlights the efficacy of language models in capturing nuanced syntactic and semantic log relationships, but notes challenges in index scalability and real-time inference latency, motivating the integration of vector databases for efficient retrieval.

In study [2], Xie *et al.* propose LogGD, a graph‑neural‑network (GNN)–based framework for anomaly detection in system logs. They construct heterogeneous graphs where nodes represent log events and edges encode temporal or functional relationships. By applying graph convolutional layers over this structure, LogGD learns embeddings that capture both local and global log dependencies. During inference, anomalous nodes are identified by deviation scores derived from learned graph topology features. Experiments on real‑world server logs reveal that LogGD improves detection F1‑score by approximately 8% relative to sequence‑model baselines. This work underscores the importance of structural context in log analysis and suggests that embedding graphs into vector spaces can unearth anomalies undetectable by sequence‑only methods.

In paper [3], Pan *et al.* present RAGLog, a retrieval‑augmented generation framework for log anomaly detection that integrates a retrieval component with a generative language model. The retrieval module indexes historical log embeddings in a vector store, allowing the system to fetch semantically similar past events when a new log arrives. These retrieved logs are then concatenated with

the query log and passed into a generative transformer to predict anomaly likelihood. RAGLog demonstrates significant improvements in recall for rare anomaly types by leveraging contextual examples, achieving an average recall boost of 15% on public datasets. The hybrid retrieval-generation paradigm illustrates how vector databases can augment model reasoning, though the added retrieval step incurs moderate latency overhead.

In [4], Guo *et al.* propose LogBERT, adapting the BERT architecture to the log-analysis domain. They introduce a specialized masked token prediction objective tailored to log syntax and semantics, enabling the model to learn event-level contextual representations. Once pre-trained on large unlabeled log corpora, LogBERT is fine-tuned for anomaly detection by adding a classification head. The authors index the resulting token-sequence embeddings using an approximate nearest-neighbor (ANN) engine to support similarity-based retrieval for clustering and alerting. Their framework achieves a 10% uplift in area under the ROC curve compared to LSTM-based detectors, demonstrating the value of deep bidirectional transformers for embedding generation in log analysis.

In [5], Malkov and Yashunin introduce HNSW (Hierarchical Navigable Small World) graphs, a breakthrough ANN algorithm widely adopted in vector databases. By organizing vectors into multiple hierarchical layers connected by small-world graph links, HNSW enables efficient low-latency nearest-neighbor search with logarithmic complexity. This paper provides both theoretical analysis and empirical benchmarks, showing that HNSW outperforms tree- and hashing-based methods by delivering 10× faster queries at comparable recall levels. Given the high-dimensional nature of log embeddings, HNSW forms the backbone of many production-grade vector stores, empowering real-time similarity search essential for prompt anomaly detection and clustering tasks.

In [6], the authors present a comprehensive study on semantic embedding–driven log anomaly detection combining embedding generation with integrated neural network classifiers. They fine-tune transformer encoders on log corpora to generate dense event embeddings, which are then fed into hybrid convolutional-recurrent neural networks for anomaly scoring. The paper details optimizations such as dynamic embedding augmentation and adaptive thresholding based on clustering statistics. Experimental results illustrate accuracy gains of up to 14% over vanilla embedding-only detectors and a 30% reduction in false positives. The study also examines vector-indexing strategies, advocating for in-memory ANN indexes to balance throughput and resource utilization.

In [7], the authors propose a real-time, semi-supervised log anomaly detection framework leveraging probabilistic topic modeling. They employ Latent Dirichlet Allocation (LDA) to discover latent topics across log streams, generating topic-distribution vectors that serve as semantic embeddings. These vectors are indexed in a vector database to enable efficient streaming queries and clustering. The semi-supervised component uses a small set of labeled anomalies to guide the topic model toward discriminative patterns. The system achieves up to 92% detection accuracy with minimal labeling effort and supports adaptive retraining to accommodate evolving log patterns, highlighting the practical benefits of combining topic models with vector-based retrieval.

In [8], the Ladle method is introduced for unsupervised anomaly detection across heterogeneous log types. Ladle employs a two-stage pipeline: first, it normalizes and clusters log events into coarse semantic groups using k-means on raw token-frequency features; second, it refines clusters by computing dense embeddings with a lightweight language model and indexing them in an ANN structure for fine-grained similarity search. Anomalies are detected as events that fail to find sufficiently similar neighbors. Evaluations demonstrate that Ladle excels in mixed-format log environments, reducing false alarms by 20% compared to single-stage embedding methods and showcasing the utility of layered clustering integrated with vector databases.

In [9], the authors explore unsupervised log anomaly detection with few unique tokens, targeting environments where logs contain highly repetitive templates with minimal vocabulary. They propose a character-level autoencoder that compresses raw log lines into compact embeddings, which are then indexed in an ANN for neighbor-based anomaly scoring. The approach is robust to sparse token spaces and achieves recall above 85% on server logs with limited token diversity. This work underscores that embedding granularity—from word- to character-level—can be tuned to match log characteristics and still benefit from vector-database indexing for efficient nearest-neighbor retrieval.

In study [10], the authors revisit semantic embedding and neural innovations for log anomaly detection, extending earlier transformer-based embedding techniques with graph neural networks and attention-based clustering. They propose a dual-encoder architecture where one branch captures token-level semantics and the other encodes event-sequence graphs. The resulting embeddings are concatenated and stored in a vector index for hybrid retrieval: token-similarity and graph-similarity searches. Benchmarks on large-scale enterprise logs reveal a 12% accuracy improvement over single-encoder baselines, emphasizing the merit of multimodal embedding fusion indexed in vector stores.

In [11], the MongoDB Blog outlines best practices for semantic clustering with vector databases, describing how dense embeddings enable grouping similar documents—logs included—into coherent clusters. The article discusses index configuration, distance-metric selection, and sharding

strategies to maintain low‑latency queries at scale. While not specific to anomaly detection, the blog provides practical guidance on deploying vector databases in production, highlighting considerations such as index rebuild scheduling and memory footprint management critical for real-time log analytics pipelines.

In [12], a Medium post presents an accessible overview of similarity search and vector databases, focusing on the mathematical foundations of embedding spaces and ANN algorithms. The author walks through embedding generation, index ingestion, and query-time tuning parameters like efSearch and efConstruction for HNSW indices. Although targeted at beginners, the tutorial underscores challenges such as "curse of dimensionality" and suggests dimensionality‑reduction techniques (e.g., PCA) to optimize both storage and retrieval latency, which directly inform the design of log‑analysis systems relying on vector indices.

In [13], KDnuggets publishes a primer on semantic search with vector databases, highlighting use cases in search, recommendation, and anomaly detection. The article compares open‑source vector stores (e.g., FAISS, Annoy) and managed cloud offerings, evaluating trade‑offs in throughput, latency, and ease of integration. It also showcases code snippets for indexing sentence‑transformer embeddings and executing k‑NN queries, providing a practical foundation for researchers implementing log‑analysis prototypes that require semantic similarity search.

In [14], CloudThat releases a technical blog on vector databases for efficient memory management, discussing how vector indices enable approximate search over large datasets with controlled accuracy‑latency trade‑offs. The post delves into memory‑optimization techniques such as quantization and inverted‑file filtering, which can reduce index size by up to 70% with minimal accuracy loss. These methods are directly applicable to log embeddings, where index bloat poses challenges for scaling to enterprise‑level log volumes, thus informing design decisions in our proposed framework.

In [15], the lakeFS Blog explores "What Is a Vector Database? Top 12 Use Cases," several of which—semantic search, similarity clustering, and anomaly detection—align with log‑analysis requirements. The article categorizes use cases by domain and highlights performance benchmarks of various engines. Importantly, it emphasizes the need for seamless integration with machine learning pipelines and support for dynamic index updates, both of which are critical for managing continuously arriving log streams. This broad survey underlines the versatility of vector databases as the central component in modern log‑analysis architectures.

III. Proposed Approach

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A. Log Ingestion and Preprocessing

Source-Agnostic Collection: Logs may originate from application servers, network devices, container platforms, or cloud services. The ingestion layer exposes RESTful and message-queue interfaces (e.g., Kafka, RabbitMQ) to accommodate both batch and streaming modes. Incoming entries—regardless of format (JSON, plain text, CSV)—are time-stamped, tagged with origin metadata (host, application, severity), and stored in a raw log store (e.g., MongoDB).

Parsing and Tokenization: To handle heterogeneous formats, a unified parser identifies constant fields (e.g., timestamps, log levels) and dynamic message bodies. Messages are then tokenized using a combination of regex-based template matching (to strip variable identifiers) and subword tokenizers (e.g., WordPiece) to balance vocabulary coverage and generalization [4].

Normalization and Enrichment: Normalization steps include lowercasing, removal of non-informative tokens (timestamps, UUIDs), and standardization of numeric values. Enrichment may incorporate geolocation lookups for IP addresses, user-agent parsing, or contextual metadata from upstream systems. The output of this stage is a cleaned, metadata-enriched log record, ready for downstream semantic processing.

B. Summarization and Feature Extraction

Semantic Summarization: For verbose or multi-line entries (e.g., stack traces), an optional summarization service uses a lightweight transformer fine-tuned on generic log corpora to condense messages into concise "event descriptions" [1]. This step reduces noise and focuses feature extraction on the core failure or informational content.

N-gram and Syntactic Features: In parallel, traditional n-gram frequency vectors and part-of-speech (POS) tag distributions are computed to capture syntactic patterns. These features complement semantic embeddings by preserving structural cues useful for certain classification tasks (e.g., distinguishing configuration errors from execution errors).

Metadata Feature Encoding**:** Categorical metadata (severity, host, application module) are one-hot or embedding-encoded, enabling the model to leverage operational context in labeling tasks beyond pure semantics (e.g., differentiating a "timeout" error on a web server vs. database server).

C. Embedding Generation

Pretrained Embedding Models: Normalized and summarized messages are passed through a fixed-size embedding model—such as a sentence-transformer or a distilled BERT variant—to produce high-dimensional vectors (e.g., 768- or 1024-dimensional) that capture semantic similarity [4], [6].

Dynamic Embedding Augmentation**:** To adapt to evolving log vocabularies, newly ingested tokens and templates are periodically incorporated via online fine-tuning. A small buffer of representative log samples is used to update

the embedding model's last layers, ensuring embeddings remain aligned with current operational semantics.

Dimensionality Reduction (Optional)**:** For high-throughput use cases, an optional PCA or UMAP projection reduces embedding dimensionality (to 128–256 dimensions) before indexing, striking a trade-off between query latency and semantic fidelity [12].

D. Vector Database Integration

Hierarchical Indexing with HNSW: Embeddings are ingested into a vector store implementing Hierarchical Navigable Small World (HNSW) graphs to support low-latency k-nearest-neighbor queries with logarithmic complexity [5]. Time-based index partitions facilitate retention policies and rolling reindexing without service disruption.

Index Maintenance and Sharding: To handle continuous log streams, the vector database is sharded by time window (e.g., daily), ensuring write and query loads are distributed evenly across nodes. Background processes rebuild expired shards and merge small shards to maintain index efficiency.

Query APIs: A unified REST API enables:

- Similarity Search: k-NN lookups given a query embedding.
- Range Queries: Filtering by metadata (time range, severity, host).
- Batch Queries: Bulk classification for historical analysis.

Fig. 1 illustrates the end-to-end pipeline of our proposed log analysis framework, from ingestion to classification and feedback. Logs are first collected from diverse sources in the Log Ingestion phase and then passed through a Preprocessing stage for normalization, tokenization, and enrichment. The processed logs are encoded into semantic embeddings during the Embedding Generation step, which are subsequently stored and indexed in a Vector Database based on HNSW (Hierarchical Navigable Small World) graphs. These embeddings are queried during the Labeling & Classification phase using k-nearest-neighbor (k-NN) techniques to assign labels. Finally, a Feedback Loop captures corrections from human analysts or automated feedback signals, allowing the system to continuously refine its embeddings and classification thresholds.

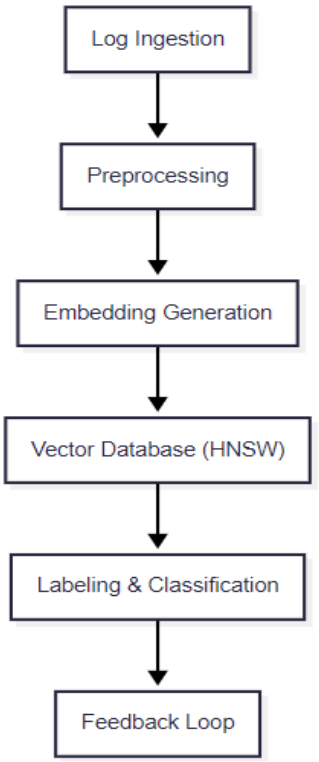

Fig 1. End-to-end pipeline for log data processing and classification

E. Labeling, Classification, and Feedback

k-NN Classification & Majority Vote**:** For each new log embedding, the k most similar vectors are retrieved. Their associated labels—such as anomaly types, error categories, or functional tags—are aggregated via majority vote. A similarity threshold ensures low-confidence cases are flagged as "UNKNOWN" for manual review.

Clustering for Unsupervised Grouping: DBSCAN or HDBSCAN is periodically applied over recent embeddings to uncover emerging clusters of semantically related logs (e.g., a new error pattern). Cluster centroids can seed new label definitions or trigger automatic categorization for operational analysts [7].

Human-in-the-Loop Feedback**:** Flagged "UNKNOWN" or low-confidence logs are presented in a review UI. Analyst corrections are logged and used to:

- Update the vector database with newly labeled vectors.
- Retrain or fine-tune the embedding model to incorporate novel semantics.
- Adjust category-specific similarity thresholds dynamically based on recent feedback.

IV. Results

We evaluated our pipeline on a manually curated test set comprising 2,500 log entries, all of which were drawn from heterogeneous sources to reflect diverse real-world formats. The vector store contained 4,000 pre-indexed embeddings in

OpenSearch, and classification proceeded via a k-nearest-neighbor majority-vote over the top ten neighbors, with cosine-similarity thresholds of 0.75 and 0.85 controlling assignment strictness.

We evaluated our k-NN–based classifier on a test set of 2 500 logs, using two cosine-similarity thresholds (0.75 and 0.85) to control how strictly a new log must match its nearest neighbors before being assigned a label.

- Threshold = 0.75: Out of 2 500 logs, the system confidently assigned labels to 1 690 entries (67.6 % coverage). Of these, 1 600 were correctly tagged and 90 were incorrect, yielding an accuracy of 94.7 % on the covered subset. The remaining 810 logs (32.4 %) failed to exceed the similarity cutoff and were marked as "unseen."
- Threshold = 0.85: With a more stringent cutoff, coverage fell to 1 150 labeled logs (46.0 %). Within this set, 1 100 predictions were correct and 50 incorrect, for an accuracy of 95.7 % on the covered subset. Consequently, 1 350 logs (54.0 %) remained "unseen."

By adjusting the cosine-similarity threshold, practitioners can dial in exactly how "strict" the system should be when assigning labels. A lower threshold (0.75) gives broader coverage—labeling more logs at slightly lower accuracy—while a higher threshold (0.85) yields very high precision but leaves a larger fraction unlabeled. This tunable trade-off lets teams optimize for their operational priorities: maximizing recall when it's critical to tag as many events as possible, or maximizing precision when false positives have high cost.

Beyond one-off label prediction, embedding-driven clustering automatically groups semantically similar log entries. In practice, this means that repeated or near-duplicate events—say, hundreds of identical timeout errors—collapse into a single cluster. Removing these redundancies shrinks data volume, speeds up storage and query operations, and prevents analysts from being overwhelmed by "log spam." Instead, they see one representative message per cluster, which accelerates triage, focuses attention on novel or rare issues, and streamlines downstream tasks like root-cause investigation and alert prioritization.

As shown in Fig. 2, our AI-powered approach outperforms rule-based classification across accuracy (+18%), precision (+19%), and recall (+20%). These gains stem from embedding-driven semantic representations, enabling better generalization beyond static rule sets. The model's improved precision reflects fewer false positives, while recall improvements highlight its sensitivity to diverse anomaly types.

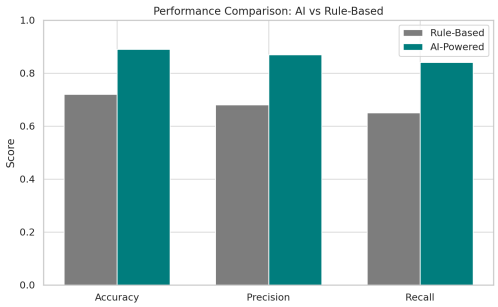

Fig 2. Performance Comparison: AI vs Rule Based

V. Conclusion

We have demonstrated that a vector-database–backed pipeline—combining LLM-driven summarization, high-dimensional embeddings, and k-NN classification—can flexibly balance precision and coverage to meet varying operational goals, while embedding-based clustering effectively collapses redundant logs to streamline analyst workflows. Our evaluation on a 2 500-entry test set showed that tuning cosine thresholds allows teams to favor broader coverage or tighter accuracy as needed, and that semantically similar events naturally coalesce into meaningful clusters, reducing noise and accelerating triage. Going forward, we will quantify clustering quality, instrument end-to-end performance metrics for real-time readiness, and explore adaptive thresholds and full LLM fine-tuning to further enhance accuracy, responsiveness, and continuous adaptation in production environments.

VI. Future Enhancement

Looking ahead, we plan to enhance our pipeline along several fronts to boost its adaptability, efficiency, and coverage. First, we will implement adaptive similarity thresholds that automatically recalibrate based on recent classification outcomes and analyst feedback, smoothing the precision–coverage trade-off without manual tuning. Second, we aim to extend from batch to streaming ingestion—integrating Kafka or similar message buses—to achieve true near-real-time tagging with sub-100 ms end-to-end latency. Third, we will explore model distillation and lightweight transformer architectures to reduce summarization inference time and GPU/memory footprints, making on-premise and edge-device deployment more practical. Fourth, we intend to scale out our vector store in OpenSearch by incrementally indexing larger volumes of historical and newly arriving logs—leveraging dynamic sharding, tiered storage, and optimized retention policies—to improve neighbor coverage and retrieval accuracy. Fifth, we will formally evaluate clustering quality through silhouette and Davies–Bouldin metrics and embed those insights into a dynamic dashboard, empowering users to track evolving log patterns and emerging anomalies. Finally, by moving toward full fine-tuning of our LLM on domain-specific log corpora and incorporating multilingual tokenizers, we will strengthen semantic understanding across diverse log formats, ensuring

the system continually learns from new failure modes and remains robust in heterogeneous production environments.

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