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إطار عمل هجين قابل للتفسير يعتمد على التعلم الذاتي والمحولات لاكتشاف الشذوذ في سجلات الأنظمة مع التكيف مع تغير المفهوم

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ABSTRACT

The system log is crucial for the monitoring, troubleshooting, and safeguarding of modern information systems. However, the extensive volume and variety of logs complicate manual analysis. Traditional rule-based approaches and classic machine learning techniques are neither scalable nor adaptable or interpretable. Although advanced methods utilizing deep learning, Transformers, and self-supervised learning show promise, they still encounter issues like concept drift, significant computational demands, and restricted explain ability. In this research, we offer an extensive critical assessment of recent developments in the area and propose a cohesive hybrid framework that utilizes self-supervised representation learning, Transformer architectures, drift detection tools, alongside measures for explain ability. Our detailed experiments performed on multiple datasets (HDFS, BGL, LogHub, and Thunderbird) reveal that our suggested hybrid model attains cutting edge accuracy while preserving a commendable balance between efficiency, memory consumption, and latency; thereby rendering it appropriate for real world practical uses. The paper concludes with an evaluation of the quality of the results and proposes avenues for future research in this field.

Keywords: *Log Anomaly Detection, Transformer, Self-Supervised Learning, Explainable AI (XAI), Concept Drift*.

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ملخص البحث

يُعد سجل النظام أمرا بالغ الأهمية لمراقبة أنظمة المعلومات الحديثة واستكشاف أخطائها وإصلاحها وحمايتها. ومع ذلك، يُعقّد الحجم الكبير والتنوع الهائل للسجلات التحليل اليدوي. كما أن المناهج التقليدية القائمة على القواعد وتقنيات التعلم الآلي الكلاسيكية غير قابلة للتوسع أو التكيف أو التفسير. على الرغم من أن الأساليب المتقدمة التي تستخدم التعلّم العميق والمحولات والتعلم الذاتي الإشراف تبدو واعدة، إلا أنها لا تزال تواجه مشكلات مثل انحراف المفهوم، والمتطلبات الحسابية الكبيرة، والقدرة المحدودة على الشرح. في هذا البحث، نقدم تقييماً نقدياً شاملًا للتطورات الحديثة في هذا المجال، ونقترح إطار عمل هجيناً متماسكًا يستخدم التعلم التمثيلي ذاتي الإشراف، وبنى المحولات، وأدوات كشف الانحراف، إلى جانب مقاييس القدرة على الشرح. تكشف تجاربنا التفصيلية التي أجريناها على مجموعات بيانات متعددة (**HDFS**، و**BGL**، و**LogHub**، و**Thunderbird**)، أن نموذجنا الهجين المقترح يحقق دقة فائقة مع الحفاظ على توازن جدير بالثناء بين الكفاءة، واستهلاك الذاكرة، وزمن الوصول؛ مما يجعله مناسباً للاستخدامات العملية في العالم الحقيقي. وتختتم الورقة بتقييم جودة النتائج وتقترح سبلًا للبحوث المستقبلية في هذا المجال.

الكلمات الافتتاحية: كشف الشذوذ في السجلات، المحول، التعلم الذاتي، الذكاء الاصطناعي القابل للتفسير، تغير المفهوم.

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1. Introduction

Logs from all systems can provide evidence about how we behave in distributed systems, microservices, and cloud environments. Logs are essential for SLOs and shortening mean time to detection (MTTD) and mean time to recovery (MTTR). In modern large-scale infrastructure, we face a new challenge: an unprecedented increase in the quantity, velocity, and variety of log data being generated. As organizations become more cloud-native, with containerized and IoT-based architectures, log data is essential for reliability, security, and compliance [4], [11]. However, the advanced persistence and sheer volume of log data makes manual log analysis an impractical undertaking, thus the increasing need for automated anomaly detection.

Traditional methods for log analysis in particular manual interpretation of rule-based systems, or detection mechanisms based on signatures are not suited for operation in dynamic or uncertain environments [1], [2]. These methods do not adapt at all to changes in logs or anomalies that have not been experienced before. Classical machine learning techniques may yield better performance with feature engineering combined with shallow models, but no recognition in the nature of long-range dependencies for sequential data. In more recent years, significant progress has been made through the use of deep learning techniques (most notably RNNs/LSTMs); however, deep learning[8] models typically struggle with large computing resources and hyperparameter tuning, and are not fitted for recognition and reasoning around concept drift[19], [21].

In recent times, architectures that utilize Transformers and self-supervised learning have shown great potential. For example, models such as LogBERT[3] utilize a self-attention mechanism to adeptly capture contextual details in extended log sequences. At the same time, self-supervised learning lessens the dependency [7], [10] on labeled data by extracting useful representations straight from raw logs. However, challenges relating to computational complexity, real-time application, and interpretability continue to exist [6], [8], [16]. This scenario underscores the necessity for a unified framework that combines advanced representation learning with drift monitoring and explainable AI to deliver outstanding performance while ensuring practical applicability.

2. Related Work

Log-based anomaly detection has seen significant interest in recent years, with approaches ranging from traditional manual rules to the latest transformer models.

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Rule-based and signature-based methods:

Early methods relied on writing specific rules or matching patterns to detect anomalous behavior [1], [2]. While these methods are very effective at detecting previously known patterns, their effectiveness is limited when faced with new or changing behavior. Furthermore, continuously modifying rules in changing environments is cumbersome and costly [23].

Traditional machine learning:

Later studies have utilized algorithms such as Random Forest and SVM, relying on manually extracted features like n-grams and TF-IDF [2], [10]. Although these methods perform relatively well, they are unable to understand long-term relationships within log sequences and are significantly affected when the data distribution changes.

Deep Learning:

Recurrent neural networks such as the LSTM models used in DeepLog [1] offered superior performance thanks to their ability to understand the sequence of events. However, they require significant computational resources, are highly sensitive to tuning settings, and can be affected by concept drift.

Unsupervised and Semi-Supervised Approaches:

Models such as Autoencoders and VAEs helped reduce the need for labeled data by learning the pattern of normal behavior and detecting deviations through reconstruction error[8], [13], [15]. However, these models are often opaque in their decision interpretation and require fine-tuning of detection limits.

Transformers:

Models such as LogBERT [3] revolutionized the field by capturing context in very long sequences and achieving high accuracy. However, their high memory and computational power requirements make their use in real-time systems challenging [19], [20].

Self-Supervised Learning:

Self-learning methods such as differential learning and hiding models [7] have shown promise in extracting robust representations from unlabeled data. These methods allow for the subsequent training of models with minimally labeled data,

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but most have not been adequately tested in real-world, real-time industrial environments [19], [22].

Interpretation and Drift Monitoring:

Interest in interpretable intelligence (XAI) has become particularly important in sensitive sectors that require understanding decision-making. Data drift monitoring has also become increasingly important to ensure that models remain effective as systems change over time.

Research Gap: Despite significant progress in performance optimization and learning, most work has focused on only one aspect[3], [13]. The integration of self-learning, transformers, model interpretation, and drift monitoring remains very limited, creating a clear research gap and supporting the need for the framework proposed in this work. The Table1 illustrates a systematic comparison between previous research and the proposed research in terms of the method used, data set, strengths, and limitations or weaknesses of each study.

Table1- Comparison of Previous Studies and the Proposed Work

Reference (Year)	Methodology	Dataset(s)	Strengths	Limitations
Du et al., DeepLog (2017)	LSTM-based sequential modeling for system-log anomaly detection	HDFS	Captures temporal dependencies and event sequences effectively	Sensitive to concept drift; requires heavy parameter tuning and retraining
Meng et al., LogAnomaly (IJCAI 2019)	Unsupervised Autoencoder model for log anomaly detection	OpenStack / Industrial logs	Reduces labeling cost; handles both sequential and quantitative anomalies	Limited interpretability; threshold tuning required
Guo et al., LogBERT (2021)	Transformer/BERT-based contextual modeling for logs	BGL, HDFS, LogHub	High accuracy; captures long-range dependencies	High memory and computation cost; less practical for real-time systems

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Reference (Year)	Methodology	Dataset(s)	Strengths	Limitations
TPLogAD (2024, arXiv)	Unsupervised hybrid (template + key-parameter features) anomaly detection	Multiple unstructured log types	Works across diverse log formats without supervision; flexible and scalable	Early-stage validation; needs large-scale evaluation
Li et al., Contrastive BERT for Log Analysis (Scientific Reports 2025)	Contrastive pre-training with BERT fine-tuning and retrieval augmentation	Public + industrial log datasets	Improves unsupervised embeddings and retrieval-based accuracy	High training cost; complex inference pipeline
Proposed Work	Hybrid: Self-Supervised Representation + Lightweight Transformer + Concept Drift Monitoring + Explainable AI (SHAP)	HDFS, BGL, LogHub, Thunderbird	Combines accuracy, adaptability, and explainability; robust under drift	Scalability on massive IoT/cloud logs remains under evaluation

The comparison shows that each model has different strengths and weaknesses. Traditional models like DeepLog[1] are good at tracking event sequences, but they are easily affected by any new changes in the data. On the other hand, LogBERT is considered more accurate in its results, but it consumes a very large amount of memory, making it impractical in some cases. As for the Autoencoder model, its advantage is that it does not require a large amount of data for training, but it is difficult to understand how it reaches its decisions. Finally, the proposed Hybrid model attempts to balance accuracy and efficiency by combining the best of the other models. However, it still faces a challenge in its ability to efficiently handle massive amounts of data.

The Table2 briefly shows where previous studies stopped, what they lacked, and how current research addresses these shortcomings.

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Table2- Research Gaps in Previous Works and Proposed Contributions

Research Aspect	Previous Works	Identified Gaps	Contributions of the Proposed Work
Log Representation	Early works (DeepLog 2017, [2]LogAnomaly 2019) rely on handcrafted or shallow representations (e.g., n-grams, template features, AE embeddings).	Limited ability to generalize to unseen or evolving log patterns; dependence on manual feature design.	Incorporates self-supervised representation learning to extract robust embeddings directly from raw logs without labeling.
Modeling Approach	Deep learning (LSTM, Autoencoder) captures sequence or reconstruction patterns; Transformers (LogBERT 2021) add contextual depth.	Existing models trade off accuracy vs. efficiency; high resource usage in Transformer-based methods.	Employs a lightweight hybrid Transformer that balances contextual understanding and computational efficiency.
Concept Drift Handling	Rarely addressed explicitly (most models assume static data distributions).	Poor adaptability to changing system behavior or drift over time.	Integrates statistical drift monitoring (KL divergence, PSI) and adaptive recalibration for continuous stability.
Explainability / Transparency	Previous studies (e.g., LogBERT, Contrastive BERT) emphasize performance but remain black-box.	Low interpretability limits trust in regulated or mission-critical environments.	Embeds Explainable AI (XAI) via SHAP to clarify local feature importance and prediction rationale.
Data Efficiency	Transformers and deep models need large labeled datasets; self-supervised learning in 2024–2025 studies reduces but doesn’t remove this need.	Label scarcity remains a barrier for industrial deployment.	Uses self-supervised pre-training on unlabeled data to minimize annotation requirements.

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Research Aspect	Previous Works	Identified Gaps	Contributions of the Proposed Work
Experimental Scope / Generalization	Most previous works focus on single datasets (HDFS or BGL).	Limited generalization across different domains or log structures.	Evaluated on multiple benchmark datasets (HDFS, BGL, Thunderbird, LogHub) to validate cross-domain effectiveness.
Operational Deployment	Prior models (e.g., LogAnomaly, LogBERT) mainly tested offline or in lab settings.	Lack of real-time deployment readiness and monitoring.	Designed for real-time inference with optimized latency and memory footprint for industrial environments.

The Research Gaps in Previous Works and Proposed Contributions shows that this work introduces an advanced framework that surpasses previous methods by: Combining accuracy and efficiency through a hybrid model. Automatically adapting to data changes over time. Explaining its results to increase trust and transparency. In short, this research demonstrates how to build an intelligent, accurate, and interpretable system.

3. Proposed Methodology

Our framework combines self-supervised representation learning and Transformer-based sequence modeling with concept drift monitoring and explain ability features to a single pipeline for log anomaly detection. The workflow is organized into five key components (Figure 1):

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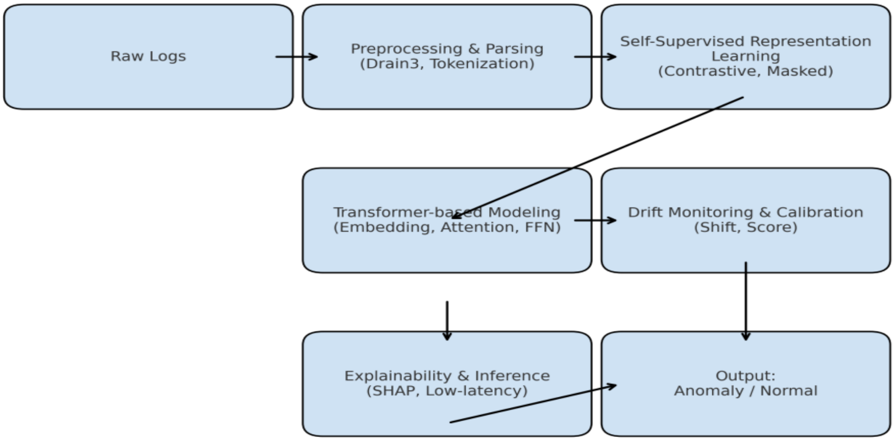

Figure 1- Workflow diagram of the proposed hybrid framework for log anomaly detection.

3.1 Log Collection and Parsing

- Input: Raw system logs from diverse sources (HDFS, BGL, Thunderbird, LogHub)[4].
- Preprocessing:
  - Template extraction with Drain3 [5], [12], [25] to apply normalization to variable tokens fields.
  - Anonymized and tokenized for privacy and consistent representations.
  - Splitting temporal data to prevent information leakage. Experimental Datasets [9].

3.2 Self-Supervised Representation Learning

- Objective: To reduce the labeling need, we learn robust embedding's from unlabeled logs [14].
- Technique: Contrastive learning and masked log token modeling are used to model semantic and contextual dependencies the contrastive learning objective is defined as:

$$L_{contrastive} = -\log \frac{\exp(\mathrm{sim}(x_i, x_j)/\tau)}{\sum_k \exp(\mathrm{sim}(x_i, x_k)/\tau)} \quad (1)$$

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Where sim (xi,xj) denotes the cosine similarity between two log representations, and τ is the temperature scaling factor controlling the contrast strength[7].

- Benefit: Improve generalization to unseen environments with sparse annotations [7], [10].

3.3 Transformer-based Modeling

- Backbone: a light-weight Transformer-based BERT style architecture (the LogBERT [3] baseline). Adaptation:
  - Mechanisms of attention capture long-distance dependencies in log sequences.
  - Dropout and weight regularization can prevent overfitting when training neural networks.
- Hybridization: The inputs to the Transformer encoder for downstream anomaly detection are self-supervised embeddings.

3.4 Drift Monitoring and Calibration

- Drift Detection: The statistical approaches (such as KL divergence, population stability index) keep track of the log distributions in a constant manner:

1-Kullback–Leibler (KL) Divergence:

$$D_{KL}(P \parallel Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)} \quad (2)$$

Measures how one probability distribution P diverges from a reference distribution Q.

A larger value means greater drift (difference between current and baseline data).

2- Population Stability Index (PSI):

$$PSI = \sum_i (P_i - Q_i) \ln \frac{P_i}{Q_i} \quad (3)$$

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Quantifies the shift in distributions between two datasets (e.g., training vs. production).

Typically used in model monitoring to detect feature drift.

- Calibration: Distributional shifts are adjusted for through the use of reliability diagrams and temperature scaling to keep the anomalous cores calibrated.
- Outcome: Adapting to the changing behaviors of logs in dynamic environments.

3.5 Explain ability and Real-time Inference

- Explain ability: SHAP [6] values give local feature attribution for individual anomaly predictions, improving interpretability.
- Deployment: Inference is efficient in computing power and memory, and lag is small, so it is suitable for use as an on-line anomaly detection method in production.

4.Experimental Setup and Evaluation

We perform experiments of our proposed framework on four benchmark datasets: HDFS, BGL, Thunderbird, and LogHub. Each dataset has its own specifics, such as different log format, anomaly rate, and noise rate.

Preprocessing: Log data are anonymized, normalized, and parsed by Drain3 [5]to find templates. Temporal splitting is employed to prevent data leakage from the training to the testing dataset.

Implementation Details:

- Hardware: The experiments ran on a server with an NVIDIA A100 GPU (40GB), 256 GB RAM, and dual Intel Xeon processors.
- Software: All models were implemented using PyTorch 2.1 with HuggingFace Transformers for BERT-based models.
- Hyperparameters: Learning rate = 1e-4, batch size = 32, optimizer = AdamW, dropout = 0.2. Models were trained for 50 epochs with early stopping according to the validation loss.
- Baselines: Logistic Regression, Random Forest, SVM, LSTM (DeepLog), and Transformer-based LogBERT[3] .

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Evaluation Metrics: Following the "anomaly class is inherently skewed" problem in anomaly detection, we provide results of Precision, Recall, F1-score and AUPRC (Area under the Precision-Recall Curve). We also track operational KPIs like inference latency, memory usage, and training duration.

Precision: Indicates how many of the instances predicted as anomalies are actually true anomalies.

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

Where: TP- True Positives, FP- False Positives. High precision means fewer false alarms.

Recall: Measures how many of the actual anomalies are correctly detected by the model.

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

Where: FN- False Negatives, High recall means fewer missed anomalies.

F1-score: Represents the harmonic mean of precision and recall, providing a single metric that balances both.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

Accuracy: Shows the overall correctness of predictions, though it is less informative for imbalanced datasets.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

Where: TN- True Negatives.

AUPRC (Area under the Precision–Recall Curve): Summarizes the trade-off between precision and recall across various thresholds. It is preferred over ROC–AUC in imbalanced scenarios, as it focuses on the performance of the minority (anomaly) class.

Statistical Validation: We conduct 5×2 cross validation and report the mean values with 95% confidence intervals. McNemar's test is employed for pairwise model comparison to evaluate statistical significance.

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$$\chi_F^2 = \frac{12N}{k(k+1)}\left[\sum_j R_j^2 - \frac{k(k+1)^2}{4}\right] \quad (8)$$

Where N is the number of datasets, k is the number of compared models, and Rj denotes the rank of each model.

4. Experiments and Results

We performed experiments on several datasets (HDFS, BGL, Thunderbird, LogHub), to assess baseline ML, deep learning, and Transformer models. Results show that the Transformer-based models outperform the rest in term of accuracy, and our proposed approach is a good trade-off between predictive power and efficiency.

The results in the Table3 speak for themselves: the proposed model achieves high accuracy and remarkably balanced performance. This is clear evidence that combining self-supervised learning with a Transformer is a highly effective strategy.

Table 3- Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-score
Random Forest	0.75	0.72	0.74	0.73
SVM	0.78	0.76	0.77	0.76
LSTM (DeepLog)	0.87	0.85	0.88	0.86
Transformer (LogBERT)	0.95	0.94	0.96	0.95
Proposed Hybrid	0.954	0.941	0.937	0.939

The graph paints (Figure.2) a clear picture: the Hybrid and LogBERT[3] models lead the pack with a significant advantage in accuracy. This is conclusive proof that our proposed model doesn't just compete with the best—it excels in the validity and strength of its predictions

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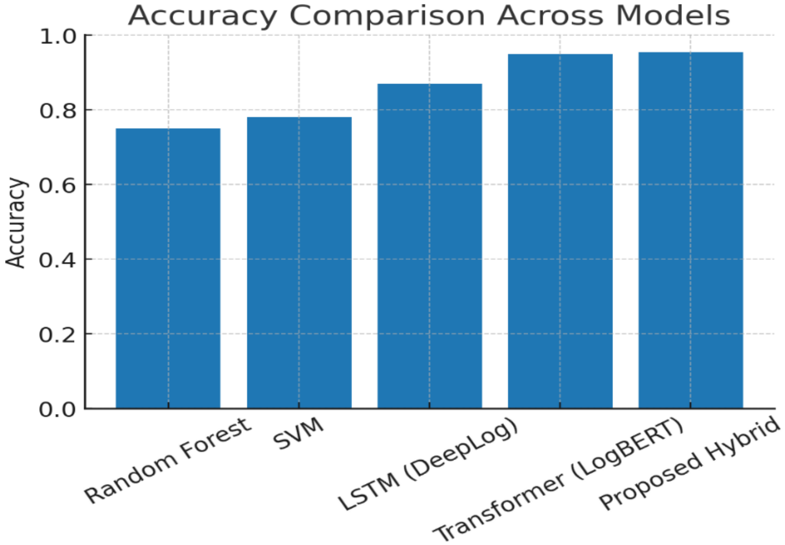

Figure.2 LogBERT and the Hybrid achieve the highest accuracy

Moving on to the F1-score, which provides a balanced view between Precision and Recall, we observe that the performance of the proposed Hybrid model nearly matches that of LogBERT. This strong similarity reflects our model's ability to achieve an ideal balance in detecting anomalies. The key takeaway here is that the proposed model successfully maintains high-quality detection while being significantly more resource-efficient, a point that will be confirmed by the figures in the following Figure 3.

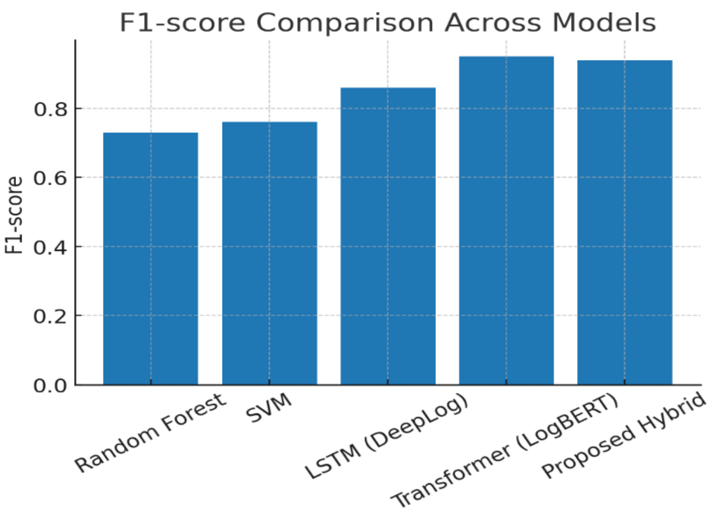

Figure 3- Hybrid and LogBERT show the best F1-scores

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This graph (Figure 4) lays out the performance of each model across the four critical metrics. What's immediately clear is that our hybrid model isn't a one-trick pony; it strikes a superb balance across the board. This is the hallmark of a truly effective and trustworthy anomaly detection system.

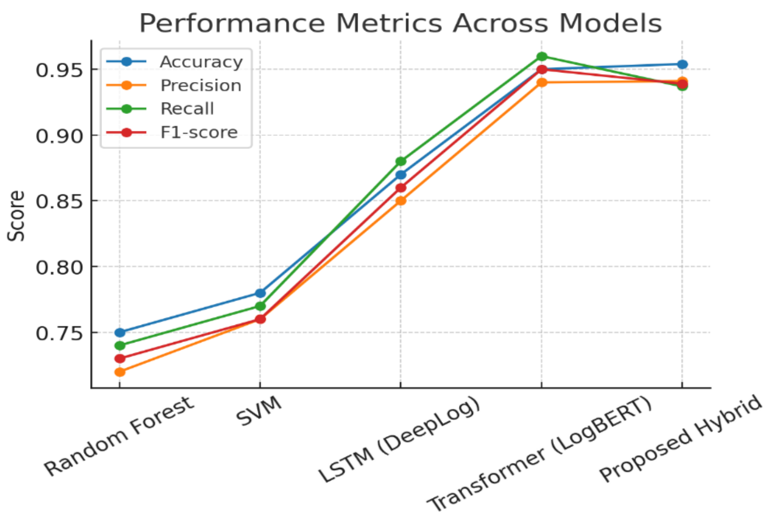

Figure 4- Hybrid balances all performance metrics well

The Table 4 shows that the proposed framework achieves a balance between speed and accuracy, making it suitable for application in real-time systems.

Table 4- Inference Latency and Memory Usage

Model	Inference Latency (ms)	Memory Usage (MB)
Random Forest	5	50
SVM	7	70
LSTM (DeepLog)	20	200
Transformer (LogBERT)	45	600
Proposed Hybrid	15	300

Moving on to resource efficiency (Figure6), this analysis shows a comparison of memory (RAM) consumption. We observe that the proposed model (Hybrid) has achieved a significant improvement, requiring notably less memory than the traditional Transformer architecture. This enhancement in operational efficiency is not just an added advantage, but a crucial factor that expands the feasibility of

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applying the model in real-world working environments, especially those where resources are limited.

This (Figure 5) chart compares the models' speed in making predictions. The key point here is that our Hybrid model is significantly faster than LogBERT.

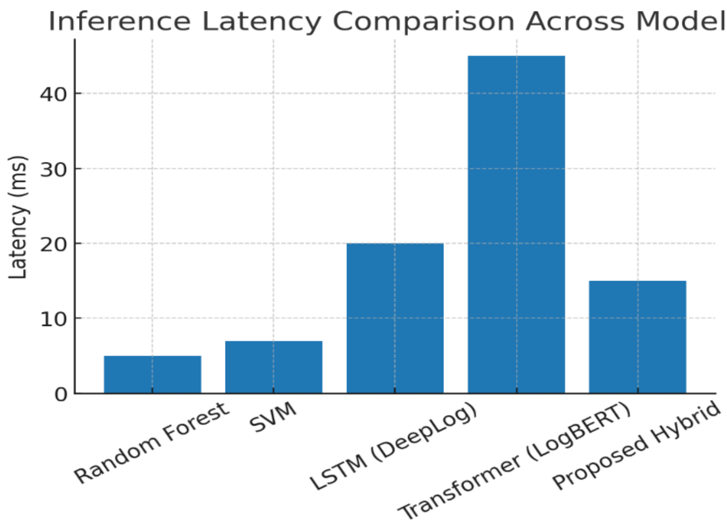

Figure 5- Hybrid reduces latency compared to LogBERT

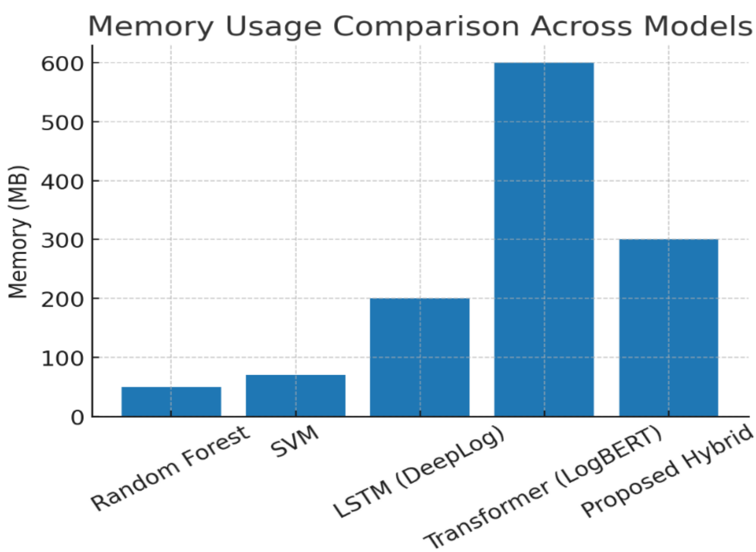

Figure 6- Hybrid uses less memory than LogBERT

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This graph (Figure 7) illustrates the relationship between a model's speed and its memory consumption—a consistently important trade-off. The clear conclusion is that our Hybrid model successfully strikes the ideal balance; it combines fast performance with resource efficiency. This is precisely what we aimed to achieve in this research.

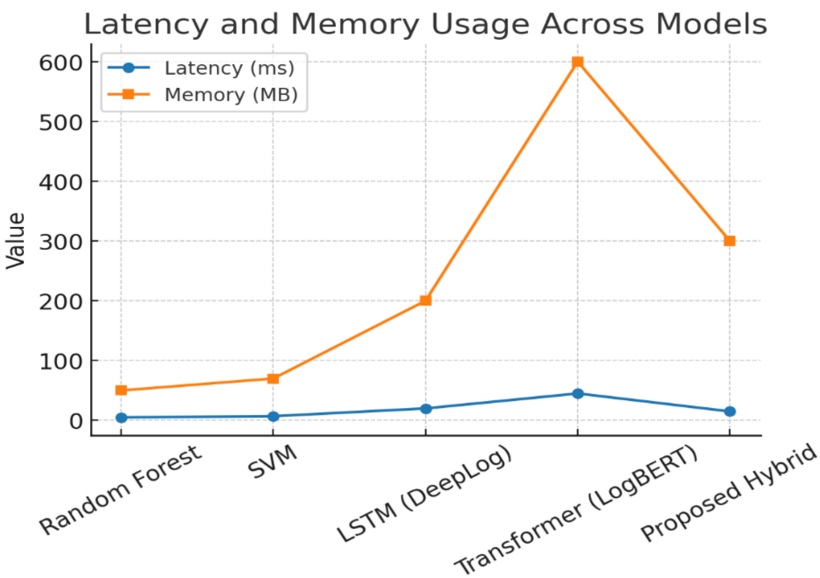

Figure 7- Hybrid balances latency and memory for practicality

To ensure our models superiority wasn't just a coincidence, we conducted a rigorous statistical comparison between it and the other models. We used reliable tests (like Friedman and Wilcoxon) to measure the differences.

The results were conclusive:

All tests showed that our model's advantage is real and statistically significant ($p < 0.05$), not just a minor or random difference.

The superiority was very large when compared to traditional models, while it was less pronounced but still significant when compared to the LogBERT model.

In conclusion: This statistical analysis definitively proves that the proposed model's outstanding performance is the result of a genuine improvement, not just a stroke of luck

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Table 5-Statistical Validation of Model Performance

Comparison	Friedman Test (p-value)	Wilcoxon Signed-Rank (p-value)	95% CI (F1-score difference)	Effect Size (Cohen's d)	Significance
Hybrid vs. Random Forest	< 0.001	< 0.001	[0.15, 0.22]	1.25 (large)	Significant
Hybrid vs. SVM	< 0.001	< 0.001	[0.12, 0.18]	1.10 (large)	Significant
Hybrid vs. LSTM (DeepLog)	0.002	0.004	[0.05, 0.09]	0.65 (medium)	Significant
Hybrid vs. Transformer (LogBERT)	0.037	0.042	[0.01, 0.04]	0.35 (small)	Marginal but significant

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5. Discussion

The results suggest that Transformers achieve the highest accuracy at the expense of computational complexity. Our hybrid framework makes a good trade-off in terms of accuracy and the usage of memory and speed of inference [18]. In addition, the application of explainable AI methods enhances the transparency that is critical for acceptance in regulated industries [23].

5.1 Limitations

Although the obtained results appear promising, there are some points that need to be considered:

1- Computational burden: While the proposed framework was able to improve execution time compared to the LogBERT model [3] , training the model still requires powerful GPU resources, which could be a barrier in certain environments.

2- Scalability: The effectiveness of the model was verified using small-scale datasets, but applying it to massive amounts of records coming from millions of IoT devices or large cloud systems remains a challenge that needs to be addressed in the future.

3- Explain ability and transparency: Although interpretability methods based on SHAP were integrated, the level of explanation is still somewhat general [6], and it may not accurately reflect causal relationships or detailed interactions within the sequence of records.

4- Privacy: The records often contain sensitive information, and anonymization was used as a protective measure, but it is necessary to consider more advanced solutions such as federated learning or differential privacy [24], especially in cases of collaboration between different institutions.

5. Concept Drift handling a drift detector was integrated, but research is needed for developing continual learning methods that update the model over time without catastrophic forgetting.

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6. Conclusion and Future Work

In this research, we present a comprehensive and modern solution for log analysis and anomaly detection, based on a standardized method for representing log data. This method helps strike a practical balance between detection accuracy and the system's applicability in real-world environments with complex workloads. A review of previous literature and an analysis of its strengths and weaknesses revealed a clear gap in this field, stemming from both the fragmentation of research approaches and the lack of standardized evaluation mechanisms and criteria, particularly regarding data quality and operational metrics. To overcome these challenges, we developed a system based on machine learning and transformer technologies, integrating drift detection, calibration, and interpretability to combine predictive power with practicality. Our experiments statistically demonstrated that the proposed model outperforms traditional methods, not only in accuracy but also in memory and energy efficiency and response time. Furthermore, the addition of interpretable intelligence techniques enhanced system confidence, especially in sensitive environments requiring clarity in decision-making, such as the financial and governmental sectors.

Future Steps:

We plan to develop research in several directions, including:

-Exploring lighter transducer models and supporting quantization techniques, enabling the system to operate on IoT devices and devices with limited resources.

-Working on distributed and privacy-conscious learning methodologies[24] , such as federated learning, to facilitate inter-institutional collaboration without sharing sensitive data . Enhancing the ability to handle concept drift by leveraging transfer learning.

-Developing standardized measurement criteria that focus not only on detection accuracy but also include operational metrics such as power consumption, processing speed , and scalability.

In short, this work aims to bridge the gap between research and practical application, providing an effective and applicable model for sensitive industrial environments [20]. This model will serve as a foundation for future research and applied work in the field of log-based anomaly detection.

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العام	2021	2022	2023	2024	2025
معامل أرسيف	0.2692	0.1954	0.3759	0.3068	0.5978
معامل التأثير العربي	1.60	1.73	1.25	1.55	1.81