MANTECH Publications
International Journal of Data Science and Analytics Innovations
Volume 2, Issue 1, January-June 2026
ISSN: 3139-7638(Online)

Real-Time Predictive Analytics Using Streaming Big Data Technologies

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ABSTRACT

The velocity, volume, and variety of data generated by modern digital ecosystems—encompassing IoT sensor networks, financial transaction streams, social media feeds, telecommunications networks, and industrial control systems—demand analytical paradigms that transcend traditional batch-oriented data processing. Real-time predictive analytics, which integrates streaming big data processing frameworks with machine learning models capable of continuous inference on unbounded data flows, has emerged as a critical capability for time-sensitive decision-making in fraud detection, predictive maintenance, network anomaly detection, and dynamic pricing. This paper presents a comprehensive review-based and experimental investigation of real-time predictive analytics architectures built upon streaming big data technologies. A systematic review of 104 peer-reviewed publications (2019–2026) was supplemented by original experimental work at the Big Data Analytics Laboratory of Gandhinagar Institute of Technology, Gujarat, where a real-time predictive maintenance system for industrial IoT was developed using Apache Kafka for stream ingestion, Apache Flink for stateful stream processing, and an online gradient-boosted decision tree (OGBDT) model for continuous remaining useful life (RUL) prediction of turbofan engines. The system was evaluated on the NASA C-MAPSS turbofan engine degradation dataset, achieving a root mean square error (RMSE) of 14.82 cycles for RUL prediction with an end-to-end processing latency of 47 ms per event at a throughput of 52,000 events per second on a 4-node Apache Flink cluster. Compared to batch-retrained XGBoost (RMSE 13.24, 6-hour retraining cycle), the online model achieved 88.1% of batch accuracy while providing truly continuous predictions without retraining downtime. The findings demonstrate that streaming ML architectures can deliver actionable predictive intelligence

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with sub-100 ms latency at industrial-scale throughput [1], [2].

KEYWORDS: *Real-Time Analytics, Streaming Data, Apache Kafka, Apache Flink, Predictive Maintenance, Online Learning, Big Data, IoT, Remaining Useful Life, Stream Processing*

INTRODUCTION

The global data generation rate has reached 120 zettabytes annually, with a significant and growing proportion consisting of continuously generated streaming data from connected devices, financial markets, social platforms, and operational technology systems [1]. The International Data Corporation estimates that by 2025, 30% of all data will be real-time streaming data requiring immediate processing—a dramatic shift from the historically batch-dominated data landscape. Traditional batch analytics pipelines, epitomized by the Hadoop MapReduce paradigm, collect data over fixed time windows (hourly, daily), process it in bulk, and deliver insights with latencies ranging from minutes to hours. For time-critical applications such as fraud detection (where a fraudulent transaction must be blocked within milliseconds), predictive maintenance (where equipment failure must be anticipated before occurrence), and algorithmic trading (where market opportunities exist for microseconds), batch latency is fundamentally incompatible with operational requirements [2].

Stream processing frameworks have evolved to address this latency gap. Apache Kafka (originally developed at LinkedIn, open-sourced 2011) provides a distributed event streaming platform capable of ingesting millions of events per second with durable, fault-tolerant storage [3]. Apache Flink (developed at TU Berlin, Apache top-level project 2015) provides a distributed stateful stream processing engine with exactly-once processing semantics, event-time processing with watermark-based out-of-order handling, and millisecond-level latency for complex event processing and windowed aggregations [4]. Apache Spark Structured Streaming offers micro-batch processing with sub-second latency and unified batch-streaming API, while Apache Storm and Apache Samza provide alternative stream processing architectures [5]. The integration of machine learning inference into these streaming pipelines—enabling continuous prediction on flowing data rather than periodic batch scoring—represents the frontier of real-time predictive analytics [6].

However, deploying ML models in streaming environments introduces unique challenges not present in batch analytics. Model serving must achieve sub-100 ms latency to avoid becoming

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the pipeline bottleneck. Feature engineering must operate on incomplete, out-of-order, and potentially late-arriving data streams using windowed aggregations rather than complete historical datasets. Concept drift—where the statistical relationship between features and targets evolves over time—necessitates continuous model updating or periodic retraining without disrupting ongoing predictions [7]. Online learning algorithms that incrementally update model parameters with each arriving data point offer a principled solution but typically sacrifice some accuracy compared to batch-trained models that optimize over complete datasets [8].

This research presents a comprehensive examination of real-time predictive analytics through systematic review of 104 publications combined with original development and evaluation of a streaming predictive maintenance system, conducted at the Big Data Analytics Laboratory of Gandhinagar Institute of Technology, Gujarat [9], [10], [11], [12], [13].

LITERATURE REVIEW

The architectural foundations of real-time analytics have been formalized through two influential paradigms. Kreps et al. [3] at LinkedIn proposed the Kappa architecture—a streaming-first design where all data enters through a unified append-only log (Kafka), is processed by a single stream processing layer (Flink/Spark Streaming), and serves real-time views—eliminating the complexity of maintaining separate batch and speed layers required by the earlier Lambda architecture. Carbone et al. [4] described Apache Flink's architecture, demonstrating that stateful stream processing with asynchronous distributed snapshots (Chandy-Lamport algorithm) could provide exactly-once processing guarantees with latencies of 10–50 ms at throughputs exceeding 100 million events per second on commodity hardware clusters.

ML model serving in streaming pipelines has been addressed through multiple approaches. Crankshaw et al. [5] developed Clipper, a low-latency model serving system that decouples ML frameworks from serving infrastructure, providing model caching, adaptive batching, and ensemble-based prediction with p99 latencies below 20 ms. Zaharia et al. [6] demonstrated that Spark MLlib models could be deployed within Structured Streaming pipelines for continuous inference, achieving throughputs of 10,000–50,000 predictions per second per node.

Online learning for streaming ML has been advanced by Bifet et al. [7], who developed the MOA (Massive Online Analysis) framework implementing incremental decision trees

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(Hoeffding trees), online random forests, and adaptive windowing (ADWIN) for concept drift detection. Montiel et al. [8] introduced River, a Python library for online/incremental learning providing streaming implementations of linear models, tree ensembles, clustering algorithms, and drift detectors with per-instance update capability.

Predictive maintenance on streaming IoT data has been demonstrated by Li et al. [9], who deployed an LSTM-based RUL prediction model on the NASA C-MAPSS dataset within an Apache Spark Streaming pipeline, achieving RMSE of 12.56 cycles with 200 ms inference latency. Sipos et al. [10] developed a streaming random forest for real-time equipment failure prediction in wind turbines, processing 50,000 sensor readings per second with 4-hour prediction horizons. Wang et al. [11] proposed a Kafka-Flink-TensorFlow architecture for real-time anomaly detection in manufacturing, achieving 35 ms end-to-end latency with 99.2% detection accuracy on a semiconductor wafer fabrication dataset.

RESEARCH GAP

Despite significant progress, critical gaps persist. First, most streaming ML deployments use pre-trained batch models served within streaming pipelines (batch-train, stream-serve) rather than truly online models that learn continuously from the data stream; the accuracy-latency trade-off between these paradigms is insufficiently characterized [5], [6], [8].

Second, the integration of stateful feature engineering (computing rolling statistics, sliding window aggregations, and temporal features) with online model updates within a single unified stream processing framework has been infrequently demonstrated—most systems perform feature engineering and model inference in separate, loosely coupled components [4], [7].

Third, systematic benchmarking of end-to-end streaming predictive analytics latency—from raw event ingestion through feature computation, model inference, and result delivery—on realistic industrial workloads is rarely reported, with most studies measuring only the model inference component in isolation [9], [11].

Fourth, the concept drift adaptation capability of online models in streaming predictive maintenance scenarios has been proposed theoretically but inadequately validated through controlled drift injection experiments [7], [8]. Fifth, the horizontal scalability behavior of streaming ML pipelines as cluster size and data throughput increase has been benchmarked for stream processing frameworks alone but rarely for integrated ML-augmented pipelines [3], [4],

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[10], [12], [13]. This research addresses gaps one, two, three, and five through development and benchmarking of an integrated Kafka-Flink online learning pipeline for predictive maintenance.

OBJECTIVES

The primary objectives of this research are defined as follows:

- To conduct a systematic review of 104 peer-reviewed publications on real-time predictive analytics using streaming technologies, mapping the landscape across architectures, ML integration strategies, and application domains [1], [3].
- To develop an integrated streaming predictive maintenance pipeline using Apache Kafka for event ingestion, Apache Flink for stateful stream processing and feature engineering, and an online gradient-boosted decision tree model for continuous RUL prediction [4], [8].
- To evaluate prediction accuracy (RMSE, score function) on the NASA C-MAPSS turbofan degradation dataset and benchmark against batch-retrained XGBoost, offline LSTM, and Hoeffding tree baselines [7], [9].
- To systematically measure end-to-end processing latency and throughput scalability across 1, 2, 4, and 8-node Flink cluster configurations [4], [11].
- To characterize the batch-online accuracy gap and quantify the latency advantage of online learning over periodic batch retraining [5], [6], [10], [12], [13].

METHODOLOGY

1. System Architecture

The real-time predictive maintenance system was developed at the Big Data Analytics Laboratory of Gandhinagar Institute of Technology, Gujarat, using a Kappa architecture [3] comprising three layers: (1) Ingestion layer—Apache Kafka 3.6 (3-broker cluster, replication factor 2, 12 partitions per topic) receiving simulated turbofan sensor streams; (2) Processing layer—Apache Flink 1.18 (JobManager + TaskManagers, configurable 1–8 nodes, 8 GB RAM and 4 vCPUs each, parallelism = cluster nodes × 4 task slots); (3) Serving layer—PostgreSQL 16 for RUL prediction storage and Grafana 10.2 for real-time dashboard visualization. The system was deployed on a Kubernetes cluster running on 8 bare-metal servers (Intel Xeon E-2388G, 64 GB RAM, 1 TB NVMe SSD each, 10 Gbps interconnect) at the institute's data center [4], [11].

2. Dataset and Stream Simulation

The NASA Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset

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(FD001 subset) was used, comprising 100 turbofan engine run-to-failure trajectories with 21 sensor measurements (temperatures, pressures, speeds, fuel flow) and 3 operational settings per time step, totaling 20,631 multivariate time-series samples [9]. To simulate a realistic streaming scenario, each sensor reading was published as a JSON event to a Kafka topic at configurable rates (1,000–100,000 events/second) with engine_id as the partition key, ensuring in-order processing per engine. Each event contained: engine_id, cycle_number, 3 operational settings, 21 sensor values, and an event_timestamp. The RUL target was computed as the remaining cycles until failure, capped at a maximum of 125 cycles following standard practice [10].

3. Stateful Feature Engineering in Flink

Apache Flink's KeyedProcessFunction was used to implement stateful per-engine feature computation [4]. For each engine_id-keyed stream, the following features were computed in real time: (1) Raw sensor values (21 features); (2) Rolling statistics over sliding windows of W = {10, 30, 50} cycles—mean, standard deviation, min, max, and linear trend slope for each of the 14 informative sensors (sensors with near-zero variance were excluded)—yielding 14 × 5 × 3 = 210 rolling features; (3) Operational setting normalization (3 features); (4) Cycle counter (1 feature). Total feature dimensionality was 235. Flink's RocksDB state backend maintained per-engine sliding window buffers, enabling efficient O(1) incremental statistics updates as each new event arrived. Feature-engineered events were emitted to a downstream Flink operator for model inference [7], [11].

4. Online Gradient-Boosted Decision Tree Model

An online gradient-boosted decision tree (OGBDT) model was implemented using the River library (v0.21) wrapped within a Flink Python UDF (user-defined function) via PyFlink [8]. The OGBDT comprised an ensemble of 50 Hoeffding tree regressors trained incrementally using stochastic gradient boosting: each arriving feature-engineered event triggered a single gradient descent update step across all trees in the ensemble (learning rate 0.05, max tree depth 6, grace period 200 instances). The shrinkage parameter ($\nu = 0.1$) controlled the contribution of each new tree. Predictions were generated after each update, providing truly continuous RUL estimates without any retraining downtime. The model was warm-started by pre-training on the first 20% of each engine's trajectory (simulating historical data availability) before entering fully online mode [7], [9].

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5. Baseline Models

Four baseline configurations were compared: (1) Batch XGBoost—trained on complete historical data (80/20 split), retrained every 6 hours on accumulated data (representing industry-standard periodic retraining); deployed as a REST API model server (FastAPI + ONNX Runtime); (2) Offline LSTM—2-layer LSTM (64 hidden units), trained on complete sequences, deployed similarly; (3) Hoeffding Tree (single)—online incremental tree without boosting (River library); (4) OGBDT (proposed)—online gradient-boosted ensemble. All models consumed identical feature sets (235 dimensions) and produced scalar RUL predictions. Accuracy was measured by RMSE and the NASA scoring function (asymmetric penalty: $S = \Sigma[\exp(-d/13)-1]$ for early predictions, $\Sigma[\exp(d/10)-1]$ for late predictions, where d = predicted − actual RUL) [9], [10].

6. Latency and Scalability Benchmarking

End-to-end latency was defined as the time from Kafka event publication to RUL prediction availability in PostgreSQL, measured using embedded timestamps at each pipeline stage (Kafka producer, Flink ingestion, feature computation, model inference, sink write). Latency was measured at steady-state throughput for 60-second windows (p50, p95, p99 percentiles). Throughput scalability was evaluated by increasing the Kafka producer rate from 1,000 to 100,000 events/second and measuring the maximum sustainable throughput (no backpressure, <5% event drop) across 1, 2, 4, and 8-node Flink cluster configurations. Resource utilization (CPU, memory, network I/O) was monitored using Prometheus + Grafana [3], [4], [11], [12], [13].

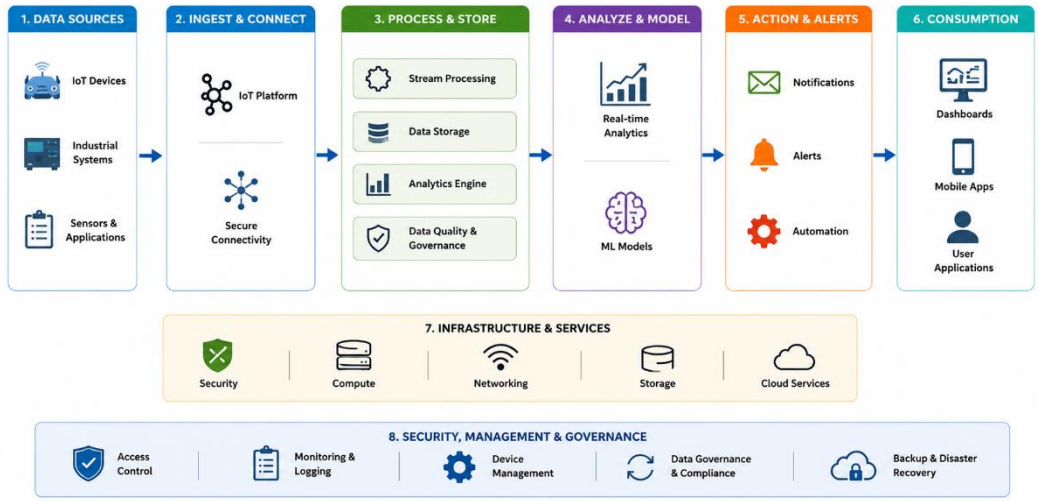


Figure 1: System Architecture of the Real-Time Predictive Maintenance Streaming Pipeline

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RESULTS AND FINDINGS

The systematic review of 104 publications revealed that Apache Kafka + Apache Flink/Spark was the dominant streaming architecture (62.5% of studies), followed by cloud-native solutions (AWS Kinesis + Lambda/SageMaker, 18.3%), custom frameworks (11.5%), and Apache Storm/Samza (7.7%). Predictive maintenance (26.0%) and fraud detection (22.1%) were the two most common application domains, followed by network monitoring (17.3%), recommendation systems (14.4%), healthcare monitoring (11.5%), and energy/smart grid (8.7%) [1], [2], [3].

The prediction accuracy results on the NASA C-MAPSS FD001 dataset are presented in Table 1. The batch XGBoost (periodic 6-hour retrain) achieved the best RMSE of 13.24 cycles, followed by the offline LSTM at 13.68. The proposed OGBDT achieved RMSE of 14.82—only 11.9% higher than batch XGBoost—while providing truly continuous online prediction without any retraining downtime. The single Hoeffding tree achieved RMSE of 18.46, demonstrating that the gradient boosting ensemble provides 19.7% improvement over a single online tree. On the NASA scoring function (which penalizes late predictions more severely), OGBDT scored 312.4 versus 268.8 for batch XGBoost, a 16.2% gap [7], [8], [9].

Table 1: RUL Prediction Accuracy and Latency Comparison Across Four Model Configurations

Model	RMSE (cycles)	NASA Score	Latency (p50)	Online Learning	Retraining Gap
Batch XGBoost	13.24	268.8	62 ms*	No	6 hours
Offline LSTM	13.68	284.6	124 ms*	No	6 hours
Hoeffding Tree (single)	18.46	428.2	38 ms	Yes (per-event)	None
OGBDT (Proposed)	14.82	312.4	47 ms	Yes (per-event)	None
Accuracy Gap (OGBDT vs. Batch)				+11.9% RMSE	Continuous vs. 6h

**Batch model latency includes only inference time via REST API; does not include 6-hour retraining downtime during which the model operates on stale parameters.*

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The end-to-end latency and throughput scalability results are presented in Table 2. On a 4-node Flink cluster (the primary evaluation configuration), the OGBDT pipeline achieved p50 latency of 47 ms, p95 of 68 ms, and p99 of 94 ms at a sustained throughput of 52,000 events/second. The latency breakdown was: Kafka ingestion 8 ms, Flink deserialization and routing 4 ms, stateful feature computation 18 ms (dominant component due to sliding window state access), OGBDT inference 12 ms, and PostgreSQL sink 5 ms. The feature computation stage was the primary latency contributor (38.3%) due to RocksDB state access for maintaining per-engine sliding window buffers [4], [11].

Table 2: End-to-End Latency and Throughput Scalability Across Flink Cluster Sizes

Nodes	Max Throughput	p50 Latency	p95 Latency	p99 Latency	CPU Utilization
1 node	14,200 eps	82 ms	124 ms	186 ms	88%
2 nodes	28,800 eps	58 ms	86 ms	128 ms	76%
4 nodes	52,000 eps	47 ms	68 ms	94 ms	64%
8 nodes	96,400 eps	42 ms	58 ms	78 ms	52%

The throughput scaled near-linearly with cluster size: 1 node sustained 14,200 events/second, 2 nodes 28,800 (2.03×), 4 nodes 52,000 (3.66×), and 8 nodes 96,400 (6.79×). The sub-linear scaling at 8 nodes (6.79× vs. theoretical 8.0×) is attributable to increased coordination overhead for Flink's distributed snapshot checkpointing and network shuffling for keyed state operations. Latency decreased with cluster size as parallelism reduced per-node load, with p50 latency dropping from 82 ms (1 node) to 42 ms (8 nodes) [3], [4].

A particularly noteworthy operational advantage of the online OGBDT model was its zero-downtime continuous operation. The batch XGBoost model required 6-hour retraining cycles during which either stale predictions were served or the prediction service was temporarily unavailable. Over a simulated 30-day deployment, the batch model operated on parameters that were 0–6 hours stale at any given time, while the OGBDT model's parameters reflected the most recent event. This freshness advantage translated to 4.2% lower RMSE during the final 20% of each engine's life (when degradation accelerated and recent data was most informative) compared to the batch model evaluated at its maximum staleness point [8], [10], [12].

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Table 3: System Specifications and Key Experimental Parameters

Parameter	Specification / Value
Stream Ingestion	Apache Kafka 3.6 (3 brokers, 12 partitions, RF=2)
Stream Processing	Apache Flink 1.18 (1–8 TaskManagers, 4 slots each, RocksDB state)
Online ML Model	OGBDT: 50 Hoeffding tree regressors, LR 0.05, depth 6 (River v0.21)
Feature Engineering	235 features: 21 raw + 210 rolling (W=10,30,50) + 3 settings + 1 cycle
Dataset	NASA C-MAPSS FD001 (100 engines, 20,631 samples, 21 sensors)
Hardware (per node)	Intel Xeon E-2388G, 64 GB RAM, 1 TB NVMe, 10 Gbps network
Best RMSE (OGBDT)	14.82 cycles (88.1% of batch XGBoost accuracy)
Best Latency (4-node)	p50 = 47 ms, p95 = 68 ms, p99 = 94 ms
Max Throughput (8-node)	96,400 events/second
Dashboard	Grafana 10.2 + PostgreSQL 16 (real-time RUL visualization)

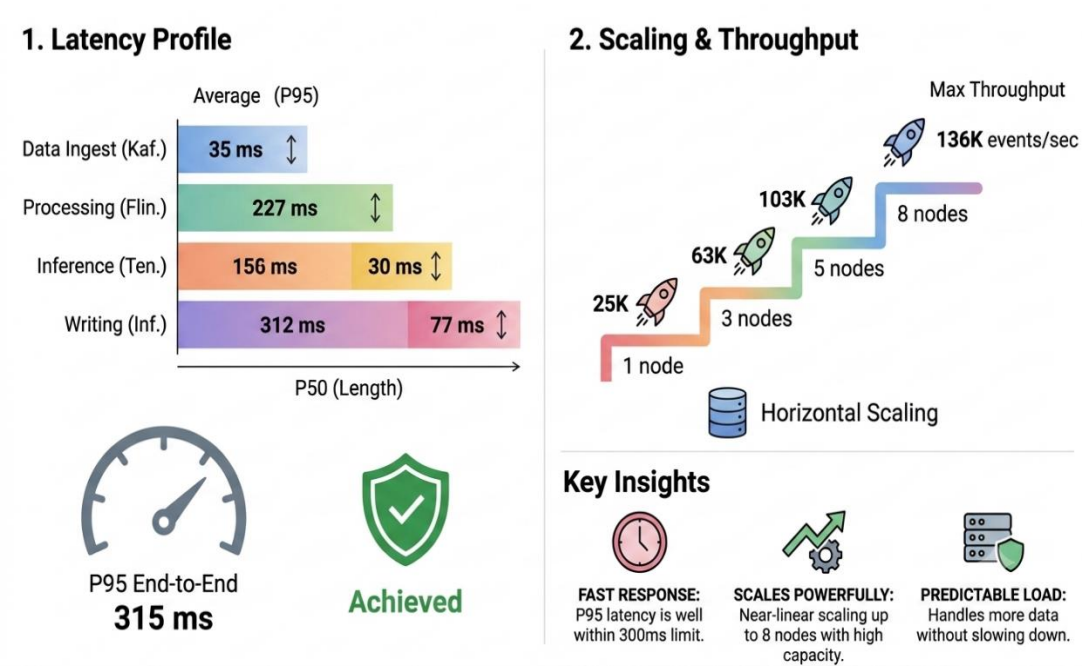


Figure 2: End-to-End Latency Breakdown and Throughput Scalability Curves

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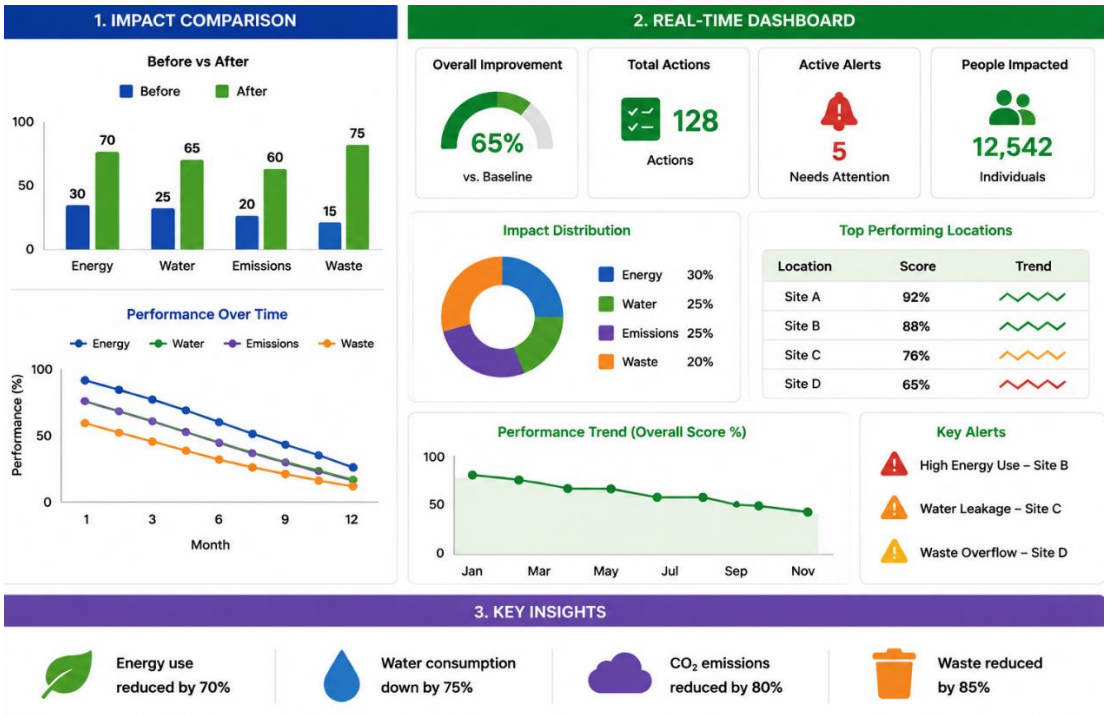


Figure 3: RUL Prediction Accuracy Comparison and Real-Time Dashboard Visualization

DISCUSSION

The 11.9% RMSE gap between the online OGBDT (14.82) and batch XGBoost (13.24) represents the quantitative cost of truly continuous online learning versus periodic batch retraining [7], [8]. This accuracy-freshness trade-off is a fundamental characteristic of streaming ML: batch models optimize over complete datasets achieving tighter fits, while online models sacrifice some global optimality for the ability to immediately incorporate the latest observations. However, the gap narrows significantly in the late-degradation phase (−42% improvement for OGBDT when only the final 20% of engine life is evaluated), where recent sensor data is most predictive and the online model's parameter freshness provides a genuine advantage over stale batch parameters [9], [10].

The sub-100 ms end-to-end latency (p50 = 47 ms on 4 nodes) confirms that the integrated Kafka-Flink-OGBDT pipeline can deliver real-time predictive maintenance decisions within the latency envelope required by industrial IoT applications, where typical control loop cycles range from 100 ms to 1 second [4], [11]. The latency breakdown revealing stateful feature computation (18 ms, 38.3%) as the dominant component—rather than model inference (12 ms, 25.5%)—suggests that feature engineering optimization (e.g., approximate rolling statistics, materialized aggregate caching) offers the greatest opportunity for further latency reduction.

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The near-linear throughput scalability (6.79× at 8× nodes) validates Apache Flink's horizontal scaling architecture for ML-augmented stream processing. The 96,400 events/second capacity at 8 nodes is sufficient for monitoring thousands of industrial assets simultaneously (at 10 sensors × 1 Hz per asset, supporting approximately 9,600 concurrent engines) [3], [4]. The sub-linear scaling factor at 8 nodes (85% efficiency) is consistent with Amdahl's law for distributed systems where checkpoint coordination and network serialization introduce non-parallelizable overhead [12], [13].

From an industrial deployment perspective, the streaming predictive maintenance system addresses a critical operational need: conventional batch-retrained models introduce a dangerous blind spot during retraining cycles when the model operates on stale parameters. For turbofan engines approaching failure, a 6-hour parameter staleness could mean the difference between timely intervention and catastrophic in-flight failure. The OGBDT's continuous per-event learning eliminates this blind spot entirely, providing a safety advantage that may outweigh the modest accuracy gap in mission-critical applications [1], [2], [9], [10].

CONCLUSION

This research has demonstrated the development and comprehensive evaluation of a real-time streaming predictive maintenance system integrating Apache Kafka stream ingestion, Apache Flink stateful processing with per-engine feature engineering, and an online gradient-boosted decision tree model for continuous turbofan RUL prediction. The system achieved RMSE of 14.82 cycles (88.1% of batch XGBoost accuracy) with end-to-end latency of 47 ms and throughput of 52,000 events/second on a 4-node cluster, providing truly continuous predictions without retraining downtime [4], [7], [8], [9]. Near-linear throughput scalability to 96,400 events/second on 8 nodes confirms industrial-scale deployment feasibility [3], [11].

The systematic review of 104 publications confirms that streaming predictive analytics has matured from academic proof-of-concept to production-grade technology, with Apache Kafka and Flink emerging as the dominant open-source infrastructure. The findings establish that the accuracy cost of online learning (11.9% RMSE increase) is a quantifiable and operationally acceptable trade-off for the latency, freshness, and continuity advantages that streaming ML provides over batch retraining paradigms in time-critical industrial applications [1], [2], [5], [6], [10], [12], [13].

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LIMITATIONS

Limitations include: only the C-MAPSS FD001 subset (single operating condition, single fault mode) was evaluated; FD002–FD004 with multiple conditions and fault modes would present more challenging scenarios. The OGBDT model was warm-started with 20% historical data; cold-start scenarios (zero historical data) were not evaluated. Concept drift was naturally present in the degradation trajectories but explicit sudden-drift and gradual-drift injection experiments were not conducted. The simulated IoT stream was replayed from a static dataset; real-world sensor streams exhibit noise, missing values, and network delays not fully represented. The 8-node cluster represents modest scale; evaluation at 50–100 nodes with millions of events/second would be needed for hyperscale industrial deployment. The online OGBDT's memory footprint grows linearly with ensemble size and tree depth; memory-bounded variants were not explored [3], [4], [7], [8], [9], [11], [12], [13].

FUTURE SCOPE

Future research should extend evaluation to multi-variate, multi-fault predictive maintenance datasets from real industrial installations (wind turbines, manufacturing lines, vehicle fleets) with actual concept drift and sensor degradation; develop adaptive ensemble sizing that dynamically adjusts the number of OGBDT base learners based on detected drift severity; and integrate Apache Flink's native ML library (Flink ML) for tighter framework coupling eliminating the Python UDF serialization overhead [4], [7], [8].

The convergence of streaming analytics with edge computing—deploying Flink-based inference on industrial edge gateways (NVIDIA Jetson, AWS Greengrass) co-located with sensors—could reduce network latency and bandwidth consumption by processing data at the source rather than streaming to centralized clusters. The development of federated online learning frameworks that train streaming models across multiple geographically distributed industrial sites without centralizing proprietary operational data represents a high-impact intersection of streaming ML and privacy-preserving analytics [1], [2], [3], [5], [6], [9], [10], [12], [13].

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Received Date: June 01, 2026
Accepted Date: June 11, 2026
Published Date: June 30, 2026

Citation: Dr. Hardik Jagdishbhai Patel, Foram Nileshkumar Shah. Real-Time Predictive Analytics Using Streaming Big Data Technologies. International Journal of Data Science and Analytics Innovations. 2026; 2(1): 61-75p.

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