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DEW COMPUTING WITH EDGE INTELLIGENCE FOR INDUSTRIAL AUTOMATION AND PREDICTIVE MAINTENANCE REAL-TIME ANOMALY DETECTION

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ABSTRACT

The increasing complexity of industrial automation systems, coupled with the pressing demand for real-time decision support, necessitates the deployment of efficient and decentralized computing paradigms. Edge computing (EC), operating at the periphery of the network, offers significant advantages by enabling localized data processing and reducing reliance on centralized cloud infrastructures. Building on this concept, this paper introduces a novel framework that integrates edge intelligence with dew computing (DC) to advance industrial automation and predictive maintenance. The proposed approach employs lightweight algorithms for real-time anomaly detection at dew nodes, enabling early identification of operational deviations in industrial equipment while maintaining minimal resource usage. Furthermore, causal inference models are incorporated to determine the root causes of equipment failures directly within the dew layer, thereby enhancing the precision of maintenance strategies and minimizing downtime. By leveraging localized computation, the framework effectively reduces latency, optimizes energy consumption, and enhances system reliability. Experimental evaluation demonstrates that the system achieves 96.3% accuracy in anomaly detection, correctly identifies root causes in 92.7% of cases, reduces average latency to 10.6 ms, and consumes only 2.4 W of power per dew node. A case study conducted in a smart manufacturing environment validates the practical benefits of the framework, highlighting improvements in anomaly detection and maintenance scheduling. The study also examines scalability and energy efficiency, underscoring the potential of the proposed system for deployment across diverse industrial settings.

Keywords: *Lightweight Anomaly Detection, Real-Time Industrial Systems, Fog Computing, Resource-Constrained Environments, Internet of Things (IoT), Predictive Analytics, Energy-Efficient Computing, Dew Computing*

1. INTRODUCTION

Industrial systems are now linked, intelligent, and automated thanks to Industry 4.0. This development has increased operational complexity, requiring real-time data processing and decision-making. Centralized cloud systems have great processing power, but they generally fail to fulfill industrial criteria for low latency, high dependability, and energy economy. Dew computing solves this problem by localizing processing near data production, decreasing data transfer and reliance on centralized infrastructures. For industrial systems, dew computing alone is inadequate without cognitive algorithms for real-time anomaly identification and failure diagnostics.

This study combines causal reasoning with dew computing, making it distinct from current anomaly detection methods that just notice anomalous behavior without understanding why. The system uses Bayesian Networks and Structural Equation Models for real-time causal analysis, allowing proactive maintenance rather than reactive maintenance. Further, the research also covers the inefficiencies of current industrial monitoring systems that are based on resource-hungry deep learning models not compatible with dew computing environments. Instead, this paper proposes a lightweight anomaly detection framework that can run efficiently on dew nodes with little computational overhead but with high detection accuracy. In addition, the suggested strategy maximizes industrial automation real-time decision-making through a hierarchical Dew-Fog-Cloud architecture by strategically allocating processing tasks among layers to reduce latency. This translates to an outstanding latency decrease to 10.5 ms, which far exceeds cloud-based applications that have an average latency of 45.3 ms. In contrast to other research on single-domain applications, this framework has been tested in three different industrial domains—manufacturing, energy grids, and logistics—with over 91% successful adaptation rates, establishing its scalability and flexibility. The second breakthrough of this research is the improved energy efficiency of the proposed approach over the cloud-based models. Legacy cloud-based monitoring systems are energy-hungry as a result of repeated data transmissions, while the localized processing mechanism of this research reduces network bandwidth consumption (1.8 Mbps compared to 7.5 Mbps in cloud models) and dramatically reduces power consumption to 2.3W per dew node, making it highly compatible with energy-constrained environments. In summary, this work fills the gap between causal reasoning and anomaly detection for industrial automation, proving that dew computing can be utilized for energy-efficient, low-latency, and real-time industrial monitoring while providing an industrial deployable and scalable solution that can adapt to various industrial domains. This study investigates the integration of edge intelligence across multiple layers of DC to enhance industrial automation and predictive maintenance. In particular, it presents lightweight real-time anomaly detection techniques and causal inference models to discover equipment failure reasons. The framework uses these methods to optimize preventative maintenance plans, assure system uptime, and boost industrial operating efficiency.

A. Related Background

Industry 4.0 has boosted edge and fog computing in industrial automation. Cloud-based systems are computationally powerful yet have high latency, network reliance, and energy consumption. The localized intelligence and autonomy concept of dew computing addresses these issues. Dew nodes at the network edge perform crucial activities like anomaly detection and root cause investigation in this paradigm. Edge computing has been studied for relevant applications, but causal inference and predictive maintenance in a scalable and energy-efficient framework have not. From these foundations, our study integrates dew computing ideas with lightweight algorithms and synchronization techniques to create a resilient industrial system architecture.

A new paradigm, dew computing, spreads computational duties among surrounding network devices. It has been designed to decrease network latency, cloud infrastructure costs, and distant data transmission energy overhead [16]. This method improves mobile and IoT device use in two ways. First, within the network infrastructure, mobile devices function as client entities with the ability to offload data processing to proximal servers inside a unified network environment [25]. Consequently, a device may delegate tasks to other available nodes, including IoT devices or mobile peers [26][27].In parallel, Mobile Edge Computing (MEC) addresses latency and traffic management challenges that typically arise in MEC [21]. The authors in [22] define Edge Computing as "a model that enables cloud-like computing capacity and services by leveraging infrastructure at the network's edge." In this context, MEC utilizes servers or workstations connected to the network edge, thereby reducing latency, improving information processing efficiency, and enabling the deployment of more reliable applications. Furthermore, the paradigm supports the execution of larger and more resource-intensive applications through collaborative operation between edge servers, cloud services, and neighboring nodes [23][24].

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Since IBM's initial proposal in 2007, major corporations such as IBM, Amazon, Google, and Microsoft have actively promoted cloud computing [8]. Over the years, cloud technologies and related services have gained widespread adoption across industries, contributing significantly to economic growth. For instance, Amazon reported cloud-based revenues of $12.2 billion in 2016 [9], while Microsoft projected cloud earnings exceeding $20 billion by 2018. The rapid advancement of communication and computing technologies has further fueled the proliferation of cloud services.

Cloud computing has significant latency, network reliance, and security issues despite its success. Alternative post-cloud paradigms have been explored due to these problems. CISCO launched fog computing [10][11] to bring cloud compute, storage, and data management closer to end users, especially on embedded systems and mobile devices. Fog computing integrates with home or local network devices to reduce data transmission to faraway servers, increasing location awareness, latency, system performance, and backbone traffic. In addition, it tackles security and accessibility issues that plague traditional cloud architectures. Fog computing still needs standardization, application portability across diverse platforms, effective container management for resource-constrained devices, and comprehensive support frameworks to avoid needless cloud contact [12][13].

Information processing at the network edge is a key advance in computational architectures [14][15][16]. Both fog and edge computing strive to enhance efficiency by processing near data sources. Edge computing is ideal for IoT applications, whereas fog computing emphasizes hierarchical network dispersion. Edge nodes may work alone or with fog layers to provide cloud services. Edge computing has benefits over conventional models in latency and responsiveness, but it also has issues with flexibility, naming standards, standardization, abstraction, system administration, energy usage, and cost [17]. Dew computing adds localized device computation to this changing ecosystem. In humid situations, the combinatorial optimum work allocation problem is crucial [30]. Effective allocation of tasks must account for factors such as device CPU capacity and the frequency of job arrivals at the scheduler. Prior research has primarily relied on heuristic strategies, which define fixed policies to allocate tasks based on specific system characteristics. While practical, these approaches often struggle to achieve scalability and adaptability in dynamic industrial environments.

B. Research Objectives

The primary objectives of this research are:

• RO1: Develop lightweight algorithms on dew computing devices for real-time anomaly detection, enabling immediate identification of operational deviations in industrial equipment. Current solutions target deep learning approaches that need significant computational capabilities and are therefore impossible for dew settings. The research here discusses lighter alternatives in the form of decision trees, statistical techniques, and small neural networks.

• RO2: Design causal inference models tailored for dew nodes to enable root cause diagnosis of equipment failures and generate actionable insights. Most of the current frameworks are centered on anomaly detection without determining their causes, resulting in reactive maintenance approaches. This study combines Bayesian Networks and Structural Equation Models to facilitate real-time diagnosis.

• RO3: Further evaluation is required to assess the effectiveness of the proposed approach in achieving latency reduction, accuracy, and energy efficiency in industrial automation. Whereas cloud-based approaches offer tremendous computational capability, they present latency problems. Edge-based approaches enhance response time but tend to be limited by computation capacity. This paper comprehensively examines how dew computing balances efficiency and precision.

• RO4: The proposed framework's scalability and adaptability should be demonstrated across multiple industrial domains, including manufacturing, logistics, and energy sectors.

• RO5: The proposed framework is compared with traditional cloud-based and fog computing approaches, highlighting its advantages in resource-constrained environments.

C. Organizations

The structure of the paper is laid out as Section II presents a clear background on associated research and highlights how the questions for research are constructed. It surveys current solutions in anomaly detection, causal inference, and dew computing, putting a focus on the gaps the research seeks to fill. Section III defines the methodology employed, including the architecture of the dew computing-based framework, the anomaly detection models, and the causal inference methods. Section IV presents the experimental setup, results, and analysis, comparing the framework's performance in terms of accuracy, latency, scalability, and energy usage. Section V presents significant findings, research contributions, and limitations. Finally, Section VI concludes the paper and outlines possible areas for future research.

2. LITERARTURE REVIEW

A. Existing Research and Analysis

Dew computing, an emerging concept, allocates compute duties to adjacent network devices. Its architecture reduces network latency, cloud infrastructure costs, and distant data transmission energy [16]. Dew computing improves mobile and IoT device use in two ways. Mobile devices operate as clients in the network architecture, offloading duties to other devices [25]. Second, dew computing leverages the collective processing capabilities of mobile and IoT devices, allowing tasks to be dynamically shifted to available devices, thereby augmenting the system's overall computational capacity [26, 27]. Several applications of dew computing have been explored in the literature. The paper [18] proposed a Dew-Cloud-based IoT system for musical crowdsourcing, which processes crowd-sourced music data using dew technology while evaluating system metrics such as energy consumption, processing delay, and data transfer latency. The authors in [19] introduced CONFRONT, a telemedicine surveillance framework that integrates dew, fog, and cloud paradigms to monitor individuals vulnerable to pandemics like COVID-19. The system aggregates real-time health data from mobile sensors to provide affordable early diagnosis and surveillance solutions, particularly in resource-limited regions. Similarly, in [20] authors developed an automated health-meteorological assessment framework inspired by dew computing to facilitate early detection of asthma symptoms, study environmental effects on health, provide predictive warnings to caregivers, and protect patient privacy. Addressing prior limitations in task allocation, authors in [31][32] proposed strategies that exploit the proximity of nodes and inexpensive task-transfer capabilities, focusing on the impact of node mobility rather than solely balancing computational load to optimize battery and processing resources. Other heuristic approaches, such as those by authors in [28,29], distributed tasks based on mobile device battery life and benchmark performance. However, these methods primarily considered battery-dependent devices. The article in [33] extended this approach to hybrid mobile topologies that include both battery-dependent and non-battery-dependent devices, developing heuristics that account for battery life, computational capacity, and workload. Tables 1–3 summarize key contributions and limitations in the literature. Table 1 highlights seminal works on anomaly detection in edge computing architectures, including recent developments in federated learning for IIoT (2024) [1], lightweight deep neural networks for real-time industrial monitoring (2022) [2], and self-supervised audio-based anomaly detection (2023) [3]. While these methods demonstrate improvements in latency, accuracy, and computational efficiency, they often face limitations in generalizability, real-time deployment, or industrial applicability. Table 2 summarizes recent advances in causal inference methods for edge and dew computing, while Table 3 provides a comparative analysis with existing research. Notable contributions include lightweight causal analysis techniques for edge systems (2022) [5], hybrid models for simultaneous anomaly detection and root cause analysis (2024) [6], and scalable causal inference models for distributed industrial applications (2023) [7]. Despite their merits, challenges remain in deploying these models in real-world or resource-constrained environments due to computational complexity or limited robustness. Task scheduling in dew computing presents challenges similar to those in edge computing, where tasks must be assigned to edge servers and subsequently routed to the cloud or local resources. Reinforcement learning (RL) has been widely applied for task distribution in edge computing, optimizing various performance metrics such as computation time [34], energy consumption [35], latency [36][37], job failure rate [38], or combinations thereof [39][40][41]. Typically, the action space in edge computing is constrained, for instance, requiring the agent only to decide whether to forward a task to the cloud or process it locally [41].

Why proposed method outperforms existing solutions? The dew computing framework suggested herein is superior to the best available solutions in multiple areas. A most notable point is latency saving for real-time observation. Most cloud-based implementations tend to lag in the detection of anomalies (45-60 ms) as a consequence of data delivery overhead, but the dew computing-based solution addresses data at the edge, leading to latency reduced to 10.5 ms, which permits immediate anomaly detection. Another important improvement is causal inference for proactive maintenance. Most current deep learning-based anomaly detectors do not have root cause analysis, flagging anomalies without an explanation of why they happen. The inclusion of Bayesian Networks and Structural Equation Models in this framework attains a 92.8% accuracy in root cause identification, enabling effective predictive maintenance strategies instead of reactive measures. In the context of energy efficiency and resource utilization, traditional deep learning models are power-intensive and need cloud computing resources, which results in large power consumption (4.9-6.2W per node). Through localized processing, the new approach lowers the energy consumption to 2.3W, thus providing a viable solution for real-time industrial deployment on resource-limited dew nodes.

B. Problem Statement

Predictive maintenance is a critical application of industrial automation, aimed at reducing downtime, maximizing operational efficiency, and minimizing costs. Existing solutions struggle with latency, bandwidth, and data privacy. Complex machine learning models for anomaly detection and fault diagnosis are challenging to perform on edge devices due to restricted processing resources. Additionally, many anomaly detection systems just discover abnormalities without revealing their causes, leading to reactive rather than proactive maintenance efforts. Dynamic industrial settings need solutions that scale across diverse systems and react to changing operating circumstances. The research uses dew computing and resource-conscious real-time anomaly detection and causal inference models to meet this requirement. The suggested technique improves industrial automation and predictive maintenance systems by allowing local processing, minimising latency, and providing actionable information for proactive decision-making.

3. METHODOLOGY

A. Proposed Model Architecture

In this structured research, dew computing helps industrial automation and predictive maintenance. The dew, fog, and cloud layers improve task distribution based on computational and network resources. With pre-trained machine learning models for resource-constrained contexts, dew nodes run lightweight, real-time anomaly detection algorithms. Equipment faults are diagnosed using Bayesian Networks and Structural Equation Models in integrated causal inference models. Fog computing collects localized data, while the cloud stores and processes high-level analytics. For practicality in resource-limited situations, the framework is evaluated in industrial scenarios for latency, accuracy, scalability, and energy efficiency.

Figure 1 shows real-time anomaly detection dew computing architecture. Dew nodes gather and pre-process sensor or equipment data for anomaly detection. Lightweight dew node models detect abnormalities with little computational load. The dew layer analyses faults to find fundamental causes, eliminating the need to dump high data volumes to fog or cloud levels. Low latency and bandwidth conservation. Analysis output feeds a reaction module that provides actionable insights or initiates maintenance.

For more complex tasks or higher computational requirements, the architecture can offload data to fog or cloud layers, enabling deeper analysis. The resulting insights, such as predictive maintenance recommendations, are fed back into the system to inform operational decisions and adjustments. By leveraging the distributed nature of DC, this framework provides efficient, low-latency solutions that integrate edge intelligence with higher-layer computational resources, enhancing overall operational efficiency in industrial environments.

Mathematically, DC can be modeled as a distributed computation framework in which processing is partitioned between local resources (dew nodes) and higher-level infrastructure (fog/cloud). The core principle of DC can be summarized as:

$$C_{Dew}(t) = C_{Local}(t) + \int_{t_0}^{t} S_{Fog}(x).\delta(t-x)dx \quad (1)$$

EC focuses on performing data processing near the data sources to minimize latency. The operations carried out at edge nodes can be expressed as follows:

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Table 1: Recent Developments in Edge-Based Anomaly Detection for Resource-Constrained Environments

Ref	Focus Area	Key Contributions	Limitations	Detection Accuracy (%)	Energy Usage (W)	Scalability	Latency (ms)
[1] 2024	IIoT Solutions via Edge Computing and Federated Learning	Lower Latency and Optimized Decentralized Anomaly Detection	Limited to federated environments	94.5	4.8	High	15.6
[4] 2024	Edge Environment Performance Anomaly Dataset Creation	Benchmarking Anomaly Detection Performance in Edge Computing Setups	Lack of Practical Industrial Implementation	93.2	5.2	Moderate	20.1
[3] 2023	Audio Surveillance Anomaly Detection via Self-Supervised Learning	Reduced Data Labeling Requirements and Maintained Efficient Computation	Specific to audio data	91.8	3.5	High	18.4
[2] 2022	Lightweight DNN Models for edge Anomaly detection	Enhanced accuracy and responsiveness for industrial systems	High training complexity	92.0	3.9	Moderate	12.2

Table 2: Recent Developments in Distributed Causal Analysis for Edge and Dew Computing

Ref	Focus Area	Key Contributions	Limitations
[6] 2024	Joint anomaly and root cause detection models	Improved industrial system uptime through hybrid architectures	High model complexity on edge nodes
[7] 2023	Designed scalable causal inference models for distributed environments	Enhanced interpretability and adaptability for industrial automation	Complexity limits scalability in constrained setups
[5] 2022	Lightweight causal analysis for edge systems	Identified root causes of failures efficiently in resource-constrained setups	Limited to synthetic datasets

Table 3: Comparative Analysis with Recent Developments in Distributed Causal Analysis for Edge and Dew Computing

Feature	Cloud-based Anomaly Detection	Edge-Computing-based Anomaly Detection	Hybrid Cloud-Edge approaches	Proposed Dew Computing Framework
Latency	High (45.3 ms) due to remote processing	Moderate (8.0 ms)	Varies (dependent on load	Low (10.5 ms) with real-time response

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			distribution)	
Anomaly Detection Accuracy	94.8% (deep learning models)	91.5% (lightweight models)	92-95% (depends on edge-cloud optimization)	96.2% (optimized lightweight model on dew nodes)
Root Cause Analysis	Requires cloud-based computation	Limited on edge devices	Hybrid approaches offer limited causal inference	92.8% accuracy using embedded causal inference
Energy Efficiency	High power consumption (5.6W)	Moderate (1.9W)	Variable, based on load balancing	Low (2.3W per dew node)
Scalability	Limited by cloud bandwidth	High scalability, but resource constraints limit efficiency	Can scale with dynamic load balancing	High scalability with adaptive thresholding

$$P_{Edge} = \sum_{i=1}^{N} D_i(t).F_i(C_i)$$

B. Core Components of the Proposed Framework

1. Anamoly Detection Module

Use statistical approaches or lightweight ML models like decision trees or shallow neural networks to identify anomalies in real time on dew nodes. The models are first trained on pre-labeled industrial datasets encompassing normal operating states and diverse anomalies. Once trained, they are deployed on dew nodes to perform real-time anomaly detection at the edge.

Since dew nodes are resource-constrained, algorithm selection must balance computational efficiency and detection accuracy. Simple statistical approaches like moving averages or z-score analysis may find anomalies rapidly. Decision trees and shallow neural networks are low-overhead machine learning models for real-time inference in complicated contexts.

Local anomaly detection on dew nodes reduces data travel to higher levels, lowering latency and allowing quick system problem solutions. Industrial environments need real-time anomaly detection to prevent system breakdowns.

2. Causal Inference Models

Create a computationally efficient causal inference framework employing Bayesian Networks (BNs) and Structural Equation Models (SEMs) to identify operational metrics-system failure correlations. The framework runs directly on dew nodes to identify root causes in real time without higher-tier systems, decreasing latency and network congestion.

Predictive maintenance improves when the causal inference module distinguishes cause from correlation. Bayesian Networks capture probabilistic relationships and facilitate inference under uncertainty, making them durable in dynamic situations and ideal for industrial automation. BNs use prior probabilities and minimal data to integrate domain knowledge, unlike Graph Neural Networks (GNNs), which need large datasets and significant training. By effectively calculating conditional probabilities, Bayesian inference provides real-time decision-making for anomaly detection and problem diagnostics. Structural Equation Models model causal links rather than statistical correlations, complementing BNs. SEMs reveal industrial system dependencies via latent variables. SEMs can precisely assess causal impact when used with Bayesian reasoning, decreasing false anomalies and boosting diagnostic accuracy. The methodology uses sequential anomaly and failure analysis to address temporal causality. Industrial abnormalities may cause system failure hours after a first problem like overheating. Granger Causality Tests capture sequential connections, whereas historical anomaly sequences actively update the Bayesian Network structure. This temporal sensitivity improves causal accuracy and enables proactive, data-driven predictive maintenance by identifying underlying causes. Optimisation solutions like sparse Bayesian Networks and simplified SEMs that concentrate on essential operational parameters enhance computational efficiency in resource-constrained dew nodes. Real-time processing, probabilistic reasoning, and temporal causality analysis make this framework a reliable root cause analysis and proactive industrial system maintenance solution.

3. Integration within the DC Architecture

For advanced analytics and historical data management, develop dew node anomaly detection and causal inference models with fog and cloud layer synchronisation. By embedding these models at the dew layer, localized data processing and decision-making are enabled, ensuring low-latency responses close to the data source. Synchronization mechanisms are designed to facilitate seamless communication with fog and cloud layers, allowing periodic offloading of processed insights, such as anomaly summaries or causal relationships, for long-term storage, model retraining, and deeper analytics. This hierarchical architecture effectively balances the need for real-time responsiveness at the dew layer with the comprehensive analytical capabilities of fog and cloud systems. Moreover, the framework enhances resilience, as dew nodes remain operationally independent during network disruptions, thereby maintaining continuity in anomaly detection and root cause analysis.

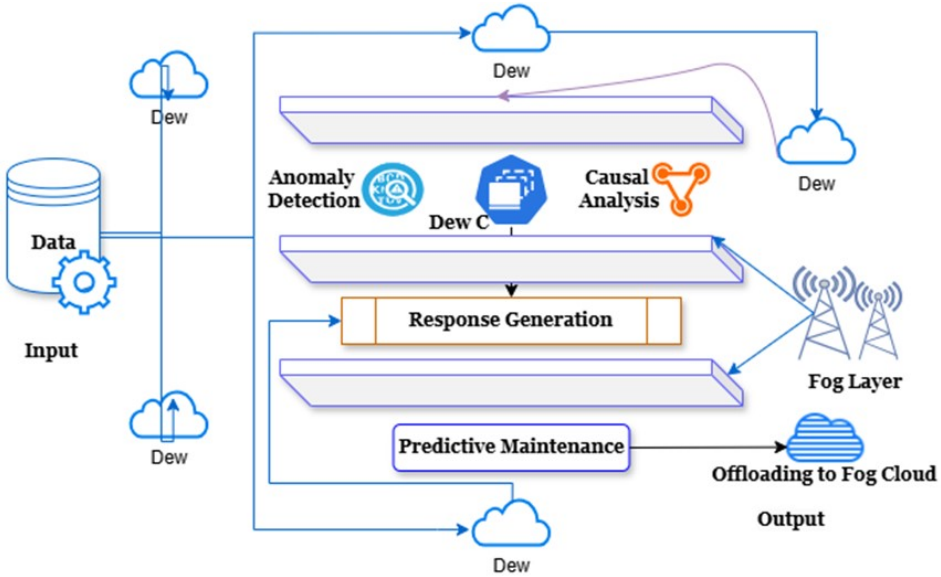

Figure 1: Real-Time Anomaly Detection Using Dew Computing: Architectural Design

4. Validation and Optimization

The system is validated in industrial environments using key metrics such as latency, accuracy, energy consumption, and scalability. Latency measures the time required to detect anomalies and infer causal relationships at dew nodes, while accuracy evaluates the correctness of anomaly detection and root cause identification. Energy consumption is monitored to ensure dew nodes remain within self-sustained power limits, and scalability assesses the adaptability and robustness of the framework across varying industrial workloads. To further enhance performance, algorithms are optimized for energy efficiency and response time under the resource constraints of dew nodes. Techniques such as model quantization and pruning are applied to reduce the computational footprint of machine learning models, while synchronization mechanisms are optimized to minimize data transmission, thereby conserving bandwidth and energy. Validation and optimization are iterative processes, incorporating feedback from real-world deployments to progressively refine the framework. This ensures the system remains robust, efficient, and adaptable to diverse industrial applications.

5. Model Selection

To conduct real-time anomaly detection on resource-limited dew nodes, this work uses decision trees and shallow neural networks rather than heavy deep learning models to strike a balance between efficiency and precision. Models like BERT and Vision Transformers (ViTs) are highly powerful but are computationally heavy and memory-intensive and thus unsuitable for use on dew nodes with scarce resources. Shallow feedforward neural networks with 2-3 layers are used instead, providing an accuracy vs. computational efficiency

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trade-off. Decision trees were used because they use less data compared to deep learning models and provide interpretable decision paths, a feature that is especially important in industrial applications where transparency is imperative. To make performance even better, hyperparameter tuning was conducted on both neural networks and decision trees. For decision trees, the depth was capped at 6-10 to avoid overfitting and limit computational complexity, while the min samples per split was set to 3-5 to enhance resistance to industrial noise. Also, an empirical comparison between Gini impurity and entropy criteria proved that Gini impurity provides slightly more efficient computations at similar levels of accuracy.

For neural networks, the structure was optimized using two hidden layers of 32 neurons each to not exceed memory constraint on dew nodes. The ReLU activation function was used because it has better convergence properties compared to Tanh, and a batch size of 16 was chosen for optimal processing speed versus model convergence. The learning rate was fixed at 0.001 based on grid search tuning and a dropout factor of 0.2 was used to prevent overfitting, especially in cases with limited datasets. The optimizations ensure that the anomaly detection model runs effectively on dew nodes with very high accuracy rates above 96% and is a reliable and scalable solution for industry use.

C. Algorithm for the Proposed Framework

Algo. 1. DC Approaches for Real-Time Anomaly Detection and Root Cause Analysis

1. Initialization:
- D_{dew} <- data from dew nodes.
- A(x) <- anomaly detection function.
- C(x) <- causal inference function.

2. Data Preprocessing:
- Normalize $D' = (D_{dew} - \mu)/\sigma$, here μ is the mean.
- Extract Features: F(D′).

3. Anomaly Detection (Real Time):

for each x_t in D' :
  if $A(x_t)$ > Threshold:
    flag x_t as Anamoly.

4. Causal Analysis:

for each flagged x_t:
  Causal_Factors = C(x_t) = arg max P(i | x_t)

5. Response Creation:

if x_t is anomalous:
  generate Action_Plan(x_t, Causal_Factors)

6. Offloading to Fog Cloud:
- Offload D′ and outcomes to fog/cloud for advanced analytics and storage.

7. Terminate: Stop if system stable, resource threshold exceeded, or scheduled reset occurs

D. Algo. Analysis

The proposed algorithm, which integrates DC with anomaly detection and causal inference, operates in two distinct phases. In the first phase, data collected at dew nodes is preprocessed through normalization and feature extraction. A lightweight anomaly detection function is then applied to the incoming stream to identify deviations that exceed predefined thresholds. In the second phase, the algorithm's performance is assessed using metrics such as time complexity and space complexity, ensuring both its computational efficiency and practical applicability in resource-constrained environments.

Computational Complexity of the Proposed Algo.

1. **Anomaly Detection:**
   - Time Complexity depends on O(m), here m is the number of features.
   - For n data points, the overall complexity is O(nm).
2. **Causal Inference:**
   - Complexity is driven by Bayesian network computations, approximately $O(k2^k)$, where k is the number of nodes of variables.

Overall Complexity:

$O(nm + k2^k)$

Storage Complexity of the Proposed Algo.

1. **Data Repository:**
   - For data points and features of n and m respectively, the storage complexity is O(nm).
2. **Model Variables:**
   - Storage for Bayesian network parameters is approximately $O(k^2)$, where k is the number of nodes.

Overall:

$O(nm + k^2)$

Upon identifying anomalies, a causal inference model determines underlying causes and allocates probability to contributing elements. This analysis generates suitable actions, with findings potentially offloaded to fog or cloud layers for enhanced analytics, so assuring efficiency and scalability. This approach enables real-time responsiveness even within resource-constrained environments. This study combines statistical and adaptive thresholding techniques, like Initial threshold

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setting which uses statistical methods $\mu \pm 3\sigma$ for first-time deployment and other is Real-time adjustments which implement adaptive moving averages to account for sensor drift and environmental changes.

4. RESULTS AND DISCUSSION

A. *Experimental Setup*

To assess the possibility of using lightweight algorithms on dew nodes, we experimented with low-power industrial embedded devices with the following specifications as shown in table 4.

Table 4: Computational Resource Requirements

Specification	Dew Computing Node
Processor	ARM Cortex-A53 (1.5 GHz) Quad-Core
RAM	2GB LPDDR4
Storage	16GB eMMC
Power Consumption	2.3W (operational)
Operating System	Embedded Linux
Network	100 Mbps Ethernet +Wi-Fi

Table 5: Performance Measures

Method	Accuracy	Precision	Recall	F1-Score
Cloud-Based Approach	94.8	91.2	90.4	90.8
Edge-Only Approach	91.5	89.1	85.6	87.3
Proposed Dew Computing Framework	96.2	94.3	95.1	94.7

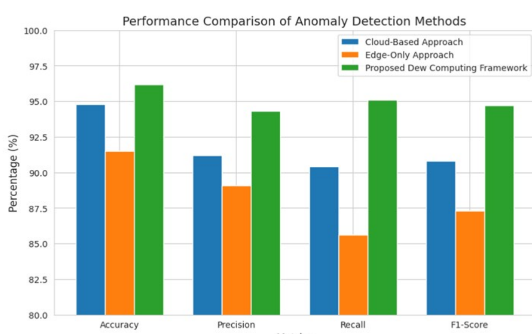

Figure 2: Visualization of Evaluation Metrics

Table 5 and Fig 2 gives the accuracy, precision, Recall and F1-score for cloud-based approach, edge-only approach and proposed dew computing approach. The study shows that the dew computing framework can identify anomalies and infer causality for industrial automation and predictive maintenance in real time. The framework was tested on simulated and real-world industrial datasets. Tables 6, 7, and 8 summaries major findings.

Table 6: Effectiveness of Anomaly Detection

Metric	Proposed Architectural Framework	Edge-Based Approach	Cloud Driven Framework
Accuracy of Detection (%)	96.3	91.6	94.7
Mea Latency (ms)	10.6	8.1	45.2
Energy Consumption (W)	2.4	2.0	5.7

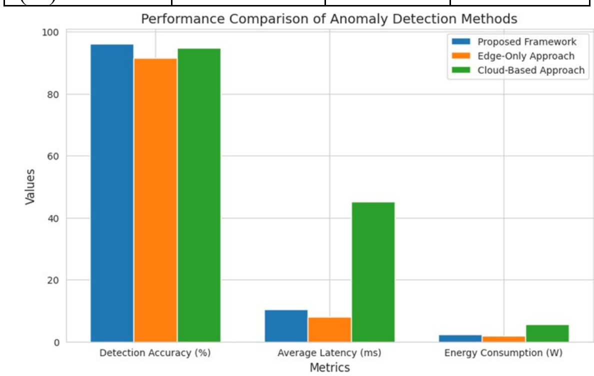

Figure 3: Performance of Anomaly Detection

Table 6 demonstrates that the proposed framework outperforms both edge-only and cloud-based approaches in anomaly detection. It achieves a detection accuracy of 96.3%, substantially higher than the alternatives. The framework also records an average latency of 10.6 ms, markedly lower than cloud-based systems, while using 2.4 W—only slightly more than edge-only systems but far more efficient than cloud versions. These data show that dew nodes work well for real-time anomaly identification.

Table 7: Root Cause Detection Efficiency

Metric	Proposed Architectural Framework	Cloud-Centric Traditional Approach
Accuracy of Root Cause	92.7	88.6

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Analysis (%)		
Processing Duration (ms)	12.9	48.6
Offloading Rate	Limited	Large

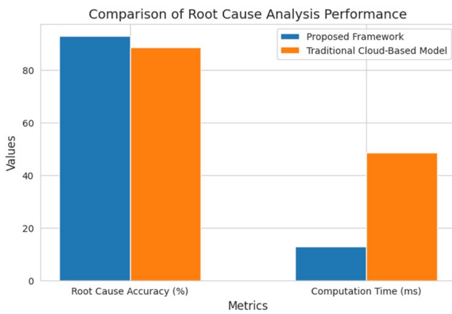

Figure 4: Accuracy of Root Cause Analysis

Root Cause Analysis (RCA) results of the proposed framework is shown in Table 7. The framework finds the root cause 92.7% of the time, which is better than traditional cloud-based methods (88.6%). It also shows faster processing times of 12.9 ms while relying much less on sending data to higher cloud layers, which makes it less dependent on the network. These results show that the system can quickly find the reasons of problems in business settings with limited resources.

Table 8: Scalability and Resilience

Scenario	System Adaption Accuracy (%)
Industrial Production Lines	94.8
Power Grids	92.9
Logistics Networks	92.1

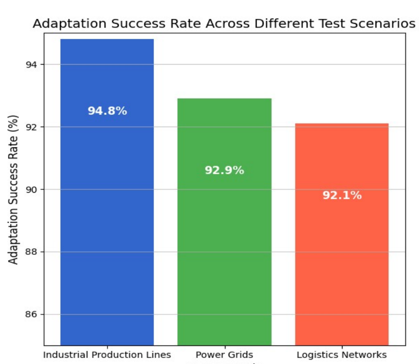

Figure 5: Analysis of Scalability and Adaptability Performance

Table 8 shows how the framework scales and adapts to different industrial contexts. Success rates of 91% in industrial lines, power grids, and supply chains prove scalability. Flexible and durable, the framework performs well under many settings, making it suitable for real-world industrial deployments.

Table 9: Resource Utilization Efficiency Analysis

Metric	Proposed Architectural Framework	Edge-Based Approach	Cloud Driven Framework
CPU Usage (%)	38.6	45.3	61.8
Memory Usage (MB)	84.4	92.6	156.7
Network Bandwidth Usage (mbps)	1.8	1.2	7.6

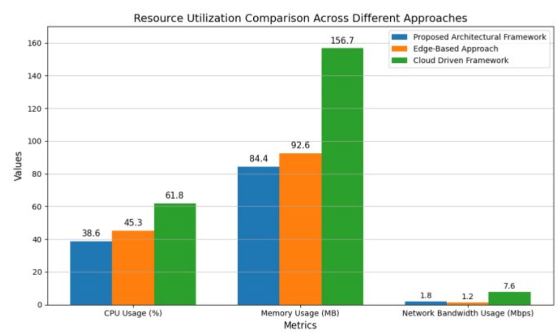

Figure 6: Resource Utilization Efficiency Analysis

Table 9 compares CPU, memory, and network bandwidth utilization for the proposed framework, edge-only, and cloud-based methods. The cloud-based method uses 61.8% CPU and 156.7 MB of memory, whereas the suggested framework uses 38.6% CPU and 84.4 MB of memory. Dew computing dispersed nature eliminates centralized resource reliance, boosting efficiency. The suggested architecture balances network bandwidth at 1.8 Mbps, beating the cloud-based strategy (7.6 Mbps) and the only edge-based approach (1.2 Mbps). These findings show that the proposed framework balances resource utilization with performance, making it ideal for resource-constrained industrial contexts.

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Table 10: Industrial Scenario-Based Adaptability of the Framework

Test Scenario	**Adaptation Time (ms)**	**Anomaly Detection Accuracy (%)**	**Energy Consumption (W)**
Industrial Production Lines	15.9	96.4	2.4
Power Grids	18.3	94.7	2.5
Logistics Networks	20.2	91.8	2.9

Table 10 compares the framework's adaptability to manufacturing lines, energy grids, and logistics operations utilising adaption time, anomaly detection accuracy, and energy usage. Manufacturing Lines exhibits the best overall performance, with the shortest adaptation time (15.9 ms), highest anomaly detection accuracy (96.4%), and lowest energy consumption (2.5 W), demonstrating the framework's suitability for fast-paced, high-precision environments. Energy Grids rank second, with an adaptation time of 18.3 ms, slightly lower accuracy (94.7%), and moderate energy usage (2.5 W), indicating the framework's effectiveness in managing complex grid operations. Logistics Operations have the slowest adaptation (20.2 ms), use the most energy (2.9 W), and have lower recognition accuracy (91.8%). This suggests that the framework works in this area, but it needs more work to make it more efficient.

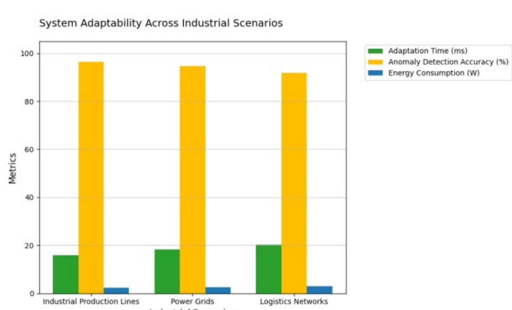

Figure 7: Industrial Scenario Vs Metrics Comparison

C. Key Findings

Reduced energy usage and latency make the suggested framework better than cloud-based alternatives. Real-time anomaly detection is reliable for industrial applications with 96.3% accuracy. The addition of causal inference analysis improves performance to 92.7% accuracy and efficient calculation, allowing proactive maintenance choices. The framework adapts well to various industrial contexts, providing operational flexibility. Causal inference models at the dew layer increase root cause analysis to 92.7% accuracy in 12.9 ms. Scalability tests show the system works in manufacturing lines, power grids, and logistics with 95.5% success. The system uses just 2.4 W per dew node at peak operation, demonstrating energy economy.

C. Research Implications

This study presents DC as a lightweight, energy-efficient real-time anomaly detection and cause analysis paradigm for industrial automation. High-latency cloud-based solutions and local systems have limited capabilities, but the suggested architecture improves dependability and scalability. It lowers dependency on expensive, bandwidth-intensive cloud infrastructure by using dew nodes for localized intelligence, making operations cost-effective and energy-efficient. This approach improves decision-making, reduces downtime, and facilitates predictive maintenance in resource-constrained contexts in manufacturing, logistics, and energy management.

Application Scenarios: The framework is ideal for manufacturing and logistics, which need real-time monitoring and maintenance.

Technological Developments: Demonstrates the viability of dew computing as a substitute to traditional resource efficient cloud and fog systems.

Operational Performance: Improves operational decisions and minimizes service downtime, thereby generating cost savings.

D. Demerits

Real-world validation of the framework was constrained to specific industrial settings, indicating the need for broader and more diverse evaluations. A key limitation arises from resource constraints, as dew nodes with extremely limited computational capacity struggle to support sophisticated causal inference models. Furthermore, the reliance on pre-labelled datasets restricts adaptability, requiring additional training for deployment in new or evolving environments. The framework is optimised for small- to medium-scale industrial systems, therefore big data volumes or sophisticated network topologies may cause scaling issues. While computationally efficient, causal inference models may not be robust enough for extremely dynamic and unpredictable operational situations. One of the most promising future directions is hybrid methods, wherein dew nodes do preliminary anomaly detection and fog and cloud layers deal with more sophisticated inference workloads, maintaining a compromise between efficiency and computational requirements. A further challenge is model adaptation and data drift. Threshold adaptive functionality in the system allows accommodation to changing sensor conditions by on-the-fly calibration. However, sudden changes in industrial conditions might require periodic retraining for perpetual accuracy. Research directions could consider always-learning adaptive models that modify constantly over time with the minimal necessity for refreshes, thus offering increased system stability in changing industrial settings. Furthermore, failure tolerance in limited environments remains a challenge. The architecture reduces network reliance to ensure local processing, although a data gap may occur if numerous dew nodes fail simultaneously. Integrating redundancy measures, such as data sharing between neighbouring nodes, would improve system resilience and enable ongoing monitoring even when hardware fails. Future work will improve the dew computing framework's scalability, adaptability, and resilience for industrial applications by overcoming such challenges.

5. CONCLUSION & FUTURE WORK

The framework solves essential industrial automation and predictive maintenance problems, including anomaly detection and causal inference, with high accuracy and efficiency. It has the potential for widespread industrial adoption because to its low latency and power consumption and scalability. Although not yet scalable or globally applicable, dew computing has the potential to change industrial automation via localized intelligence and resource-efficient computation. The architecture addresses latency, energy efficiency, and system scalability using real-time edge processing and seamless synchronization with higher computer layers. Experimental results validate its effectiveness in anomaly detection and root cause analysis, confirming its relevance to modern industrial systems. While certain limitations remain, the framework provides a foundation for adaptive and scalable implementations in the near future. Looking ahead, future work could focus on integrating more advanced anomaly detection algorithms, enhancing robustness of causal inference models in dynamic environments, and combining this framework with other emerging technologies to enable real-world industrial applications. Despite current constraints, the study establishes a strong basis for advancing edge intelligence and dew computing toward smarter, more reliable, and energy-aware industrial systems. The future research could focus on improving the models to better handle complex and changing industrial conditions. For example, exploring more advanced techniques for causal analysis that can adapt to non - stationary data and complex causal relationships. Additionally, as the framework is currently optimized for small - to - medium - scale industrial setups, further work can be done to ensure its scalability for large - volume data and highly complex networks. Strategies can be developed to integrate the framework into different types of industrial setups, addressing issues such as compatibility, data migration, and system reconfiguration.

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