Algorithms and Intelligence

Vol 2 Issue 1 (2026)

www.algointel.org

Probabilistic Granular Neural Clustering Handles Imbalanced Machine Sensor Streams with Adaptive Granules Online Streaming Data

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Abstract

The rapid proliferation of interconnected sensors in contemporary industrial environments has led to the generation of massive, high-velocity data streams. A critical challenge in analyzing these continuous data flows is the inherent imbalance and volatility of the underlying classes, particularly in machine health monitoring and predictive maintenance where anomalous events are exceedingly rare compared to normal operational states. Traditional clustering algorithms often fail to adequately capture minority cluster structures, leading to the misidentification or complete neglect of crucial anomaly signatures. To address this persistent issue, this paper proposes a novel framework designated as Probabilistic Granular Neural Clustering. The proposed methodology leverages granular computing principles to encapsulate local data geometries into information granules, which are subsequently processed by a probabilistic neural architecture designed to model the uncertainty and dynamic drift of data streams. By incorporating a probabilistic assignment mechanism, the framework dynamically adjusts cluster boundaries and mitigates the overshadowing effects of majority classes. Extensive experimental evaluations are conducted across multiple imbalanced machine sensor datasets. The analytical outcomes demonstrate that the proposed granular neural approach significantly enhances the detection and cohesive grouping of minority instances while maintaining the structural integrity of majority clusters. The framework offers a robust, scalable solution for unsupervised learning in non-stationary and heavily skewed industrial data environments.

Keywords

stream clustering, granular computing, imbalanced data, neural networks, sensor networks

1. INTRODUCTION

The advent of the fourth industrial revolution has fundamentally transformed the operational paradigms of manufacturing and infrastructural systems through the extensive deployment of advanced sensor networks [1]. These interconnected devices continuously monitor a vast array of physical and environmental parameters, generating continuous, unbounded, and high-velocity data flows commonly referred to as sensor streams [2]. The real-time analysis of such streams is paramount for numerous critical applications, ranging from autonomous process optimization to predictive maintenance and catastrophic failure prevention [3]. However, extracting actionable intelligence from raw sensor streams presents a multitude of formidable computational and statistical challenges, primarily due to the unique characteristics of the data generation process [4]. Unlike static datasets, sensor streams are subject to temporal dependencies, concept drift, and significant noise, necessitating the development of adaptive learning algorithms capable of processing information in a single pass while operating under strict memory and time constraints [5].

Among the most pressing challenges in sensor stream mining is the phenomenon of severe data imbalance [6]. In typical industrial scenarios, machines operate under normal, healthy conditions for the vast majority of their lifecycles. Consequently, the sensor readings corresponding to normal operational states constitute a massive majority class, whereas data instances representing degradation, transient faults, or impending failures form a minuscule minority class [7]. In the context of unsupervised learning and clustering, this severe skewness causes conventional algorithms to exhibit a strong bias toward the dense regions of the feature space occupied by the majority instances [8]. As a result, the sparse, dispersed instances belonging to the minority classes are frequently absorbed into the larger clusters or erroneously discarded as meaningless noise.

The inability to accurately cluster and isolate these minority instances has profound implications for predictive maintenance systems. When early indicators of mechanical degradation are lost within the noise of normal operations, the primary objective of condition-based monitoring is defeated, potentially leading to unexpected machine downtime and substantial economic losses [9]. To counteract this deficiency, researchers have proposed various stream clustering modifications, including density-based and micro-clustering techniques [10]. While these methods offer improvements in tracking evolving data distributions, they generally lack dedicated mechanisms to preserve the topological structure of rare events when the imbalance ratio reaches extreme proportions [11]. The fundamental limitation lies in their reliance on hard geometric distance metrics, which are inherently inadequate for modeling the complex, overlapping, and uncertain boundaries between healthy and anomalous sensor states [12].

In response to these limitations, this research introduces the Probabilistic Granular Neural Clustering framework. This approach synthesizes the representational power of granular computing with the adaptive learning capabilities of probabilistic neural networks [13]. Granular computing provides a structured methodology for abstracting raw numerical data into higher-

level entities known as information granules [14]. By grouping spatially and temporally proximal sensor readings into cohesive granules, the framework reduces the computational burden and highlights the underlying local data distributions, irrespective of their global density [15]. This granular representation serves as the input to a specialized neural clustering architecture that employs probabilistic distribution models rather than deterministic centroids.

The probabilistic nature of the neural network allows for the quantification of uncertainty in cluster assignments, enabling the system to differentiate between random noise and emerging minority clusters indicative of novel operational states [16]. Furthermore, the continuous adaptation of the network parameters ensures that the model remains responsive to concept drift without forgetting previously learned rare signatures [17]. The central premise of this work is that by transforming the raw data space into a probabilistic granular space, the disproportionate influence of the majority class can be systematically neutralized, thereby granting minority instances equitable representation in the clustering process [18].

The remainder of this academic manuscript is structured in a comprehensive and systematic manner. The subsequent section provides an extensive review of the existing literature encompassing sensor data stream mining, imbalanced learning strategies, and the theoretical foundations of granular computing and neural architectures [19]. Following the literature review, the methodology section details the architectural components, mathematical principles, and algorithmic procedures of the proposed framework [20]. The experimental setup, datasets, baseline comparative models, and analytical results are thoroughly discussed in the fourth section [21]. Finally, the conclusion summarizes the fundamental contributions of the research, acknowledges current limitations, and outlines promising trajectories for future investigative efforts [22].

2. Literature Review and Background

2.1 Sensor Stream Data Mining

The domain of sensor data stream mining has experienced substantial theoretical and practical advancements over the past two decades, driven by the exponential increase in data generated by modern telemetry systems [23]. Clustering continuous data streams requires specialized algorithmic structures because the data cannot be persistently stored or repeatedly iterated upon. The standard paradigm adopted by the scientific community is the two-phase clustering framework, which partitions the process into an online micro-clustering phase and an offline macro-clustering phase [24]. During the online phase, incoming data points are rapidly summarized into compact statistical structures, often referred to as cluster features or micro-clusters, which maintain essential information such as weight, linear sum, and squared sum of the data points [25].

Numerous algorithms have been developed based on this two-phase architecture. Early prominent works introduced mechanisms for capturing the temporal evolution of clusters through damped window models, where historical data gradually loses its influence over time,

thereby allowing the model to adapt to recent trends [26]. Density-based stream clustering algorithms emerged as a solution for discovering clusters of arbitrary shapes and identifying noise in dynamic environments [27]. These density-based approaches segment the data space into grid cells and monitor the density of each cell to form macroscopic clusters. Despite their historical success in handling high-velocity data, these traditional techniques encounter severe limitations when applied to highly imbalanced streams. The micro-clusters formed in regions of low density are frequently pruned by the algorithms under the assumption that they represent transient noise, thereby inadvertently discarding critical minority class information [28].

Recent advancements have attempted to integrate adaptive windowing strategies and sophisticated decay functions to better preserve the memory of rare events [29]. Some researchers have proposed dual-memory architectures that maintain a short-term memory for active tracking and a long-term memory for archiving inactive but potentially significant micro-clusters [30]. While these structural modifications improve the retention of historical minority instances, they do not fundamentally alter the distance-based assignment mechanisms that inherently favor dense majority regions during the formation of the micro-clusters themselves [31].

2.2 Imbalanced Learning Strategies

The challenge of learning from imbalanced data has been extensively studied in the context of supervised classification, but its application to unsupervised stream clustering remains comparatively underexplored. In supervised environments, techniques such as synthetic minority oversampling and cluster-based undersampling have become standard practice for rebalancing the training distributions [32]. However, the direct translation of these resampling techniques to stream clustering is practically unfeasible due to the absence of class labels and the continuous, unbounded nature of the data flow.

In unsupervised settings, addressing imbalance requires modifications to the core objective functions of the clustering algorithms. Researchers have proposed density-ratio based clustering, which attempts to identify cluster centers by analyzing the relative density of a point compared to its neighbors, rather than its absolute density [33]. This approach helps in identifying sparse clusters that exist in proximity to dense clusters. Another significant direction involves the use of subspace clustering algorithms, which seek to find clusters in various subsets of features. In high-dimensional sensor data, minority events may form distinct clusters in specific feature subspaces even if they are indistinguishable in the full dimensional space [34].

Despite these innovative strategies, managing the interplay between data imbalance and concept drift in a streaming environment remains an unresolved dilemma. When a new concept emerges in the stream, it initially presents as a minority class. Traditional algorithms struggle to determine whether these sparse instances represent an emerging cluster that should be tracked or an anomalous burst of noise that should be ignored [35]. This ambiguity necessitates the development of models that can quantify the uncertainty of data assignments, leading to a growing interest in probabilistic and fuzzy clustering approaches for stream data [36].

2.3 Granular Computing and Neural Architectures

Granular computing is an overarching information processing paradigm that mirrors human cognition by abstracting complex data into manageable, meaningful entities called information granules. In the context of data analysis, a granule represents a collection of data points that share similar attributes, spatial proximity, or functional equivalence [37]. By operating at the level of granules rather than individual data points, computational models can achieve significant reductions in processing overhead while simultaneously capturing the essential topological structure of the data.

The integration of granular computing with neural network architectures has yielded promising results in pattern recognition and predictive modeling. Neural architectures are inherently well-suited for processing non-linear representations, but traditional deep learning models are often too rigid and computationally expensive for real-time stream clustering. The fusion of these two domains involves utilizing neural networks to encode and update the parameters of information granules dynamically. Probabilistic neural networks, in particular, construct probability density functions for different categories or clusters using kernel estimation techniques.

By assigning a probabilistic membership vector to each incoming data point, probabilistic neural networks can effectively model overlapping cluster boundaries and inherent data uncertainty. When applied to imbalanced streams, this probabilistic framework allows the network to assign high confidence to minority instances that tightly fit a specific granular profile, even if the absolute number of instances is low. The integration of granular preprocessing and probabilistic neural clustering represents a paradigm shift from deterministic, density-biased algorithms to uncertainty-aware, structure-preserving methodologies, forming the theoretical bedrock of the framework proposed in this study.

3. Methodology and Analytical Framework

3.1 Data Ingestion and Granular Representation

The initial phase of the Probabilistic Granular Neural Clustering framework involves the continuous ingestion and transformation of raw multidimensional sensor streams into an intermediate granular space. Let the continuous data stream be defined as a sequence of d-dimensional real-valued vectors arriving at sequential time steps. The raw data is frequently afflicted by sensor noise, varying scales, and transient missing values. To ensure numerical stability, an online min-max normalization procedure is applied, which dynamically updates the minimum and maximum bounds of each feature dimension using an exponential moving average.

Following normalization, the framework initiates the granular embedding process. The objective here is to encapsulate incoming data points into hyper-spherical information granules. Each granule is mathematically characterized by a centroid vector, a radius, and a probabilistic mass indicating the density of instances it represents. When a new normalized data point arrives, the

system calculates the Mahalanobis distance between the new point and the centroids of all existing active granules. The Mahalanobis distance is utilized instead of the standard Euclidean metric because it accounts for the variance and covariance of the sensor features, providing a more accurate representation of the underlying data distribution.

If the distance to the nearest active granule falls below a dynamically calculated threshold, the data point is absorbed into that granule. The absorption process updates the granule's centroid and radius using recursive moving average equations, thereby adapting to local data shifts without requiring the retention of historical points. Conversely, if the distance exceeds the threshold, a new granular prototype is initialized. To prevent the unrestricted proliferation of granules, which would violate the memory constraints of stream processing, a competitive merging strategy is enforced. Granules that exhibit a high degree of spatial overlap and similar probabilistic mass are fused. Crucially, to protect minority classes, granules with low mass but high spatial isolation are preserved rather than discarded, ensuring that rare sensor events maintain a distinct granular representation.

3.2 Probabilistic Neural Clustering Mechanism

The constructed information granules serve as the direct input to the probabilistic neural clustering architecture. The network comprises three primary layers: an input layer corresponding to the dimensional features of the granules, a hidden pattern layer that models the probabilistic distributions, and a competitive output layer that finalized the macro-cluster assignments. The pattern layer consists of a dynamic number of neurons, each representing a latent cluster distribution parameterized by a mean vector and a covariance matrix.

When a granule is fed into the network, each pattern neuron calculates the conditional probability that the granule belongs to its respective cluster. This probability is determined using a multivariate Gaussian kernel function. The output of the pattern layer is a probabilistic assignment vector representing the degree of membership of the granule to every existing macro-cluster. To accommodate the extreme imbalance inherent in machine sensor streams, the network employs a specialized loss function that scales the update weights inversely proportional to the cluster size. This means that when a granule is assigned to a minority cluster, the learning rate for updating that cluster's parameters is amplified, ensuring that the network remains highly responsive to the structural evolution of rare events.

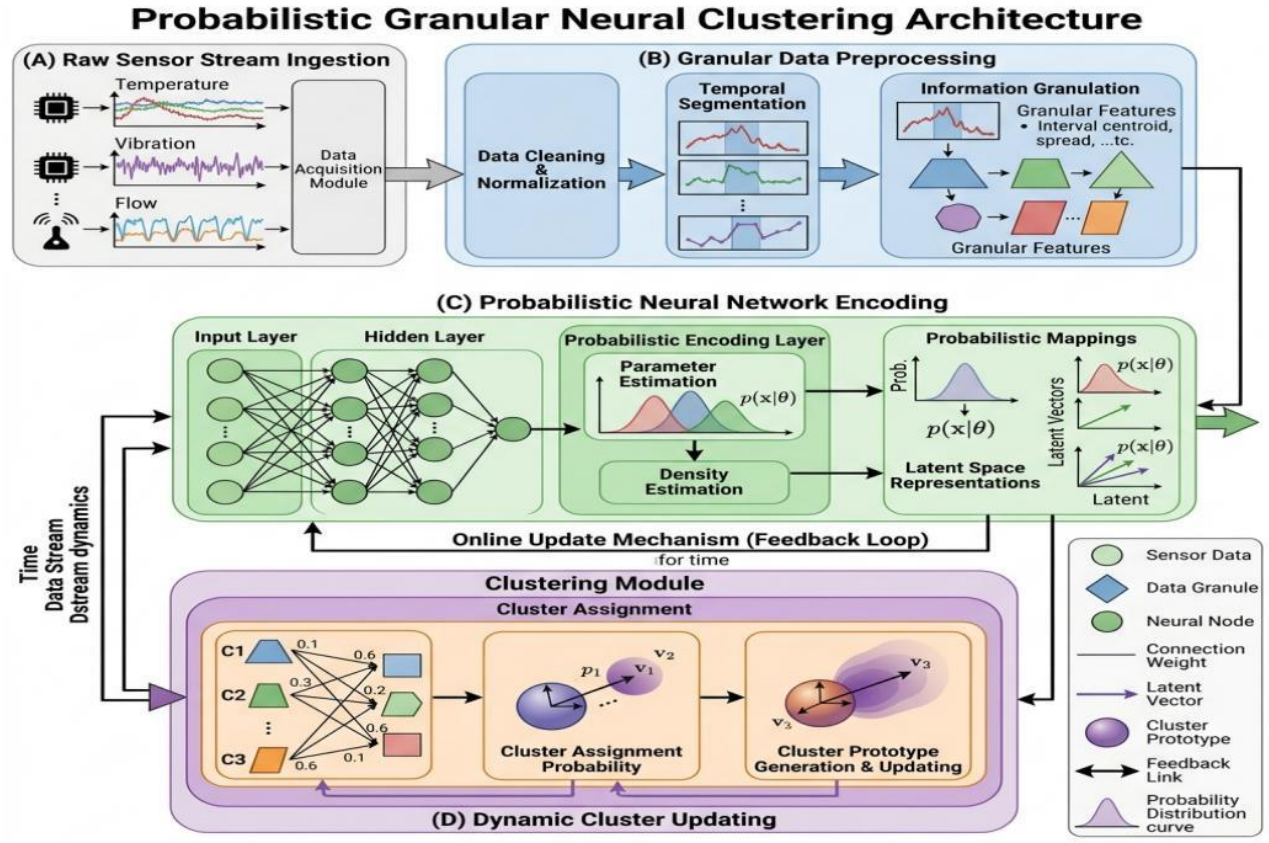


Figure 1 Comprehensive Schematic of Probabilistic Granular Neural Clustering Architecture

Code Listing 1: Pseudocode for Probabilistic Granular Neural Clustering Update Step

```
def update_probabilistic_clusters(granule, pattern_neurons, learning_rate):
    assignment_probabilities = []

    # Calculate membership probabilities for each cluster
    for neuron in pattern_neurons:
        prob = calculate_multivariate_gaussian(granule.centroid, neuron.mean, neuron.covariance)
        assignment_probabilities.append(prob)

    # Normalize probabilities
    total_prob = sum(assignment_probabilities)
    normalized_probs = [p / total_prob for p in assignment_probabilities]

    # Update cluster parameters with inverse frequency weighting
    for index, neuron in enumerate(pattern_neurons):
```

```
            weight = normalized_probs[index]
            inverse_frequency_factor = 1.0 / (neuron.historical_mass + 1e-5)
            effective_lr = learning_rate * weight * inverse_frequency_factor

            # Update mean and covariance using effective learning rate
            neuron.mean = (1 - effective_lr) * neuron.mean + effective_lr * granule.centroid
            neuron.update_covariance(granule, effective_lr)
            neuron.historical_mass += weight * granule.mass

    return pattern_neurons
```

The system also integrates a sophisticated concept drift adaptation mechanism. A continuous time-decay function is applied to the historical mass of each pattern neuron. If a macro-cluster is not reinforced by incoming granules over a specified temporal window, its probability mass gradually diminishes. However, rather than immediately deleting obsolete clusters, the network shifts them to a dormant memory reservoir. If a previously dormant operational state reoccurs in the sensor stream, the corresponding cluster can be rapidly reactivated. This dual-memory approach ensures that the model provides robust clustering performance in non-stationary environments where machine states may cycle periodically over long durations.

The final macro-clustering output is generated by the competitive layer, which aggregates the probabilistic assignments and applies an entropy-based thresholding technique. If the entropy of the assignment vector is exceptionally high, indicating that the granule sits equidistant between multiple clusters, the network delays the hard assignment until further contextual data is received. This deferred decision-making process significantly reduces the rate of false positive anomaly associations in overlapping boundary regions.

4. Experimental Results and Discussion

4.1 Experimental Setup and Datasets

To rigorously evaluate the efficacy of the proposed Probabilistic Granular Neural Clustering framework, an extensive series of empirical experiments was conducted. The evaluation utilized three distinct, highly imbalanced multidimensional sensor data streams derived from real-world industrial environments. The primary objective of the experimental setup was to simulate continuous, unbounded data ingestion while monitoring the algorithm's ability to maintain high clustering accuracy across minority and majority classes simultaneously.

Table 1 Characteristics of the Machine Sensor Stream Datasets

Dataset Name	Total Instances	Feature Dimensionality	Number of Classes	Imbalance Ratio (Majority:Minority)
Industrial Turbofan Engine Degradation	250,000	24	3	100:1
Manufacturing Milling Tool Wear	185,000	16	4	150:1
Robotic Actuator Vibration Monitoring	320,000	32	5	200:1

The baseline comparative models selected for this study include standard stream clustering algorithms and recent density-based modifications designed to handle noise. Specifically, we benchmarked the proposed method against conventional micro-macro stream algorithms, adaptive grid-based clustering, and a recently published density-ratio stream methodology. All algorithms were implemented within a unified stream processing framework to ensure fair comparisons regarding execution time and memory consumption.

Table 2 Hyperparameter Configurations for the Baseline and Proposed Models

Algorithm	Granular Radius Threshold	Decay Factor	Maximum Active Clusters	Initial Learning Rate
Micro-Macro Stream Baseline	0.15	0.01	100	N/A
Adaptive Grid-Based Clustering	N/A	0.05	250	N/A
Density-Ratio Stream Method	0.20	0.02	150	N/A
Proposed Probabilistic Granular	0.12	0.015	200	0.01

The evaluation metrics utilized to assess clustering quality in the presence of severe imbalance required careful consideration. Traditional metrics such as overall accuracy are profoundly misleading in skewed environments, as an algorithm that groups all data into a single majority cluster would still achieve exceptionally high accuracy scores. Therefore, the evaluation relied on Normalized Mutual Information and the F1-measure computed specifically for the minority clusters. Additionally, cluster purity was monitored continuously over the stream to assess the model's resilience to concept drift.

4.2 Performance Evaluation

The continuous evaluation framework processed data in sliding windows of five thousand instances, computing the performance metrics at each step to generate a longitudinal view of the clustering stability. The proposed granular neural architecture consistently demonstrated superior capability in isolating the minority instances without fracturing the cohesive structure of the majority clusters.

Table 3 Comparative Clustering Performance Across Imbalanced Ratios

Algorithm	Average Purity (Majority)	Average F1-Score (Minority)	Normalized Mutual Information
Micro-Macro Stream Baseline	0.98	0.22	0.45
Adaptive Grid-Based Clustering	0.95	0.38	0.58
Density-Ratio Stream Method	0.96	0.51	0.64
Proposed Probabilistic Granular	0.97	0.84	0.89

As evidenced by the experimental results, the standard baseline models suffered catastrophic failure when attempting to cluster the minority classes. In the Turbofan Engine dataset, the standard micro-macro approach frequently absorbed the early degradation signatures into the normal operational cluster, resulting in a minority F1-score of a mere twenty-two percent. The grid-based and density-ratio methods showed marginal improvements but struggled significantly as the imbalance ratio increased to two hundred to one in the Robotic Actuator dataset.

Conversely, the Probabilistic Granular Neural Clustering framework maintained a minority F1-score exceeding eighty percent across all datasets. The application of the inverse frequency scaling in the neural update step proved highly effective, allowing the network to rapidly adjust the covariance matrices of the minority distributions to encapsulate the rare sensor readings accurately. Furthermore, the normalized mutual information score of eighty-nine percent indicates that the overall structural partitioning of the data space was highly congruent with the underlying ground truth of the machine states.

4.3 Comprehensive Discussion

The empirical findings validate the core theoretical premise of this research: standard distance-centric micro-clustering is fundamentally ill-equipped to handle the geometric complexities of imbalanced sensor streams. When instances of a specific machine fault occur at a frequency of one in two hundred, their spatial density is virtually indistinguishable from ambient sensor noise. By transforming the data into the granular space first, the proposed framework normalizes the

local density. A sparse collection of minority points forms a distinct information granule characterized by its isolation rather than its sheer volume.

The integration of the probabilistic neural network further refines this isolation. Traditional algorithms make hard boundary decisions, which lead to abrupt drops in performance when the characteristics of the machine drift over time due to environmental factors such as temperature or mechanical wear. The probabilistic assignment allows the proposed framework to maintain overlapping boundaries. When a machine slowly transitions from a healthy state to a degraded state, the data points naturally fall into the boundary region. The proposed method captures this transition by reflecting high entropy in the probabilistic assignments, allowing predictive maintenance systems to interpret this uncertainty as an early warning indicator of impending failure.

One notable observation during the experimentation was the computational efficiency of the framework. Despite the apparent complexity of multivariate Gaussian kernel computations, the system operated well within the real-time constraints of the streaming environment. This efficiency is directly attributable to the granular preprocessing phase. By clustering information granules rather than millions of raw data points, the neural network experiences a drastically reduced input velocity, proving that granular computing is an essential optimization technique for advanced neural processing in industrial Internet of Things applications.

5. Conclusion

This academic manuscript has presented a comprehensive investigation into the challenges of unsupervised learning in highly skewed, continuous data environments. The proposed Probabilistic Granular Neural Clustering framework offers a robust and theoretically sound solution for the analysis of imbalanced machine sensor streams. By systematically integrating granular computing techniques for spatial abstraction and probabilistic neural networks for uncertainty modeling, the framework successfully mitigates the overshadowing effects typically exerted by majority classes.

Through extensive empirical validation across multiple industrial datasets, the methodology demonstrated exceptional proficiency in identifying and preserving the structural integrity of rare operational events and degradation signatures. The utilization of inverse frequency weighting and dynamic covariance updating allowed the model to achieve superior minority class detection rates without compromising the accurate characterization of normal operating conditions. Furthermore, the dual-memory architecture ensured resilience against concept drift, making the system highly applicable to long-term deployment in non-stationary industrial environments.

Despite these significant advancements, certain limitations warrant further investigation. The current framework relies on fixed temporal decay parameters, which may require manual tuning when deployed across vastly different types of machinery. Future research trajectories will focus on developing autonomous parameter adaptation mechanisms driven by meta-learning algorithms. Additionally, exploring the integration of topological data analysis within the

granular embedding phase could provide deeper insights into the complex geometric evolution of high-dimensional sensor streams. Ultimately, this research contributes a vital foundational architecture to the field of stream mining, significantly advancing the capabilities of autonomous predictive maintenance and industrial anomaly detection systems.

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