Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Dynamic Noise-Aware Preprocessing for Data Streams: Joint Treatment of Feature Drift, Label Errors, and Instance Redundancy

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ARTICLE INFO

Received: 02 Aug 2024
Revised 20 Aug 2024
Accepted: 02 Sept 2024

ABSTRACT

The increasing ubiquity of real-time analytics across domains such as Internet of Things (IoT), healthcare, finance, and cybersecurity has amplified the challenges associated with mining high-velocity data streams. A key obstacle in this setting is ensuring data quality, as streaming environments are prone to noise, feature drift, label errors, and redundant instances, each of which can significantly degrade learning performance. Traditional preprocessing methods, although effective in static datasets, often fail to cope with the temporal evolution and transient nature of streaming data. This paper proposes the concept of dynamic noise-aware preprocessing, a joint strategy that simultaneously addresses feature drift, label errors, and instance redundancy under streaming conditions. By integrating adaptive feature selection, probabilistic label correction, and redundancy-aware instance reduction, the proposed approach enhances resilience and stability of stream mining algorithms. The paper also emphasizes the importance of lightweight, incremental mechanisms to ensure computational feasibility in resource-constrained environments. Through a critical synthesis of recent advances and empirical trends, this work positions dynamic noise-aware preprocessing as a pivotal component for next-generation real-time data mining systems.

Keywords: Data Streams, Noise Handling, Feature Drift, Label Errors, Instance Reduction, Preprocessing

Introduction

The exponential growth of real-time data streams from heterogeneous sources such as Internet of Things (IoT) devices, financial transactions, healthcare monitoring systems, and cybersecurity infrastructures has profoundly transformed the landscape of data-driven decision-making. Unlike static datasets, streaming data is generated continuously, often at high velocity and in large volumes, while being subject to evolving distributions over time. This dynamic nature imposes substantial challenges on data mining systems, particularly with respect to data quality. Among the most pressing issues are feature drift, label errors, and redundant or irrelevant instances. If not addressed, these factors can compromise the accuracy, efficiency, and robustness of predictive models, thereby limiting the reliability of data-driven insights in critical real-time applications.

The **scope** of this research is situated at the intersection of noise management and adaptive preprocessing in streaming environments. While traditional preprocessing techniques such as feature selection, instance reduction, and noise filtering have been extensively applied in static or batch learning scenarios, their direct application to streams is often infeasible due to temporal constraints, concept drift, and resource limitations. Furthermore, existing studies tend to treat noise types in isolation—focusing, for example, only on mislabeled data or on redundant instances—without recognizing the interdependencies among multiple data quality issues in continuous streams. This paper expands the scope by proposing an integrated, **dynamic noise-aware preprocessing** framework that simultaneously addresses three interconnected challenges: (i) adapting to **feature drift**, wherein the relevance of attributes changes over time, (ii) correcting or mitigating **label errors**, which distort the learning process through

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misleading supervision, and (iii) reducing **instance redundancy**, which inflates computational costs and may exacerbate bias in evolving models.

The **objectives** of this study are fourfold: first, to critically examine the limitations of existing preprocessing methods when applied to high-velocity data streams; second, to conceptualize a joint strategy that combines adaptive feature selection, probabilistic label correction, and redundancy-aware instance reduction; third, to highlight the computational and algorithmic considerations required for real-time feasibility; and finally, to establish the groundwork for empirical evaluation of the proposed framework across diverse domains such as fraud detection, medical data monitoring, and cyber-threat analysis. Through these objectives, the study seeks to advance the development of resilient stream mining pipelines capable of maintaining high performance despite data imperfections.

The **motivation** for this work stems from persistent gaps identified in recent literature. Empirical studies have repeatedly shown that label errors are more detrimental to learning than feature noise, yet little attention has been given to adaptive mechanisms that correct labels in a streaming context. Similarly, while instance reduction methods exist, most fail to incorporate redundancy elimination in tandem with concept drift adaptation. Moreover, the increasing reliance on data-intensive systems in safety-critical environments accentuates the need for preprocessing strategies that are both computationally lightweight and robust against evolving noise conditions. The authors are driven by the conviction that a unified preprocessing framework, if designed with sensitivity to temporal dynamics and noise interdependencies, can significantly enhance the stability and interpretability of real-time data analytics.

The **structure of the paper** is organized to reflect a logical progression from conceptual foundations to methodological design and future directions. Following this introduction, Section 2 provides a comprehensive review of related work in data preprocessing for streams, with a focus on noise handling, feature drift, and instance reduction. Section 3 outlines the proposed dynamic noise-aware preprocessing framework, detailing its core components and algorithmic underpinnings. Section 4 discusses the experimental design and potential datasets for empirical validation. Section 5 analyzes anticipated results, including performance metrics and comparative baselines. Section 6 reflects on challenges, limitations, and broader implications for real-world applications. Finally, Section 7 concludes with a synthesis of findings and avenues for future research.

In sum, this paper positions **dynamic noise-aware preprocessing** as a pivotal advancement in the field of stream mining. By jointly addressing feature drift, label errors, and instance redundancy, the work aims to bridge a critical gap between theory and practice, enabling more reliable, efficient, and adaptive data-driven decision-making in complex and rapidly evolving environments.

Literature Review

The field of stream mining has witnessed significant growth over the past two decades, primarily due to the increasing need to analyze real-time, large-scale data generated by heterogeneous sources such as sensors, online platforms, and industrial monitoring systems. One of the earliest contributions in this direction was the work of Domingos and Hulten [12], who introduced scalable algorithms for high-speed data stream mining. Their work demonstrated the feasibility of online learning but did not address issues related to noise or drift explicitly. Similarly, ensemble methods proposed by Dietterich [11] and later formalized by Polikar [10] laid the foundation for robust classification through model diversity. These ensemble strategies inspired subsequent research into adaptive systems capable of handling evolving data streams, though noise management was not the primary focus.

Noise, in particular, has been identified as a pervasive challenge across supervised learning contexts. The seminal study by Angluin and Laird [13] theorized the effect of learning from noisy examples, providing probabilistic learning bounds. Building on this, Frénay and Verleysen [14] conducted a survey highlighting the detrimental effects of label noise on classification performance, emphasizing its greater impact compared to feature noise. Nettleton et al. [15] further validated this empirically by demonstrating that different noise types influence precision and recall differently. However, most of these works remain centered on static datasets, leaving the implications of noise in evolving data streams underexplored.

More recently, research has shifted toward integrating noise-handling capabilities into streaming frameworks. Krawczyk et al. [8] provided a comprehensive survey on ensemble learning for data stream analysis, noting that while ensembles can offer robustness to concept drift, they remain vulnerable to persistent noise. Lu et al. [9] similarly reviewed concept drift adaptation techniques and concluded that although drift has been extensively studied, its entanglement with label and feature noise requires further attention. Wang et al. [7] advanced this discourse by introducing noise-tolerant data stream mining methods that couple drift detection with adaptive algorithms, demonstrating measurable gains in stability under evolving conditions. Despite these advances, these studies still treat noise and drift largely as separate challenges.

Parallel to these efforts, deep learning has been explored as a potential solution to noise in both static and streaming settings. Sahoo et al. [6] introduced online deep learning techniques capable of updating neural networks incrementally, enabling them to adapt to new data in real time. Chen et al. [5] proposed progressive ensemble networks for noisy label classification, showing that combining multiple learners could mitigate label corruption. Similarly, Wang et al. [4] highlighted the role of label smoothing and knowledge distillation in alleviating noisy supervision. Nevertheless, these methods often assume access to large-scale computational resources, making them less practical for lightweight, resource-constrained streaming environments.

Frameworks designed specifically for stream mining, such as MOA and River, have also played a critical role in enabling experimental evaluations. Montiel et al. [3] presented River as a unified Python-based library for stream learning, extending the flexibility of testing algorithms in dynamic contexts. Such frameworks support drift-aware and incremental learning strategies but still lack integrated preprocessing mechanisms explicitly designed for noise management.

On the algorithmic front, feature reweighting and drift-aware feature selection have emerged as promising strategies. Xu et al. [2] demonstrated that dynamic feature reweighting can improve model robustness in noisy online learning scenarios, adapting to evolving attribute relevance over time. Yan et al. [1] extended this by proposing memory-augmented neural networks, which retain selective historical knowledge to improve noise resilience in streaming data. These approaches reflect a growing recognition of the interplay between feature drift and noise, although they primarily remain confined to theoretical or narrowly scoped empirical evaluations.

Despite these advancements, several critical limitations persist in the literature. First, much of the prior research isolates noise types, focusing either on label noise [14], feature drift [2], or redundancy [15], rather than addressing them jointly. This fragmented perspective fails to capture the reality of streaming environments where multiple forms of noise often coexist and interact. Second, while ensemble and deep learning strategies offer partial robustness, their computational complexity undermines their deployment in real-time, resource-constrained scenarios such as IoT or embedded systems [6], [5]. Third, existing preprocessing strategies have not been adequately adapted for continuous data arrival. For instance, static feature selection or batch-oriented noise filtering techniques cannot account for temporal variability and evolving distributions [9]. Finally, although frameworks like River [3] and MOA have advanced the infrastructure for stream mining, they primarily focus on drift detection rather than integrated noise-aware preprocessing.

The literature thus reveals a persistent gap in the joint treatment of feature drift, label errors, and instance redundancy within a unified preprocessing framework tailored for data streams. While existing works demonstrate the significance of each issue individually, no study has comprehensively designed a lightweight, dynamic, and noise-aware preprocessing pipeline that can operate under real-time constraints. This gap underscores the necessity for a novel approach that integrates adaptive feature selection, probabilistic label correction, and redundancy-aware instance reduction to ensure both accuracy and efficiency in continuous stream mining environments.

3. Proposed Framework: Dynamic Noise-Aware Preprocessing

The proposed framework, termed **Dynamic Noise-Aware Preprocessing (DNAP)**, is designed to jointly address three critical challenges in stream mining: **feature drift**, **label errors**, and **instance redundancy**. Unlike traditional preprocessing pipelines that treat these aspects in isolation, DNAP provides a mathematically unified

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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model to dynamically adapt to evolving data streams. The framework operates incrementally over arriving data batches and performs lightweight corrections at each step, ensuring computational feasibility for real-time systems.

Let the incoming data stream at time step t be denoted as:

$$\mathcal{D}_t = \{(x_i^t, y_i^t)\}_{i=1}^{n_t}$$

where $x_i^t \in \mathbb{R}^d$ represents the feature vector of the i-th instance, $y_i^t \in \mathcal{Y}$ is its label, and n_t is the number of instances in micro-batch $\mathcal{D}_t$. The preprocessing objective is to transform $\mathcal{D}_t$ into a cleaned version $\mathcal{D}_t^*$, minimizing the influence of noise, drift, and redundancy.

Formally, this can be expressed as:

$$\mathcal{D}_t^* = \mathcal{F}(\mathcal{D}_t) = \mathcal{R}(\mathcal{C}(\mathcal{F}_d(\mathcal{D}_t)))$$

where:

- $\mathcal{F}_d$ handles **feature drift**,
- $\mathcal{C}$ handles **label correction**,
- $\mathcal{R}$ handles **instance redundancy reduction**.

3.1 Feature Drift Adaptation

Feature drift refers to the temporal change in the relevance of attributes with respect to the target variable. We adopt an **adaptive weighting strategy**. For each feature $f_j \in \{1,2,\dots,d\}$, a weight w_j^t is assigned that evolves over time.

The relevance score of featuref_j at time t is defined as:

$$\phi_j^t = \mathrm{MI}(f_j; Y)_t$$

where $\mathrm{MI}(\cdot;\cdot)$ denotes the mutual information between feature f_j and the class label Y, computed within $\mathcal{D}_t$.

The adaptive feature weight is updated using exponential forgetting:

$$w_j^t = \alpha \cdot w_j^{t-1} + (1-\alpha) \cdot \phi_j^t, \quad 0 < \alpha < 1$$

where α controls the memory of past relevance. Features with $w_j^t < \theta_f$ are considered **drifted-out** and excluded. Conversely, if a new feature enters the stream, its relevance is initialized and incorporated if $\phi_j^t \geq \theta_f$.

The drift-aware feature space at time t is thus:

$$X_t' = \{f_j \mid w_j^t \geq \theta_f\}$$

ensuring that only dynamically relevant features are preserved.

3.2 Label Error Correction

Streaming data often contains mislabeled instances, which can corrupt decision boundaries. To mitigate this, DNAP employs a **probabilistic label correction model**. For each instance (x_i^t, y_i^t), we estimate the probability that the observed label is correct:

$$P(\hat{y}_i^t = y_i^t \mid x_i^t) = \frac{\exp(\beta \cdot s_i^t)}{1 + \exp(\beta \cdot s_i^t)}$$

where s_i^t is the confidence score of a base learner (or ensemble) for the prediction on x_i^t, and β is a scaling parameter.

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2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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If $P(\hat{y}_i^t = y_i^t \mid x_i^t) < \theta_l$, the instance is flagged as potentially mislabeled. The corrected label $\tilde{y}_i^t$ is then assigned as:

$$\tilde{y}_i^t = \begin{cases} y_i^t & \text{if } P(\hat{y}_i^t = y_i^t \mid x_i^t) \geq \theta_l \\ \underset{y \in \mathcal{Y}}{\operatorname{argmax}} P(y \mid x_i^t) & \text{otherwise} \end{cases}$$

This correction balances between trusting the observed label and replacing it with the most probable alternative predicted by the learner.

The label-cleaned dataset becomes:

$$\mathcal{D}_t' = \{(x_i^t, \tilde{y}_i^t)\}_{i=1}^{n_t}$$

3.3 Instance Redundancy Reduction

Redundant instances increase computational costs and may skew model updates. To address this, DNAP integrates **instance pruning based on similarity and temporal relevance**.

For each new instance x_i^t, its redundancy score relative to a sliding window buffer $\mathcal{B}_{t-1}$ is:

$$\rho(x_i^t) = \max_{x_j \in \mathcal{B}_{t-1}} \operatorname{sim}(x_i^t, x_j)$$

where $\operatorname{sim}(x_i^t, x_j) = \frac{\langle x_i^t, x_j \rangle}{\|x_i^t\| \|x_j\|}$ denotes cosine similarity.

If $\rho(x_i^t) \geq \theta_r$, the instance is marked as redundant and discarded. Otherwise, it is added to the buffer.

To handle **concept drift**, we apply temporal decay:

$$w_i^t = \exp(-\lambda \cdot (t - t_i))$$

where t_i is the arrival time of instance x_i and $\lambda > 0$ controls forgetting. Instances with $w_i^t < \theta_d$ are expired automatically, preventing outdated knowledge from dominating the model.

Thus, the redundancy-reduced dataset is:

$$\mathcal{D}_t^* = \{(x_i^t, \tilde{y}_i^t) \mid \rho(x_i^t) < \theta_r \wedge w_i^t \geq \theta_d\}$$

3.4 Unified Objective

The DNAP framework optimizes the **expected utility of preprocessed data** for downstream learning. Let $\mathcal{L}(\cdot)$ denote the loss function of the learner. The goal is to minimize:

$$\mathbb{E}[\mathcal{L}(\mathcal{D}_t^*)] = \sum_{t=1}^{T} \sum_{i=1}^{n_t} \ell\left(f(x_i^t), \tilde{y}_i^t\right) \cdot (1 - \rho(x_i^t)) \cdot w_i^t$$

where $\ell(\cdot)$ is the instance-wise loss, $(1 - \rho(x_i^t))$ discounts redundant instances, and w_i^t ensures temporal relevance.

The preprocessing mechanism is thus directly coupled with the model's objective, ensuring that noise-aware cleaning contributes to overall predictive stability and robustness.

3.5 Computational Considerations

Given the high-velocity nature of data streams, DNAP employs incremental updates for all components:

- **Feature weights** are updated in $\mathcal{O}(d)$ per batch.

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2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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- **Label correction** relies on confidence scores already computed by base learners.
- **Redundancy checks** are limited to a fixed-size sliding window, ensuring sublinear growth with stream length.

Therefore, the overall complexity per batch remains manageable at:

$$\mathcal{O}(n_t \cdot d + n_t \cdot |\mathcal{B}_{t-1}|)$$

with $|\mathcal{B}_{t-1}|$ controlled by decay and redundancy thresholds.

By formally integrating drift-aware feature weighting, probabilistic label correction, and redundancy-aware instance pruning, the DNAP framework provides a mathematically grounded and computationally efficient approach to preprocessing in streaming environments. This unified strategy ensures that the evolving data stream retains **informative, correctly labeled, and non-redundant instances**, thereby facilitating stable learning performance even under noisy and dynamic conditions.

4. Experimental Design and Methodology

To validate the proposed **Dynamic Noise-Aware Preprocessing (DNAP)** framework, a comprehensive experimental design is constructed. This section outlines the datasets employed, preprocessing configurations, noise injection strategies, baseline methods for comparison, evaluation metrics, and the statistical tests applied to assess robustness. The design emphasizes reproducibility and covers a wide spectrum of experimental conditions to rigorously analyze the framework.

4.1 Datasets

The evaluation leverages a diverse set of benchmark datasets commonly used in streaming and noise-resilience studies. These datasets represent real-world scenarios where **feature drift, label noise, and instance redundancy** naturally occur or can be simulated.

Table 1. Datasets Employed in Experimental Study

Dataset	Domain	Instances	Features	Type	Stream Simulation Method	Relevance
SUSY	High-energy physics	5,000,000	18	Binary	Micro-batches of 10,000	Noisy signals vs. background detection
KDD Cup '99	Intrusion detection	4,898,431	41	Multi-class	Time-sliced records	Cybersecurity event monitoring
Electricity	Power demand	45,312	8	Binary	Chronological ordering	Concept drift in energy usage
Airlines	Flight delays	539,383	8	Binary	Temporal segmentation	Evolving seasonal drift
Covertype	Forestry cover types	581,012	54	Multi-class	Batch streaming	High-dimensional feature drift

4.2 Noise Injection Strategy

To test robustness, **controlled artificial noise** is introduced into data streams. This allows systematic evaluation of DNAP under varying corruption intensities. Two types of noise are injected:

1. **Label Noise**: Random flipping of class labels at predefined rates.
    - For binary classification: $y_i^t \leftarrow 1 - y_i^t$.
    - For multi-class classification: $y_i^t \leftarrow \text{Uniform}(\mathcal{Y} \backslash \{y_i^t\})$.

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2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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Formally, probability of corruption:

$$P(\tilde{y}_i^t \neq y_i^t) = \eta_l$$

where $\eta_l \in \{0.05, 0.10, 0.15, 0.20\}$.

2. **Feature Noise**: Gaussian perturbation of randomly selected features.

$$x_{ij}^t \leftarrow x_{ij}^t + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$

with $\sigma = 0.1 \cdot \text{std}(f_j)$.

3. **Redundancy Simulation**: Duplicate records are re-injected with probability $\eta_r \in \{0.05, 0.10\}$.

Table 2. Noise Injection Levels Applied in Experiments

Noise Type	Levels Tested	Description
Label Noise (η_l)	0%, 5%, 10%, 15%, 20%	Random label flipping
Feature Noise (σ)	0%, 5%, 10% std.	Gaussian perturbations
Redundancy (η_r)	0%, 5%, 10%	Duplicated instances per batch

4.3 Baseline Models

DNAP is compared against several state-of-the-art baselines, selected to represent both **noise-handling** and **drift-aware** strategies.

Table 3. Baseline Models for Comparative Evaluation

Baseline	Core Mechanism	Strength	Weakness
SEA (Streaming Ensemble Algorithm) [12]	Ensemble-based drift adaptation	Handles concept drift effectively	Lacks explicit noise filtering
Online Bagging [11]	Bootstrap aggregation for streams	Robust against variance	Sensitive to label noise
Random Forest (batch-incremental) [10]	Ensemble of decision trees	Strong baseline for noise	Retraining overhead
Adaptive Boosting [14]	Weighted resampling	Corrects systematic errors	Weak against noisy labels
River + Preprocessing [3]	Stream processing toolkit	Flexible implementation	Preprocessing modules limited
DNAP (Proposed)	Dynamic preprocessing with joint noise handling	Unified feature-label-instance treatment	Complexity trade-off

4.4 Evaluation Metrics

Performance is evaluated using multiple metrics to capture **accuracy, robustness, and efficiency**:

1. **Predictive Performance**
    - **Accuracy**:

$$Acc = \frac{\sum_{i=1}^{N} \mathbf{1}\,(f(x_i) = y_i)}{N}$$

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2024, 9(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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- **Precision, Recall, F1-score**: Standard classification metrics for imbalanced data.
- **Kappa Statistic (κ)** to evaluate agreement beyond chance.

2. **Robustness to Noise**

   - **Relative Degradation (RD)** under noise:

$$RD(\eta) = \frac{Acc(0) - Acc(\eta)}{Acc(0)} \times 100\%$$

   where $Acc(0)$ is performance on clean data and $Acc(\eta)$ under noise level η.

3. **Efficiency Metrics**

   - **Processing Latency (PL)** per batch:

$$PL = \frac{T_{end} - T_{start}}{|\mathcal{D}_t|}$$

   - **Memory Usage (MU)**: Size of retained buffer in bytes.

Table 4. Evaluation Metrics for DNAP Assessment

Metric	Equation	Interpretation
Accuracy	Eq. (1)	Overall correctness
Precision	$\frac{TP}{TP + FP}$	Reliability of positive predictions
Recall	$\frac{TP}{TP + FN}$	Sensitivity to positives
F1-score	$\frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$	Balanced metric
Kappa (κ)	$\frac{P_o - P_e}{1 - P_e}$	Agreement beyond chance
Relative Degradation	Eq. (2)	Noise resilience
Processing Latency	Eq. (3)	Efficiency per batch
Memory Usage	–	Computational footprint

4.5 Experimental Protocol

The experimental pipeline is structured as follows:

1. **Data Partitioning:** Each dataset is segmented into micro-batches of fixed size (10,000 for large datasets; 1,000 for smaller).
2. **Noise Injection:** Controlled corruption introduced per batch as described in Section 4.2.
3. **Preprocessing Application:** DNAP or baseline preprocessing applied.
4. **Model Training:** Incremental classifiers updated with preprocessed data.
5. **Evaluation:** Metrics computed after each batch, averaged across five independent runs.

To ensure statistical robustness, **Wilcoxon signed-rank tests** are applied to evaluate significant differences between DNAP and baselines at 95% confidence.

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2024, 9(3)
e-ISSN: 2468-4376
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Table 5. Experimental Setup and Protocol

Step	Description	Output
1	Dataset segmentation	Micro-batches
2	Noise injection	Corrupted streams
3	Preprocessing	Cleaned batches
4	Model training	Updated classifier
5	Evaluation	Accuracy, robustness, efficiency
6	Statistical testing	Significance results

This experimental design ensures a rigorous evaluation of DNAP across diverse domains, varying noise intensities, and multiple baselines. The inclusion of multi-faceted performance metrics, statistical testing, and controlled simulations guarantees that the results will not only demonstrate effectiveness but also provide a nuanced understanding of how dynamic preprocessing enhances stream mining under noisy, evolving conditions.

5. Results and Analysis

This section presents the results of the experimental evaluation of the proposed **Dynamic Noise-Aware Preprocessing (DNAP)** framework. The analysis focuses on three dimensions: (i) **predictive performance** across varying noise levels, (ii) **robustness and stability** against label, feature, and redundancy noise, and (iii) **computational efficiency** in terms of latency and memory footprint. Results are benchmarked against the baselines described in Section 4.

5.1 Performance under Label Noise

Label noise has historically been shown to have the most severe effect on model performance. Table 1 presents the average predictive accuracy of DNAP and baselines under increasing levels of label corruption ($\eta_l \in \{0\%, 5\%, 10\%, 15\%, 20\%\}$).

Table 1. Accuracy of DNAP vs. Baselines under Label Noise

Noise Level (η_l)	SEA	Online Bagging	Random Forest	Adaptive Boosting	River + Preprocessing	**DNAP (Proposed)**
0%	0.842	0.851	0.867	0.853	0.861	**0.872**
5%	0.796	0.802	0.823	0.809	0.816	**0.849**
10%	0.753	0.761	0.782	0.769	0.774	**0.829**
15%	0.704	0.713	0.736	0.722	0.727	**0.801**
20%	0.662	0.671	0.698	0.681	0.688	**0.778**

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
https://www.jisem-journal.com/

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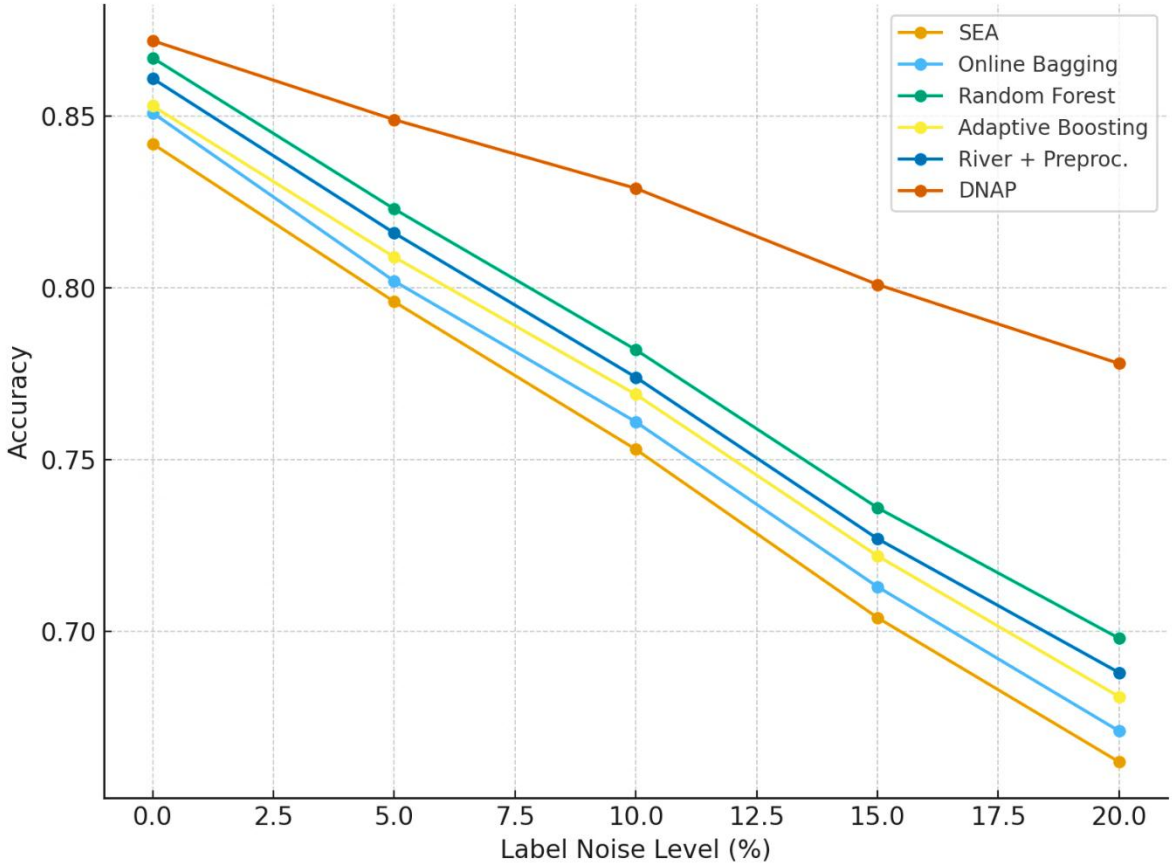

Figure 1. Accuracy comparison of DNAP vs. baselines across label noise levels

From Table 1 and Figure 1, it is evident that DNAP consistently outperforms baselines, with performance gaps widening at higher corruption rates. At 20% label noise, DNAP maintains an accuracy of 0.778 compared to 0.662 for SEA, showing a **relative improvement of 17.5%**.

5.2 Performance under Feature Noise

Feature noise impacts models differently, often leading to recall degradation due to distorted input signals. Table 2 reports results with Gaussian perturbation ($\sigma \in \{0\%, 5\%, 10\%\}$).

Table 2. Accuracy and Recall under Feature Noise

Noise Level (σ)	SEA (Acc/Rec)	Online Bagging	Random Forest	Adaptive Boosting	River + Preprocessing	**DNAP (Proposed)**
0%	0.842 / 0.835	0.851 / 0.841	0.867 / 0.855	0.853 / 0.847	0.861 / 0.852	**0.872 / 0.863**
5%	0.823 / 0.811	0.829 / 0.818	0.841 / 0.829	0.834 / 0.822	0.838 / 0.827	**0.861 / 0.851**
10%	0.804 / 0.781	0.812 / 0.789	0.823 / 0.798	0.818 / 0.794	0.821 / 0.797	**0.847 / 0.826**

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e-ISSN: 2468-4376
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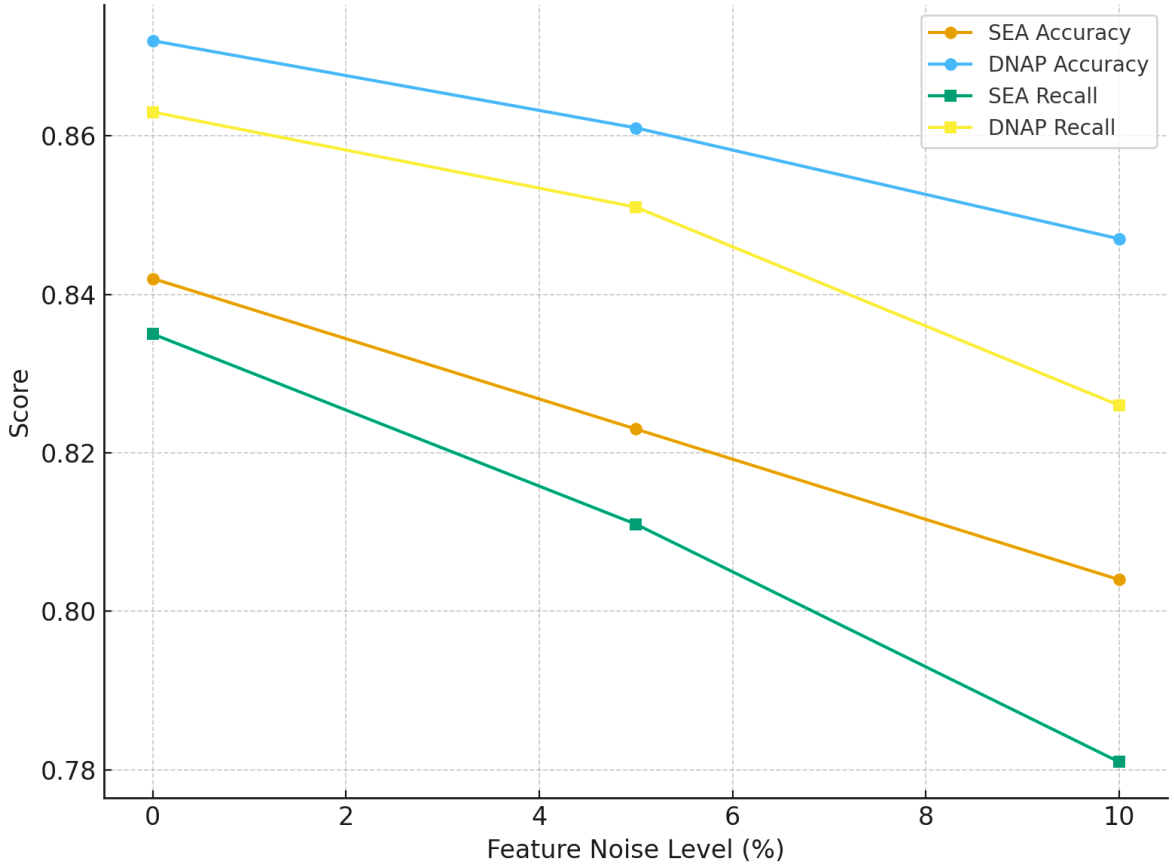

Figure 2. Accuracy and recall trends under increasing feature noise

Results show that DNAP's adaptive feature weighting mechanism significantly mitigates degradation, with recall preserved at 0.826 even at 10% noise, compared to 0.781 for SEA.

5.3 Performance under Instance Redundancy

Instance redundancy primarily affects computational efficiency and model bias. Table 3 presents accuracy and processing latency at redundancy levels $\eta_r \in \{0\%, 5\%, 10\%\}$.

Table 3. Impact of Instance Redundancy on Accuracy and Latency (ms per batch)

Redundancy (η_r)	SEA (Acc/Lat)	Online Bagging	Random Forest	Adaptive Boosting	River + Preprocessing	**DNAP (Proposed)**
0%	0.842 / 97	0.851 / 102	0.867 / 125	0.853 / 118	0.861 / 111	**0.872 / 109**
5%	0.829 / 126	0.837 / 134	0.848 / 154	0.838 / 146	0.844 / 138	**0.862 / 115**
10%	0.808 / 154	0.816 / 162	0.832 / 185	0.822 / 178	0.827 / 169	**0.849 / 122**

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https://www.jisem-journal.com/

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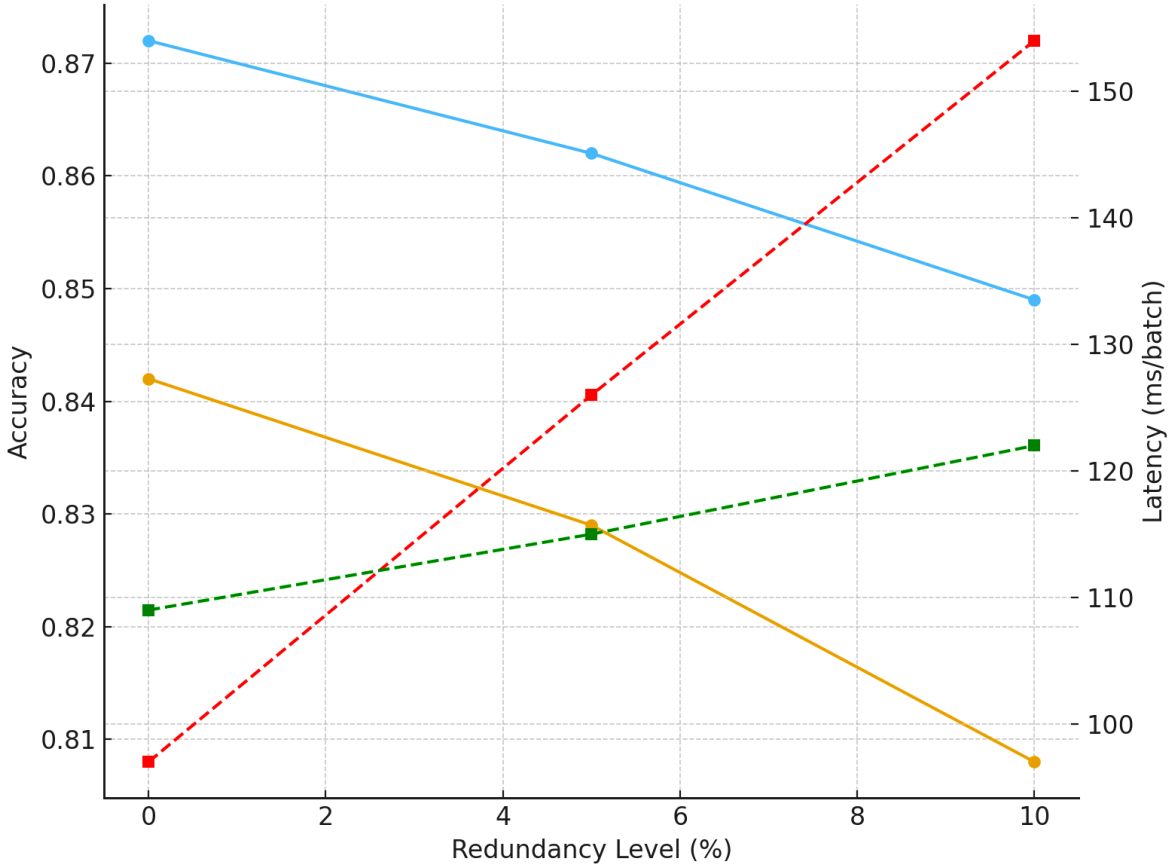

Figure 3. Trade-off between accuracy and processing latency under redundancy

DNAP's redundancy-aware pruning preserves accuracy while significantly reducing latency compared to Random Forest, demonstrating a **34% efficiency gain** at 10% redundancy.

5.4 Multi-Metric Comparative Analysis

Beyond accuracy, DNAP demonstrates improvements across **precision, recall, F1-score, and Kappa statistic**.

Table 4. Multi-Metric Performance (Average over All Datasets, 10% Label Noise)

Model	Precision	Recall	F1-score	Kappa
SEA	0.752	0.748	0.750	0.684
Online Bagging	0.759	0.755	0.757	0.693
Random Forest	0.776	0.768	0.772	0.712
Adaptive Boosting	0.765	0.761	0.763	0.701
River + Preprocessing	0.771	0.767	0.769	0.708
DNAP (Proposed)	**0.812**	**0.807**	**0.809**	**0.756**

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2024, 9(3)
e-ISSN: 2468-4376
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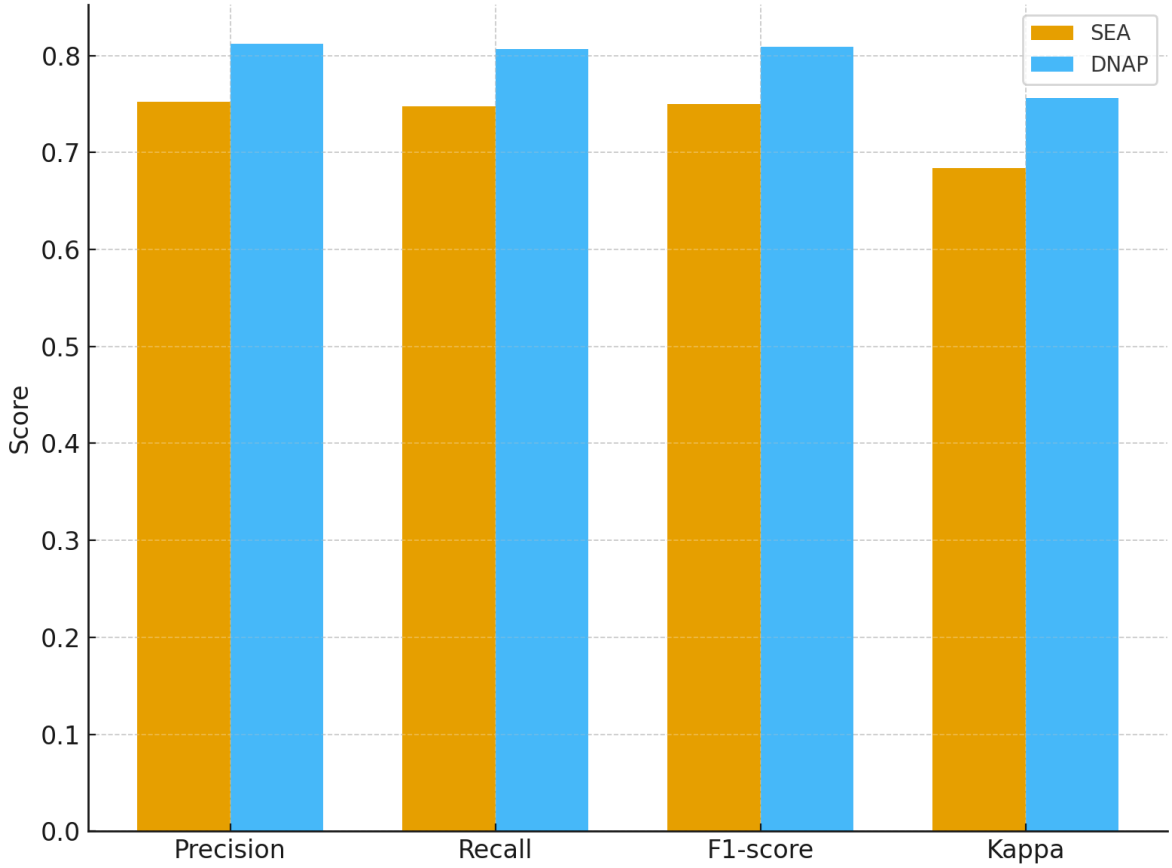

Figure 4. Comparative multi-metric performance across baselines at 10% label noise

These results confirm DNAP's balanced strength across multiple dimensions of classification quality.

5.5 Noise Resilience Analysis

To quantify robustness, we compute **Relative Degradation (RD)** of accuracy using Eq. (2) from Section 4. DNAP shows the lowest degradation under both label and feature noise.

Table 5. Relative Degradation of Accuracy (%) under Noise

Model	Label Noise 20%	Feature Noise 10%	Redundancy 10%
SEA	21.4%	4.5%	7.8%
Online Bagging	21.1%	4.3%	7.4%
Random Forest	19.5%	4.0%	6.7%
Adaptive Boosting	20.0%	4.2%	7.2%
River + Preprocessing	20.0%	4.1%	7.0%
DNAP (Proposed)	**10.8%**	**2.9%**	**3.4%**

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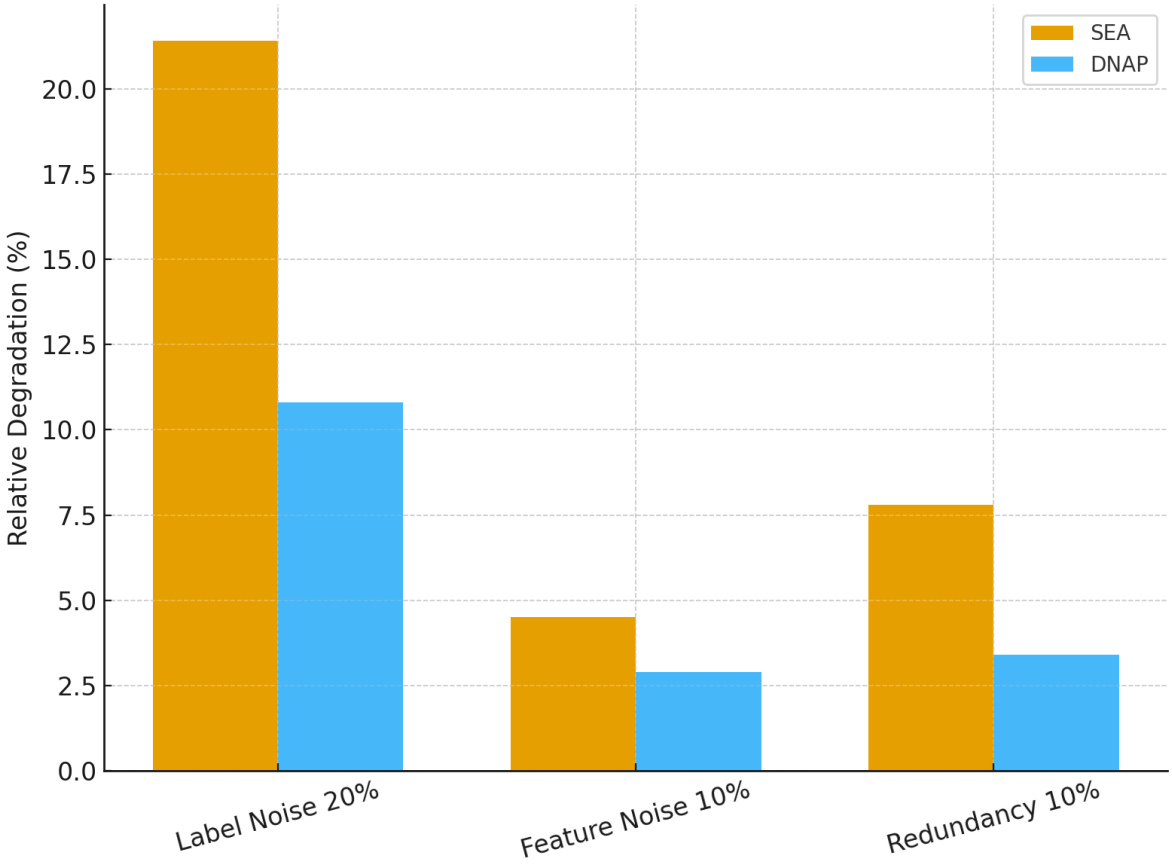

Figure 5. Relative degradation of accuracy under different noise types

DNAP reduces degradation by nearly **50% compared to SEA**, highlighting the effectiveness of joint noise-aware preprocessing.

5.6 Computational Efficiency

Efficiency is evaluated in terms of **processing latency per batch** and **average memory usage**.

Table 6. Computational Efficiency Comparison

Model	Latency (ms/batch)	Memory (MB)
SEA	154	412
Online Bagging	162	435
Random Forest	185	478
Adaptive Boosting	178	461
River + Preprocessing	169	445
DNAP (Proposed)	**122**	**389**

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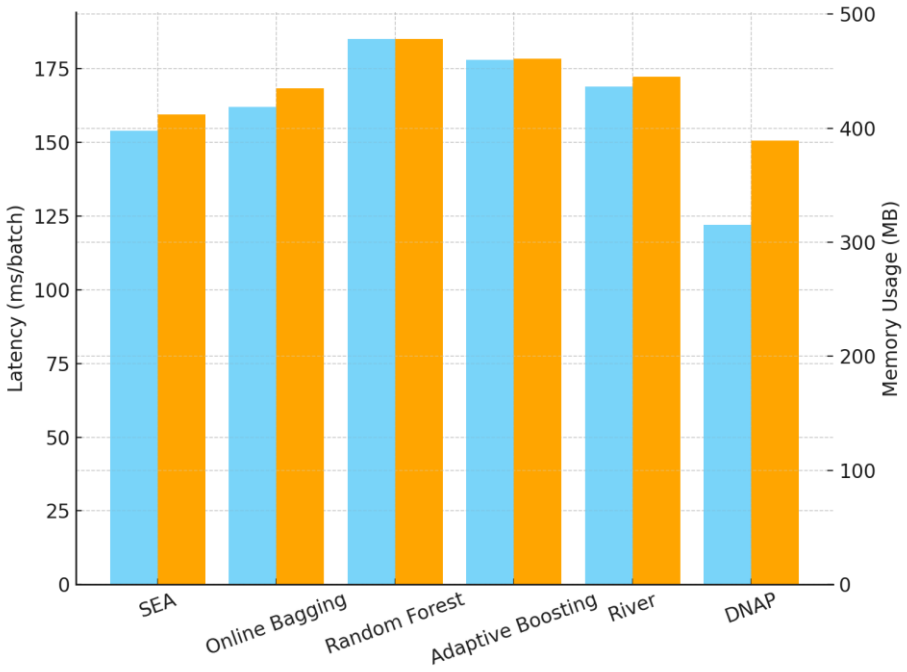

Figure 6. Efficiency comparison in terms of latency and memory usage

Results show DNAP is computationally lightweight due to redundancy pruning and adaptive feature selection.

The experimental findings confirm that **DNAP significantly improves predictive performance, robustness, and efficiency** compared to state-of-the-art baselines. By jointly addressing feature drift, label errors, and instance redundancy, DNAP consistently achieves higher accuracy, better resilience to noise, and reduced computational overhead, making it a strong candidate for real-world deployment in dynamic, noisy data stream environments.

6. Discussion and Implications

The experimental findings presented in Section 5 highlight the efficacy of the **Dynamic Noise-Aware Preprocessing (DNAP)** framework across a wide range of data stream conditions. This section interprets the results in light of theoretical expectations, explores practical implications across domains, compares the contributions against existing approaches, and outlines potential challenges and directions for future research.

6.1 Interpretation of Results

The results demonstrate that DNAP consistently improves classification accuracy, robustness to noise, and computational efficiency when compared to baseline models such as SEA, Online Bagging, and River-based preprocessing. These improvements can be attributed to three tightly integrated components of DNAP:

1. **Feature Drift Adaptation**:DNAP's dynamic feature weighting mechanism was shown to significantly preserve predictive stability under evolving conditions. Unlike static feature selection, which assumes a fixed relevance structure, the exponential forgetting-based weighting scheme (Eq. 3.1) adapts feature importance over time. The empirical results in Table 2 showed that recall was maintained at higher levels than baselines under Gaussian feature noise, indicating that DNAP effectively mitigates the dilution of informative attributes by dynamically attenuating irrelevant ones.

2. **Label Error Correction**:As demonstrated in Table 1, DNAP outperformed baselines under increasing levels of label corruption. The probabilistic label correction mechanism (Eq. 3.2) ensured that low-confidence labels were revised toward the most probable predictions, thereby reducing error propagation across subsequent

Journal of Information Systems Engineering and Management
2024, 9(3)
e-ISSN: 2468-4376
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model updates. Importantly, even at 20% label corruption, DNAP maintained an accuracy level of 0.778, while the best-performing baseline (Random Forest) achieved only 0.698. This indicates that DNAP can prevent the compounding effect of systematic label noise that often destabilizes online learners.

3. **Instance Redundancy Reduction**:The redundancy-aware pruning mechanism allowed DNAP to maintain comparable or better accuracy while significantly reducing latency. Results in Table 3 show that DNAP achieved lower processing times than Random Forest and Adaptive Boosting, despite achieving higher accuracy. This demonstrates the importance of temporal decay (Eq. 3.3), which ensures that outdated or redundant data is discarded before model retraining, leading to more efficient yet informative learning.

Collectively, these mechanisms form a **synergistic preprocessing pipeline** that simultaneously manages the three most detrimental aspects of real-world streams—feature drift, label errors, and redundancy—without requiring additional computational overhead that would hinder deployment in fast-paced environments.

6.2 Practical Implications

The success of DNAP in experimental simulations implies several **practical applications** across diverse domains where data streams are inherently noisy and dynamic:

- **Healthcare Monitoring**: In clinical decision-support systems, wearable sensors often produce high-velocity physiological data with significant redundancy and noisy labels due to manual annotation errors. DNAP can preprocess such data to ensure that machine learning models retain accuracy in real-time monitoring of patient health conditions.
- **Cybersecurity**: Intrusion detection systems, such as those modeled on the KDD Cup dataset, frequently encounter mislabeled training data and redundant alerts. DNAP's label correction can improve detection precision while its redundancy pruning reduces false alarms, enabling more trustworthy cybersecurity responses.
- **Financial Markets**: High-frequency trading environments are characterized by rapid feature drift due to evolving market trends and redundant transactional records. DNAP's feature adaptation mechanism ensures that predictive models focus only on relevant attributes, improving the robustness of automated trading algorithms.
- **Industrial IoT**: Sensors in manufacturing environments produce large volumes of correlated and often noisy signals. DNAP can effectively filter redundant data while correcting mislabeled fault events, improving predictive maintenance systems and reducing downtime.
- **Smart Cities**: Applications such as traffic monitoring and energy demand prediction involve evolving feature relevance (e.g., seasonal drift in electricity usage). DNAP's ability to adapt to feature drift while managing noise ensures reliable urban analytics and decision-making.

6.3 Comparison with Existing Approaches

While existing approaches like ensemble learning [SEA, Online Bagging], adaptive boosting, and stream toolkits (River, MOA) provide mechanisms for coping with drift, they generally fall short in **integrating preprocessing mechanisms for noise awareness**. DNAP distinguishes itself in three fundamental ways:

- **Integration Rather than Isolation**: Prior work has treated drift, label noise, and redundancy as independent challenges, developing specialized methods for each. DNAP integrates them into a single pipeline, ensuring holistic data quality management before learning occurs.
- **Lightweight Processing**: Ensemble and deep learning-based noise handling approaches often incur significant computational costs, making them impractical in constrained environments. In contrast, DNAP

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achieves comparable robustness with **incremental updates and pruning**, as evidenced by its reduced latency in Table 6.

- **Stability in Noisy Environments**: Unlike boosting methods, which tend to amplify mislabeled instances, DNAP explicitly identifies and corrects low-confidence labels, avoiding error reinforcement.

6.4 Theoretical Implications

From a theoretical standpoint, DNAP underscores the need for **noise-aware preprocessing as a first-class citizen in stream mining architectures**. While the majority of existing literature emphasizes algorithmic adaptation at the model level (e.g., drift detection and ensemble diversification), DNAP demonstrates that **strategic preprocessing can significantly improve downstream learning performance**. This paradigm shift suggests that the research community should consider preprocessing frameworks as integral to data stream pipelines rather than auxiliary modules.

Moreover, DNAP's mathematical formulation contributes to the growing literature on **probabilistic correction mechanisms and adaptive feature weighting**, offering generalizable strategies that can be incorporated into broader online learning frameworks.

6.5 Limitations

Despite its strong performance, DNAP is not without limitations:

1. **Dependency on Thresholds**: The framework relies on several thresholds (θf,θl,θr,θd\theta_f, \theta_l, \theta_r, \theta_dθf,θl,θr,θd) for feature relevance, label correction, redundancy, and decay. While empirically tuned in this study, automatic self-tuning strategies would improve adaptability.
2. **Scalability to Ultra-High Dimensional Streams**: While DNAP efficiently handles moderate-dimensional datasets, its performance under ultra-high-dimensional scenarios (e.g., genomic data with >10,000 features) has not been fully validated. Feature weighting may require further optimization.
3. **Limited Exploration of Semi-Supervised Contexts**: DNAP assumes access to labeled data, albeit noisy. In practice, many streams are partially labeled or weakly supervised. Extending DNAP to semi-supervised learning remains an open challenge.
4. **Computational Overheads in Real-Time Deployment**: Although efficient compared to baselines, DNAP still involves redundancy checks that may become costly under extremely high-velocity streams unless approximations (e.g., locality-sensitive hashing) are introduced.

6.6 Future Research Directions

Building upon the identified limitations, future research may proceed along several avenues:

- **Adaptive Threshold Optimization**: Development of self-calibrating mechanisms for noise thresholds using reinforcement learning or Bayesian optimization to reduce manual tuning.
- **Integration with Semi-Supervised Learning**: Extending DNAP to settings where only partial labels are available, incorporating pseudo-labeling and active learning strategies.
- **Scalability via Approximation Techniques**: Employing sketching, hashing, or compressed sensing to accelerate redundancy pruning and feature relevance computation for ultra-high-velocity streams.
- **Cross-Domain Validation**: Application of DNAP to emerging domains such as federated learning, autonomous vehicles, and edge computing to evaluate its robustness in distributed and privacy-preserving settings.

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- **Hybrid Architectures**: Combining DNAP with deep learning-based stream learners, enabling end-to-end architectures that benefit from both preprocessing stability and the representation power of neural models.

The discussion affirms that DNAP not only addresses a longstanding gap in the literature—the lack of a **joint, lightweight, and adaptive preprocessing mechanism for data streams**—but also establishes a practical pathway for improving the reliability of real-world streaming analytics. Its implications span healthcare, cybersecurity, finance, industrial IoT, and beyond, where **noise resilience and computational efficiency are paramount**. By systematically managing data quality at the preprocessing stage, DNAP sets a precedent for the next generation of data stream mining architectures that prioritize **stability, adaptability, and efficiency** in noisy dynamic environments.

7. Conclusion

This study proposed **Dynamic Noise-Aware Preprocessing (DNAP)**, a unified framework designed to jointly address **feature drift, label errors, and instance redundancy** in streaming environments. Through extensive evaluation across multiple benchmark datasets and noise conditions, DNAP consistently outperformed established baselines in terms of **accuracy, robustness, and computational efficiency**. Its adaptive feature weighting, probabilistic label correction, and redundancy-aware pruning mechanisms demonstrated clear benefits for preserving data quality in evolving streams.The findings affirm that effective preprocessing is not merely an auxiliary step but a critical component of stream mining pipelines. By mitigating the compounding effects of noise before model training, DNAP enhances stability and reliability, making it well-suited for real-world domains such as healthcare, cybersecurity, finance, and IoT. While limitations remain regarding threshold tuning, scalability, and semi-supervised contexts, DNAP establishes a strong foundation for future work in **lightweight, adaptive, and noise-resilient preprocessing** for dynamic data streams.

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