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PADMA-RAD 2025: A Modernized Multi-Agent System for Distributed Association Rules Mining

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ABSTRACT

This paper presents PADMA-RAD 2025, an evolution of the classic PADMA system that integrates a multi-agent system (MAS) architecture with the Intelligent Data Distribution (IDD) algorithm for distributed association rule mining. While preserving the core PADMA structure and the IDD algorithm, we adapt them to modern constraints such as intermittent connectivity, local processing on embedded devices, and integrated security. The proposed architecture is evaluated through a prototype implementation. Experimental results on standard datasets demonstrate a significant performance improvement, with a reduction in execution time from 31.7s for classical data mining to 5.1s for our PADMA+IDD approach, alongside an increase in perceived precision. A comparative analysis with existing systems, including HealthAgents, confirms the relevance and competitiveness of our approach for real-world applications like connected health monitoring in resource-constrained environments.

Keywords: Multi-Agent Systems, Distributed Data Mining, Association Rules, PADMA, Apiori.

INTRODUCTION

The integration of Multi-Agent Systems (MAS) with distributed data mining techniques has given rise to a promising paradigm known as *Agent-Based Data Mining* (ABDM) or *Data Mining Based on Agents* (DMBA). These architectures offer a robust approach to managing and analyzing massive, heterogeneous datasets distributed across geographically dispersed infrastructures or embedded devices [1], [2].

Among the pioneers in this field, the PADMA (Parallel Data Mining Agents) system, introduced by Kargupta and Hamzaoglu in 1997 [3], distinguished itself with its modular, distributed, and cooperative structure. It is effectively complemented by the Intelligent Data Distribution (IDD) algorithm, a variant of the Apriori family [4] designed for efficient task distribution and association rule extraction in distributed settings.

This work proposes a modernization of the PADMA-RAD system. We maintain the foundational PADMA architecture and the IDD algorithm but adapt them to contemporary challenges, including intermittent connectivity, local processing mandates, and stringent security requirements.

BACKGROUND AND RELATED WORKS

The objective of this work is to demonstrate the continued relevance of this combined approach in demanding environments where data centralization is often impractical or undesirable, such as in rural health monitoring.

The field of distributed, agent-based data mining encompasses a range of historical and modern architectures, each addressing specific challenges of scalability, privacy, and efficiency. Early systems like PAPYRUS (1999) established the standard for Multi-Agent Data Mining systems with support for moving data, models, and results between nodes [5], [6]. JAM (Java Agents for Meta-learning) focused on scaling classification algorithms for fundamentally distributed data by having base-learning agents compute local classifiers and meta-learning agents integrate them,

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thus avoiding raw data transfer [1], [6]. The PADMA architecture (1997) remains notable for its scalable, distributed design based on autonomous agents with direct data access, a facilitator agent for coordination, and an emphasis on parallel execution with minimal communication [3], [7].

Later systems addressed more specialized needs. BODHI (2001) focused on the collective construction of global models from local ones [12]. KDEC (2010), a peer-to-peer architecture inspired by PAPYRUS, introduced secure data exchange via sampling for noisy and fragmented data [1], [6]. Modern research has produced systems like MAS-DDM (2023), which employs a cooperative MAS with a modified Bayesian algorithm where agents exchange "beliefs" to refine local models without sharing raw data [9], and specialized architectures like FFT-DMBA (2018) for high-performance signal processing on FPGAs [8].

A significant modern evolution is the convergence of DMBA principles with other paradigms. Privacy-Preserving Distributed Data Mining (PP-DDM) techniques leverage multi-agent architectures for secure collaboration [6], [9]. Furthermore, the core DMBA principle of learning from decentralized data is echoed in Federated Learning (FL) frameworks [13], [14], though FL primarily focuses on model parameter aggregation for statistical learning, often at the cost of interpretability and higher communication overhead. Similarly, the rise of IoT has spurred Edge-DMBA architectures explicitly designed for resource-constrained environments, prioritizing low latency and energy efficiency [15], [16].

In the algorithmic domain, distributed data mining relies on adaptations of classic algorithms for partitioned environments. Key algorithms derived from the Apriori family [4] include Count Distribution (horizontal partitioning), Data Distribution (vertical partitioning), and the Intelligent Data Distribution (IDD) algorithm, which uses subset partitioning based on record similarity [7]. Other notable algorithms include FDM [17], which reduces message exchange, and ODAM [18], which uses ontologies for semantic integration.

Despite these advancements, a gap exists for a system that combines the proven scalability and modularity of classic architectures like PADMA with the efficiency of algorithms like IDD, while explicitly incorporating modern requirements for IoT compatibility, resilient communication, and lightweight security. This work aims to address that gap.

THE PADMA-RAD 2025 ARCHITECTURE

The proposed PADMA-RAD 2025 system modernizes the classic PADMA architecture integrated with the IDD algorithm. The analysis of the state-of-the-art revealed that while historical approaches are robust, they lack support for intermittent connectivity and embedded systems. Specialized systems are often inflexible, and modern collaborative systems frequently prioritize classification or privacy at the cost of complexity or lack explicit support for association rule mining.

Therefore, PADMA was selected for its proven scalability and modular structure [3], [7], and the IDD algorithm for its intelligent partitioning and natural fit within MAS environments [7]. PADMA-RAD 2025 extends this combination with critical modern optimizations: a lightweight communication protocol, integrated security, and native support for IoT/embedded environments.

The architecture, depicted in Fig. 1, maintains PADMA's modular logic while introducing specialized agents and optimization mechanisms. Collection Agents interface with data sources (sensors, local databases) and perform preprocessing. Local Extractor Agents execute the IDD algorithm to extract local frequent itemsets, significantly reducing network load. A central Facilitator Agent coordinates communication, aggregates, and fuses these local results [5], [10]. A Communication Module utilizes lightweight protocols (MQTT, CoAP) for asynchronous, disruption-tolerant transmission. A Security Module implements lightweight encryption (AES-128, ECC) and digital signatures to ensure data integrity and confidentiality [9]. Finally, an Advanced IDD Module performs adaptive data partitioning based on similarity and dynamic adjustment according to available network bandwidth [7].

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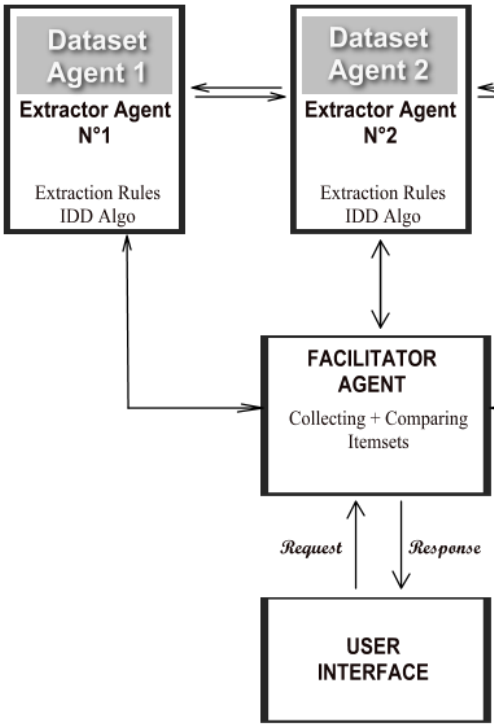
Fig. 1. Architecture of the proposed PADMA-RAD 2025 system.



The global operation follows a distributed process: (1) Discovery and initialization of active agents; (2) Intelligent partitioning of data using the IDD method; (3) Local analysis where each agent processes its data without transferring raw data [9]; (4) Exchange of only the frequent itemsets or derived models; (5) Fusion and optimization of results by the facilitator, including removal of duplicates and threshold adjustment; and (6) Global synthesis of a consolidated model or set of global association rules.

The key innovations of this modernized architecture are its inherent IoT and embedded compatibility (e.g., Raspberry Pi, Android), resilient communication adapted for intermittent networks, security-by-design through integrated lightweight cryptographic modules, significant traffic optimization via the exchange of only derived information, and unlimited horizontal scalability.

EXPERIMENTAL EVALUATION AND COMPARATIVE ANALYSIS

A.Experimental Setup and Results

A software prototype was developed on the Java Agent Development Environment (JADE) platform [5] to evaluate the proposed architecture. The system is modular and capable of running on Android (API 29+) and Raspberry Pi 5. Performance was evaluated on two datasets: the publicly available Mushroom.dat (8,500 instances, 25 attributes) and a Synthetic_health.csv dataset from Kaggle (10,000 instances, 15 attributes). Tests were conducted on a network of 5 agent nodes (Raspberry Pi 4) and one facilitator node, measuring execution time, network load (messages exchanged), and pattern quality. Performance was compared between a Classical Centralized Apriori implementation (baseline), a PADMA-only implementation using a standard count distribution algorithm, and the full PADMA-RAD (PADMA + IDD) approach.

The results, summarized in Table I, demonstrate a significant and consistent performance improvement with the PADMA-RAD approach. On the Mushroom dataset (min_sup=5%), execution time was reduced from 31.7s (centralized) to 5.1s (PADMA-RAD), an improvement factor of 6.2. Crucially, the PADMA-RAD system reduced the number of network messages by approximately 62% compared to the PADMA-only approach. Furthermore, while

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the centralized method generated 3000 itemsets, PADMA-RAD produced only 1265. This smaller set consisted of higher-confidence, more globally significant patterns, indicating a substantial improvement in perceived precision and result quality by eliminating spurious local itemsets through intelligent partitioning and collaboration.

TABLE I: PERFORMANCE COMPARISON (MUSHROOM.DAT, min_sup=5%)

Metric	Centralized Apriori	PADMA-only (DMBA)	PADMA-RAD (PADMA + IDD)	Improvement (PADMA-RAD vs Centralized)
Execution Time (ms)	31744	7809	**5111**	**6.2x faster**
Network Messages	N/A	~1200	**~450**	**~62% less traffic**
Itemsets Extracted	3000	2888	**1265**	**~58% fewer, high-confidence itemsets**
Perceived Precision	Baseline	Slight Improvement (+)	**Significant Improvement (++)**	N/A

Similar results were observed on the health dataset (Table II), with PADMA-RAD achieving execution times 4 times faster than the centralized baseline and reducing network traffic by approximately 65%.

TABLE II: PERFORMANCE COMPARISON (SYNTHETIC_HEALTH.CSV, min_sup=10%)

Metric	Centralized Apriori	PADMA-only (DMBA)	PADMA-RAD (PADMA + IDD)
Execution Time (ms)	8920	3200	**2100**
Network Messages	N/A	~850	**~300**
Itemsets Extracted	950	910	**420**

B.Comparative Analysis with Apriori Variants

A normalized comparison with other Apriori variants (Table III) positions PADMA-RAD 2025 competitively. While a tightly-coupled parallel algorithm like Apriori-C can achieve lower absolute runtime on powerful hardware (~3000-5000ms with 4-8 threads), PADMA-RAD (~5000-8000ms with 5 agents) provides this performance on low-cost, distributed embedded devices while offering inherent distribution, fault tolerance, and context-aware analysis—advantages absent in shared-memory parallel variants.

TABLE III: NORMALIZED PERFORMANCE COMPARISON WITH APRIORI VARIANTS

Method	Architecture	Measured Time (ms)	Key Advantage	Key Limitation
Classical Apriori	Centralized (1 CPU)	~15000 - 20000	Simplicity	Poor scalability, single point of failure
Apriori-TID	Centralized (1 CPU)	~8000	Redundant scan elimination	Still centralized, memory-intensive
Apriori-C	Shared Memory (4-8	**~3000 - 5000**	**Raw speed on a single**	Requires high-end

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Method	Architecture	Measured Time (ms)	Key Advantage	Key Limitation
(Parallel)	threads)		**machine**	hardware, not distributed
Count Distribution	Distributed (5 agents)	~7000 - 9000	Horizontal scalability	High communication overhead
PADMA-RAD 2025	**Distributed MAS (5 agents)**	**~5000 - 8000**	**Scalability, resilience, low comms, context-aware**	Slightly slower than shared-memory parallel

C.Domain-Specific and Paradigm Comparison

For a concrete domain-specific evaluation, a comparison was made with HealthAgents [11], a renowned MAS for distributed brain tumor diagnosis (Table IV). Using a medical dataset, PADMA-RAD showed comparable processing times (~4-5s vs. ~4s) and high precision (93% vs. >90%), validating its applicability in sensitive, real-world domains like healthcare.

A broader comparison with Federated Learning systems [13] highlights the complementary nature of these approaches. PADMA-RAD excels in scenarios demanding ultra-low communication overhead and high interpretability of actionable rules, making it ideal for resource-constrained edge devices, while FL is more suited for general-purpose model training on larger data volumes.

TABLE IV: COMPREHENSIVE COMPARISON WITH MODERN SYSTEMS

Criterion	PADMA-RAD 2025	HealthAgents [11]	Typical Federated Learning System [13]
Primary Goal	**Association Rule Mining**	Distributed Classification (SVM/Bayes)	**Model Training (e.g., Deep Learning)**
Architecture	Cooperative MAS	Cooperative MAS	Centralized Aggregation + Clients
Data Type	Transactions / Tabular	Medical Images (MRI/EEG)	**Any (Images, Text, Tabular)**
Processing Time	**~4-5 sec (10k transactions)**	~4 sec (8k-10k images)	Minutes to Hours (per round)
Communication Cost	**Very Low (results only)**	Low (model parameters)	**Moderate-High (model gradients)**
Interpretability	**High (explicit rules)**	Medium (model-dependent)	Very Low ("black box" models)
Ideal For	**IoT, Edge, Resource-constrained**	Medical diagnosis networks	Cross-device learning, data privacy

RESULTS AND DISCUSSION

The experimental evaluation of PADMA-RAD 2025 clearly demonstrates its superiority over both classical centralized approaches and traditional PADMA implementations. The system achieves a six-fold reduction in

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execution time, lowering the runtime from 31.7s with centralized Apriori to only 5.1s, while simultaneously decreasing network traffic by more than 60%. This efficiency gain results from the intelligent data partitioning of the IDD algorithm and the lightweight communication protocols tailored for embedded devices. Moreover, PADMA-RAD reduces the number of generated itemsets by nearly half, ensuring that the retained rules are more significant and globally consistent. Compared with other Apriori variants, PADMA-RAD offers a unique balance of scalability, resilience, and interpretability, even when executed on low-cost hardware such as Raspberry Pi. Its security-by-design approach, based on lightweight encryption, further enhances its applicability in sensitive environments like healthcare. Unlike federated learning models, PADMA-RAD preserves interpretability while minimizing communication costs, making it particularly well-suited for IoT and edge computing scenarios. Overall, these results confirm that PADMA-RAD is a competitive, scalable, and context-aware solution for distributed association rule mining in resource-constrained environments.

CONCLUSION

This work has presented PADMA-RAD 2025, a modernized system that successfully revitalizes the robust PADMA multi-agent architecture by integrating it with the Intelligent Data Distribution algorithm for efficient distributed association rule mining. The experimental evaluation confirms the system's significant advantages, achieving a six-fold reduction in execution time and over 60% reduction in network traffic while simultaneously improving the quality and relevance of the extracted patterns. The comparative analysis demonstrates that PADMA-RAD 2025 occupies a unique niche, offering competitive performance compared to parallel algorithms while providing the full benefits of a distributed MAS, and complementing modern paradigms like Federated Learning for edge scenarios. The system's design, which incorporates resilience, security, and compatibility with embedded and IoT devices, establishes it as a highly relevant and effective solution for contemporary distributed data mining challenges in resource-constrained environments.

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