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Performance Evaluation of AI-Enhanced Unsupervised CART Models for High-Dimensional Data Classification

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Abstract
This study evaluates the performance of AI-enhanced unsupervised Classification and Regression Tree (CART) models for high-dimensional data classification, addressing the growing need for interpretable and scalable unsupervised learning techniques in domains where labeled data are limited or unavailable. Traditional clustering and dimensionality reduction methods often struggle with nonlinear relationships, noise, and complex feature interactions, motivating the integration of advanced artificial intelligence mechanisms into CART frameworks. The research investigates how deep learning–based feature representation, hybrid clustering-tree architectures, reinforcement learning–driven decision policies, and evolutionary optimization contribute to improved clustering accuracy, boundary formation, and structural adaptability. Using multiple benchmark datasets representing healthcare, cybersecurity, remote sensing, and text analytics, the study compares enhanced CART models with conventional unsupervised algorithms based on metrics such as silhouette coefficient, Davies–Bouldin index, cluster purity, cohesion, and interpretability. Experimental results demonstrate that AI-augmented CART variants significantly outperform standalone methods by producing more coherent clusters, reducing sensitivity to noise, and offering transparent rule-based explanations.

Keywords: Unsupervised CART; High-dimensional data; Hybrid AI models; Reinforcement learning; Explainable clustering

Introduction

The exponential growth of high-dimensional data across domains such as healthcare, cybersecurity, finance, bioinformatics, and remote sensing has intensified the demand for advanced unsupervised learning models capable of identifying meaningful structures without relying on labeled inputs. Traditional unsupervised algorithms—including K-Means, DBSCAN, PCA, and hierarchical clustering—often struggle with scalability, noise sensitivity, and the curse of dimensionality, limiting their ability to produce reliable and interpretable results in complex environments. In contrast, Classification and Regression Trees (CART), known for their inherent interpretability and rule-based decision-making, are increasingly being adapted for unsupervised settings. By incorporating artificial intelligence enhancements such as deep feature extraction, hybrid clustering mechanisms, reinforcement learning–driven optimization, and evolutionary algorithms, unsupervised CART models have evolved into powerful tools for high-dimensional data classification. These enhanced models enable dynamic feature selection, improved boundary formation, and better handling of

heterogeneous data types, offering greater transparency than black-box deep clustering methods while maintaining competitive performance.

Despite these advancements, rigorous performance evaluation of AI-enhanced unsupervised CART models remains limited, particularly in the context of complex, high-dimensional datasets where feature interactions are nonlinear and patterns are difficult to detect. This research addresses that gap by assessing how different AI-driven enhancements—including deep embeddings, hybrid clustering-tree frameworks, and reinforcement-guided split optimization—impact classification quality, computational efficiency, and model interpretability. Through comparative experiments involving benchmark datasets and state-of-the-art clustering algorithms, the study aims to provide empirical insights into the strengths, limitations, and practical applications of enhanced CART variants. By emphasizing quantifiable metrics such as silhouette scores, Davies–Bouldin index, purity, cohesion, and rule interpretability, this study establishes a robust foundation for evaluating the effectiveness of unsupervised CART in high-dimensional environments. Ultimately, the findings contribute to the development of more reliable, scalable, and explainable classification models, supporting data-driven decision-making in diverse real-world applications where labeled data remain scarce or costly to obtain.

Scope of the Study

The scope of this study encompasses a comprehensive evaluation of AI-enhanced unsupervised CART models tailored for high-dimensional data classification across diverse application domains. Specifically, it focuses on analyzing how different AI-driven enhancements—such as deep learning–based feature transformation, hybrid clustering-tree architectures, reinforcement learning strategies for dynamic split optimization, and evolutionary algorithms for structural refinement—influence the performance and interpretability of unsupervised CART frameworks. By using benchmark datasets from fields including healthcare diagnostics, cybersecurity anomaly detection, satellite imagery classification, and textual data grouping, the study assesses the robustness, scalability, and adaptability of these enhanced models. It also examines their ability to overcome common challenges associated with high-dimensional data, such as sparse feature distributions, noise sensitivity, nonlinear relationships, and the curse of dimensionality. Through systematic comparison with traditional clustering algorithms and baseline unsupervised methods, the study aims to quantify improvements in clustering quality, computational efficiency, model stability, and rule-based explainability.

The scope includes a detailed investigation of evaluation metrics that capture both the structural and functional performance of the models, such as silhouette scores, Davies–Bouldin index, cohesion and separation measures, impurity reduction, and interpretability indices. The study also extends its analysis to the practical applicability of AI-enhanced CART models by exploring their use in real-world decision-making contexts where transparency and explainability are critical. While the research primarily focuses on unsupervised learning scenarios, it lays the foundation for subsequent exploration of semi-supervised and hybrid learning paradigms that further enhance the utility of CART-based

systems. Additionally, the study identifies methodological gaps, computational constraints, and optimization challenges that require attention in future research. Overall, the scope of this work is broad yet focused, aiming to bridge theoretical advances and practical implementations in the development of next-generation interpretable models for high-dimensional data classification.

Novelty of AI-Enhanced CART Approach

The novelty of the AI-enhanced CART approach lies in its ability to transform a traditionally supervised, rule-based decision-tree framework into a powerful, flexible, and interpretable model capable of performing high-quality unsupervised classification in high-dimensional and heterogeneous data environments. Unlike conventional clustering algorithms that rely solely on distance metrics or density estimation, AI-enhanced CART introduces multi-layered intelligence through deep feature extraction, adaptive optimization, and hybrid decision mechanisms, allowing it to detect complex nonlinear patterns without labeled data. Deep learning–driven embeddings provide richer data representations that significantly improve CART's ability to identify meaningful structures, while hybrid clustering-tree integrations combine the strengths of algorithms like K-Means and DBSCAN with interpretable decision rules, resulting in clusters that are both accurate and transparent. Reinforcement learning (RL) further elevates the novelty of this approach by treating tree construction as a sequential decision process, enabling the model to learn optimal actions—such as split selection and branch pruning—based on reward signals linked to cluster quality metrics. Evolutionary algorithms introduce population-based optimization, evolving multiple tree configurations simultaneously and selecting the most effective structures, thereby overcoming the limitations of greedy, locally optimal splits inherent in classical CART. Together, these enhancements create a uniquely adaptive, self-organizing classification model that is capable of handling noisy data, irregular cluster shapes, and mixed attribute types while maintaining interpretability, a feature often lost in deep or ensemble models. The integration of explainable AI principles further strengthens the novelty of AI-enhanced CART, offering clear, rule-based insights that support decision-making in high-stakes domains like healthcare, finance, and cybersecurity. The innovation lies not in any single enhancement but in the synergistic fusion of modern AI techniques with the transparent architecture of CART, resulting in a next-generation unsupervised system that balances performance, scalability, and interpretability in ways that traditional methods cannot achieve.

Literature Review

The integration of Artificial Intelligence with traditional machine learning frameworks has shown notable progress across multiple domains, particularly in classification tasks that require both accuracy and interpretability. Seera and Lim (2014) provided early evidence of this trend through their hybrid intelligent system designed for medical classification, demonstrating that combining neural networks with rule-based decision-tree structures significantly enhances diagnostic performance. Their work underscored the importance of hybridization, where symbolic reasoning and computational intelligence jointly improve predictive capacity and reliability. This foundational insight is directly relevant to the

development of AI-enhanced CART systems, as it highlights how combining complementary learning paradigms can mitigate limitations inherent in standalone algorithms. Their model's success in medical applications also indicates that interpretable hybrid classifiers can play a vital role in safety-critical decision-making environments.

Building upon similar principles, later research extended hybrid AI systems into cybersecurity domains. Shaik and Shaik (2021) explored AI-enabled anomaly detection mechanisms, illustrating how machine learning enhances the detection of unusual behavior in networked systems. Their work demonstrated that hybrid learning architectures outperform conventional threshold-based methods, particularly in the early detection of subtle anomalies. In their subsequent contribution, Shaik and Shaik (2024) focused on adaptive cybersecurity models capable of responding to evolving digital threats. These AI-enhanced methods integrated pattern recognition, behaviour modelling, and real-time learning components, enabling more dynamic defence strategies. Together, these studies emphasize the necessity of hybrid, adaptive, and explainable AI systems for cyber-infrastructure protection—principles that strongly parallel the need for stable and interpretable unsupervised CART frameworks. Meanwhile, Volk (2021) reinforced this perspective by highlighting the essential role of AI in safeguarding critical infrastructures, where transparency and reliability are paramount. His findings support the argument that interpretable tree-based AI hybrids offer a viable pathway for secure and accountable intelligent systems.

In parallel, hybrid machine learning techniques have gained traction in domains beyond security, including agriculture and sensor data analytics. Shah et al. (2024) demonstrated the potential of AI-enhanced farming systems, where machine learning models improve crop monitoring, classification, and resource optimization. Although not directly decision-tree based, their approach illustrates the scalability and adaptability required for AI models deployed in dynamic, high-dimensional environments—conditions well aligned with unsupervised CART enhancements. Similarly, Vinayaka and Prasad (2024) applied AI-driven methods to remote sensing for sugarcane analysis, achieving improved accuracy in classifying aerial agricultural imagery. Their use of enhanced feature extraction aligns with the principle of embedding-based improvements in unsupervised CART. Tan and He (2021) further contributed to hybrid modelling through their fuzzy decision tree integrated with genetic algorithms, showcasing how evolutionary optimization can refine rule generation and improve performance consistency. This work provides methodological inspiration for evolutionary-enhanced CART models, where genetic search techniques can optimize split selection and structural integrity.

The literature also reflects substantial exploration of unsupervised and semi-supervised learning applied to complex data environments. Usama et al. (2019) provided a comprehensive overview of unsupervised machine learning for networking applications, identifying clustering-based anomaly detection as a major research direction. Their findings reveal the need for unsupervised models that maintain interpretability while managing large-scale, unlabelled data streams—an ideal use case for AI-enhanced CART frameworks. Their emphasis on robustness, scalability, and adaptability resonates strongly with the challenges

addressed by AI-driven tree-based systems. Collectively, these studies highlight the ongoing shift toward hybrid and interpretable machine learning models across multiple sectors. Each contribution reinforces key methodological principles—feature enrichment, evolutionary optimization, pseudo-labelling, and adaptive learning—that underpin the development of an effective AI-enhanced unsupervised CART model capable of operating reliably in complex and data-scarce environments.

Methodology

The methodology employed in this study is designed to systematically investigate how Artificial Intelligence (AI) techniques can be integrated with the Classification and Regression Tree (CART) algorithm to enable effective and interpretable unsupervised classification, particularly in high-dimensional and structurally complex datasets. This approach begins with an exploratory–descriptive research design, ensuring that both conceptual development and empirical validation are addressed. The methodological framework is structured around four key components: data preprocessing and representation, pseudo-labelling and clustering-assisted learning, hybrid CART model construction, and iterative refinement with performance evaluation. Preprocessing involves normalisation, feature encoding, and dimensionality reduction through techniques such as Principal Component Analysis (PCA), autoencoders, or manifold learning. These methods help generate compact, noise-reduced feature spaces suitable for unsupervised analysis. The next phase incorporates clustering algorithms—such as K-Means, DBSCAN, or hierarchical clustering—to generate initial pseudo-labels that approximate latent structures within the dataset. These pseudo-labels form the foundation for adapting CART to function in a supervised-like manner despite the absence of ground truth classes. Deep representation learning is used when datasets exhibit significant nonlinear relationships or high sparsity, enabling the model to capture more meaningful embeddings and support improved splitting decisions. The conceptual development of the AI-enhanced CART involves integrating clustering-assisted feature augmentation, pseudo-labelling feedback loops, and iterative self-training mechanisms. These enhancements reformulate how CART determines split criteria, impurity measures, and tree structure, allowing it to infer meaningful partitions from unlabeled data.

The second major component of the methodology focuses on empirical implementation, evaluation, and refinement of the hybrid model. Using benchmark datasets from cybersecurity (NSL-KDD), healthcare diagnostics, financial fraud detection, and other UCI repositories, the study tests the hybrid CART model across domains characterised by high dimensionality, noise, and ambiguous class boundaries. Each dataset undergoes a standardised preprocessing protocol to ensure comparability. The empirical phase adopts an iterative experimental design where model parameters, pseudo-labelling thresholds, clustering configurations, and embedding dimensions are systematically varied to optimise performance. A controlled simulation environment ensures consistency across experiments, with baseline unsupervised algorithms such as K-Means, DBSCAN, and hierarchical clustering serving as comparative models. Evaluation metrics include silhouette coefficients,

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Davies–Bouldin indices, Calinski–Harabasz scores, cluster stability measures, and reconstruction losses for embedding-based models. Computational metrics—such as training time, memory usage, and tree complexity (depth, node count, branching patterns)—are also assessed to ensure that enhancements do not compromise interpretability or efficiency. Qualitative evaluation centres on the interpretability of the resulting decision-tree structures, analysing splitting behaviour, surrogate splits, feature importance rankings, and rule clarity. A cross-validation–like process tailored for unsupervised learning, including subsampling, perturbation testing, and sensitivity analysis, reinforces the reliability of the findings. Throughout the methodology, transparency and replicability are prioritised through detailed documentation of data transformations, parameter settings, and experimental procedures. Together, this multilayered methodological approach provides a rigorous and comprehensive foundation for assessing the feasibility, effectiveness, and practical relevance of AI-enhanced CART models for unsupervised classification.

Result and Discussion

Table 1: Unsupervised CART Performance (Numerical / Compact Format)

Dimension	**Observed Value / Behaviour**
Split Quality	Unstable; variance-only splits
Silhouette Score	0.05 – 0.18
Davies–Bouldin Index	2.5 – 3.2
Tree Depth	2 – 3 levels (average)
Feature Stability	Low; changes in >70% of runs
Noise Sensitivity	High; noise selected as split >40% of time
High-Dimensional Performance	Severe degradation above 50+ features
Computational Overhead	+35% – 60% vs. supervised CART
Run-to-Run Stability	Structural similarity < 0.30
Interpretability	Low due to meaningless rules
Compared to Baselines	Lower Silhouette, higher DB index

Table 1 summarizes the numerical performance of traditional CART when applied in an unsupervised setting, revealing significant structural and statistical limitations. Because CART relies on impurity-based supervised splitting criteria, its unsupervised variant is forced

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to use variance-only thresholds, resulting in unstable and low-quality splits. This weakness is reflected in extremely poor cluster validity indices, with Silhouette scores between 0.05 and 0.18 and Davies–Bouldin values ranging from 2.5 to 3.2, indicating weak cohesion and high overlap among clusters. Tree structures remain shallow or erratic, feature selection is highly inconsistent, and noise heavily influences split decisions. High-dimensional datasets further degrade performance, producing sparse or meaningless tree patterns. Computational efficiency suffers due to the need to evaluate numerous uninformative splits, and model reproducibility remains low with structural similarity below 0.30 across runs. Overall, the table highlights that traditional CART severely underperforms compared to standard clustering baselines.

Table 2: AI-Enhanced CART vs. Clustering Algorithms (Numeric Summary)

Metric / Dimension	AI-Enhanced CART	K-Means	DBSCAN	GMM	Spectral
Silhouette Score	0.32 – 0.51	0.20 – 0.35	0.10 – 0.45	0.22 – 0.40	0.30 – 0.42
Davies–Bouldin Index	0.9 – 1.4	1.8 – 2.3	1.2 – 2.7	1.5 – 2.0	1.4 – 2.1
Stability Score	> 0.80	< 0.50	0.50 – 0.70	0.60 – 0.75	< 0.60
Parameter Sensitivity	Low	High	Very high	High	High
High-Dimensional Performance	Excellent	Poor	Weak	Moderate	Poor
Noise Handling	Good	Poor	Good (ε-sensitive)	Weak	Moderate
Interpretability	High	None	None	Low	None
Scalability	High	Very high	Moderate	Moderate	Low

Table 2 presents a comparative numerical assessment of AI-enhanced CART against classical clustering algorithms, demonstrating the hybrid model's superiority across multiple dimensions. AI-enhanced CART achieves higher-quality clusters, reflected in Silhouette scores of 0.32–0.51 and significantly lower Davies–Bouldin indices (0.9–1.4), outperforming K-Means, DBSCAN, GMM, and Spectral Clustering. Structural stability is also markedly stronger (>0.80), due to pseudo-label refinement and latent embedding consistency. Unlike traditional clustering algorithms—many of which are sensitive to initialization, ε thresholds, or covariance assumptions—AI-enhanced CART maintains low parameter sensitivity and robust high-dimensional performance. Its interpretability is a major advantage, delivering clear decision rules absent in other models. Additionally, it balances scalability and noise handling, giving it broad applicability in domains requiring transparency. Overall, the table shows that AI-enhanced CART combines interpretability, stability, and performance more effectively than standard clustering approaches.

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Table 3: Structural Performance Metrics of AI-Enhanced CART

Metric	Value / Range
Average Tree Depth	**4 – 9 levels**
Node Count	**25 – 80 nodes**
Splitting Accuracy (pseudo-label alignment)	**68% – 84%**
Feature Importance Consistency	**0.72 stability index**
Embedding Compression Rate	**40% – 65%** reduction
Pseudo-Label Confidence Threshold	**0.60 – 0.85**
Re-labelling Iterations	**3 – 7 cycles**
Rule Clarity Score	**0.70 – 0.88**
Structural Coherence	**0.78 – 0.91**
Latent Cluster Match Rate	**55% – 72%**

Table 3 details structural performance metrics of the AI-enhanced CART model, illustrating how integrated AI components improve tree quality, stability, and clustering coherence. The enhanced trees exhibit deeper and more meaningful structures (4–9 levels) with 25–80 nodes, indicating improved partitioning capability. Splitting accuracy aligned with pseudo-labels ranges between 68% and 84%, reflecting reliable internal structure detection. Feature importance consistency (0.72) and high structural coherence (0.78–0.91) demonstrate increased model stability across runs. Representation learning significantly compresses feature space—reducing dimensionality by 40–65%—while improving rule clarity (0.70–0.88). Pseudo-label confidence thresholds of 0.60–0.85 ensure that only reliable cluster assignments influence the tree. Additionally, 3–7 re-labelling iterations help refine boundaries and enhance cluster match rates (55–72%). Overall, the table highlights how AI integration strengthens CART's interpretability and performance, enabling consistent unsupervised classification.

Table 4: Computational Efficiency Comparison

Metric	AI-Enhanced CART	K-Means	DBSCAN	GMM	Spectral
Training Time	**1.0× – 1.6×** baseline	1.0×	1.4× – 2.5×	1.8× – 3.0×	3.5× – 6.0×
Memory Usage	**Low–Moderate**	Low	Moderate	High	Very

					High
Embedding Cost	**Primary overhead**	N/A	N/A	N/A	High
Model Complexity	**Medium**	Low	Medium	High	Very High
Scalability (Dataset Size)	**Excellent**	Excellent	Moderate	Moderate	Poor
Iteration Count	**5 – 12**	10 – 25	N/A	50 – 120 (EM)	20 – 40
Convergence Stability	**High (>0.85)**	Medium	Low–Medium	Medium	Low
Runtime Variance	**Low**	High	Medium	Medium	High

Table 4 compares the computational efficiency of AI-enhanced CART with leading clustering algorithms, highlighting its balanced performance across resource usage, stability, and scalability. Although AI-enhanced CART incurs additional cost during embedding generation, its training time remains moderate (1.0×–1.6× baseline) and more efficient than DBSCAN, GMM, and Spectral Clustering. Memory usage stays low to moderate, much lower than spectral or GMM models. Its model complexity remains manageable, and scalability across large datasets is excellent. Convergence stability is high (>0.85), significantly outperforming other clustering methods that exhibit medium or low stability due to noise, initialization issues, or covariance estimation. Runtime variance is also low, showing consistent computational behaviour across runs. In contrast, baseline methods show sensitivity to dataset size, parameter tuning, and noise. Overall, the table demonstrates that AI-enhanced CART achieves a strong balance of efficiency, stability, and scalability while maintaining interpretability.

Conclusion

This study provides a comprehensive evaluation of AI-enhanced unsupervised CART models and demonstrates their substantial advantages over both traditional CART and standard clustering algorithms when handling high-dimensional, unlabeled datasets. The integration of AI techniques—such as deep representation learning, pseudo-label refinement, clustering-assisted feature augmentation, and iterative self-training—effectively overcomes the inherent limitations of classical CART, enabling the model to construct meaningful partitions, achieve higher structural stability, and maintain interpretability even in complex data environments. Empirical results show that AI-enhanced CART consistently outperforms baseline clustering methods in terms of silhouette scores, Davies–Bouldin indices, stability metrics, and rule clarity, demonstrating enhanced cohesion, reduced cluster overlap, and improved reproducibility across multiple runs. The model also delivers strong computational efficiency, scalability, and robustness to noise, which are critical for real-world applications such as cybersecurity, healthcare diagnostics, and financial anomaly detection. Furthermore, the hybrid architecture preserves the transparency of decision-tree structures, ensuring that

clustering outcomes remain explainable and suitable for domains requiring accountability and traceability. Despite its strengths, the study also acknowledges challenges related to embedding cost, iterative tuning, and dependency on pseudo-label quality, indicating areas for future refinement. The research confirms that AI-enhanced CART represents a powerful and interpretable alternative for unsupervised high-dimensional data classification, offering a balanced blend of performance, stability, and explainability that traditional clustering methods and standalone CART models cannot achieve.

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