A SIMPLE AND ACCURATE CLASSIFICATION METHOD BASED ON CLASS ASSOCIATION RULES: ADAPTIVE SUPERVISED DISCRETIZATION WITH RANDOM FOREST ENSEMBLE

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Abstract

Class Association Rule (CAR)-based classifiers combine the transparency of rule-based models with the predictive power of supervised learning, yet classical methods such as CBA, CMAR, and CPAR suffer from rule explosion, sensitivity to threshold parameters, and degraded performance on imbalanced datasets. This paper proposes an improved two-phase classification pipeline — Adaptive Supervised Discretization combined with a Random Forest ensemble (ASD-RF) — that addresses these limitations. In the first phase, continuous features are discretized using shallow decision trees trained per feature on the class label, deriving cut points that maximise class homogeneity within each bin. In the second phase, a Random Forest of 100 trees is trained on the resulting one-hot-encoded binary feature matrix. Empirical evaluation on two public benchmark datasets (Pima Indians Diabetes and Banknote Authentication) demonstrates that ASD-RF achieves mean accuracy of 90.14%, outperforming CBA (87.28%), CPAR (88.38%), CMAR (79.03%), and an unprocessed Decision Tree baseline (86.14%). The method is fully reproducible, requires no manual threshold tuning, and produces a compact, interpretable feature representation suitable for high-stakes domains such as healthcare and finance.

Keywords: class association rules, associative classification, supervised discretization, random forest, data preprocessing, interpretable machine learning.

1. Introduction

The rapid growth of structured tabular data in healthcare, finance, and education has intensified the demand for classifiers that are simultaneously accurate and explainable. Black-box models are increasingly rejected in high-stakes domains due to regulatory requirements (e.g., the EU AI Act) and the need for clinical or financial auditability. Class Association Rules (CARs) of the form $X \rightarrow c$, where the antecedent X is a conjunction of human-readable conditions and c is a class label, offer a natural solution: the model is its own explanation.

Classical CAR-based classifiers — CBA [1], CMAR [2], CPAR [3], MCAR, and L3 — are known to suffer from three recurrent limitations: (i) the rule base grows combinatorially with the number of frequent itemsets; (ii) accuracy is sensitive to minimum support and confidence thresholds; and (iii) coverage-based pruning (as used in CBA) discards individually informative rules on imbalanced datasets.

This paper presents ASD-RF, a CAR-based classification pipeline that couples a supervised discretization scheme with a Random Forest ensemble. The core contribution is an Adaptive Supervised Discretization (ASD) procedure that derives class-aligned bin boundaries from shallow decision trees, replacing unsupervised equal-width or equal-frequency binning. The resulting binary feature representation is then exploited by a Random Forest ensemble, which aggregates class-discriminative rules through bagging-based variance reduction. Experimental

results confirm that ASD-RF matches or exceeds established CAR-proxy methods on two benchmark datasets without requiring any manual threshold tuning.

2. Theoretical Background

2.1. Association Rules and Class Association Rules

Let $I = \{i_1, i_2, \ldots, i_m\}$ be a set of items and $D = \{T_1, T_2, \ldots, T_n\}$ a transactional database. An association rule $X \Rightarrow Y$ ($X, Y \subset I$, $X \cap Y = \emptyset$) is characterised by three interestingness measures:

support: $\text{supp}(X \Rightarrow Y) = P(X \cup Y)$; **confidence:** $\text{conf}(X \Rightarrow Y) = P(Y \mid X)$; **lift:** $\text{lift}(X \Rightarrow Y) = P(X \cup Y) / (P(X) \cdot P(Y))$.

Table 1 summarises the principal interestingness measures used in this work.

Table 1. Principal Interestingness Measures

Measure	Formula	Range	Interpretation
Support	$P(X \cup Y)$	[0, 1]	Statistical significance
Confidence	$P(Y \mid X)$	[0, 1]	Reliability of rule
Lift	$P(X \cup Y) / (P(X) \cdot P(Y))$	$[0, +\infty)$	Independence deviation

A Class Association Rule (CAR) is a specialised association rule in which the consequent is restricted to a single class label: $X \rightarrow c$. The generation of CARs follows the two-stage pipeline of frequent itemset mining — using Apriori [4] or FP-Growth [5] — followed by confidence-based filtering and pruning.

2.2. Limitations of Classical CAR-Based Classifiers

CBA selects the single highest-ranked rule per instance, which discards valid minority-class rules under coverage-based pruning. CMAR weights multiple rules via a χ^2 measure but relies on the conditional independence assumption, which is violated by correlated features. CPAR iteratively generates rules using a gain-ratio criterion but inherits the sensitivity to minimum support and confidence thresholds. All three methods treat discretization as a pre-processing detail independent of rule generation, which degrades rule quality when continuous features are binned without reference to the class distribution.

3. Proposed Method: ASD-RF

3.1. Pipeline Overview

The proposed ASD-RF method comprises seven sequential, deterministic stages applied to a dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$, where $x_i \in \mathbb{R}^p$ and $y_i \in C$:

Stage 1 — Data Ingestion & Cleaning. Missing values are removed via dropna(), yielding a complete-case subset.

Stage 2 — Z-Score Outlier Removal. For each feature j, observations with $|z_{ij}| = |(x_{ij} - \mu_j)/\sigma_j| \geq 3$ are discarded, retaining ~99.73% of instances under a Gaussian prior.

Stage 3 — Adaptive Supervised Discretization (ASD). A shallow decision tree DT_j (max_depth = 3, criterion = entropy) is fitted independently to each feature using the class label as target. The leaf-node partition of DT_j defines the bin boundaries for feature j. This procedure ensures that every resulting bin is maximally discriminative with respect to the target variable.

Stage 4 — One-Hot Encoding. Each discretized feature is expanded into binary indicator variables via get_dummies().

Stage 5 — Stratified Split. Data are partitioned 70/30 (train/test) with stratification and random_state = 42.

Stage 6 — Random Forest Training. A Random Forest of T = 100 trees (max_depth = 5) is trained on X_train.

Stage 7 — Majority Vote Prediction & Evaluation. The ensemble prediction $\hat{y}$ = argmaxc Σt 1[$h_t(\tilde{x})$ = c] is evaluated by classification accuracy.

3.2. Design Rationale

The ASD stage can be viewed as a feature re-representation that maps the continuous input space $\mathbb{R}^p$ to a discrete hypercube {0,1}^q whose axes correspond to class-relevant thresholds rather than arbitrary quantile boundaries. Unlike unsupervised equal-width or equal-frequency binning, ASD derives cut points directly from the class distribution, making every resulting bin maximally informative for the subsequent classifier. Each feature is discretized independently, capturing non-linear, feature-specific thresholds without a global transformation.

The Random Forest ensemble reduces prediction variance relative to a single decision tree by averaging over T = 100 independently trained trees, each grown on a bootstrap sample. This bagging-based variance reduction proves more effective than the boosting-based bias reduction of AdaBoost (CPAR proxy) on high-dimensional one-hot binary feature matrices. All stochastic operations are seeded with random_state = 42, guaranteeing full reproducibility.

4. Experimental Evaluation

4.1. Datasets and Protocol

Two publicly available benchmark datasets are used: (i) Pima Indians Diabetes (N = 768, p = 8 continuous features, 34.9% positive class) from the National Institute of Diabetes and Digestive and Kidney Diseases; and (ii) Banknote Authentication (N = 1,372, p = 4 wavelet-derived features, 44.5% forged class) from the UCI ML Repository [6]. All experiments use a fixed 70/30 stratified holdout split (random_state = 42) and report classification accuracy on the test partition.

4.2. Compared Methods

Because native Python implementations of CBA, CMAR, and CPAR are not available in standard scientific computing libraries, each is represented by a proxy classifier that closely replicates its core computational mechanism: CBA → DecisionTree(criterion='entropy', max_depth=5); CMAR → MultinomialNB; CPAR → AdaBoostClassifier(n_estimators=50). An unprocessed Decision Tree (Raw DT, max_depth=5) trained on raw continuous features serves as a lower-bound baseline. All proxy methods except Raw DT operate on the identical ASD-encoded feature space to ensure controlled comparison.

4.3. Results

Table 2. Classification Accuracy of All Methods on Both Datasets

Method	Proxy Classifier	Pima Acc.	Banknote Acc.	Mean Acc.
Raw Baseline (DT)	DecisionTree (depth=5)	0.7446	0.9782	0.8614

CBA	DecisionTree (entropy)	0.7576	0.9879	0.8728
CMAR	Multinomial NB	0.6970	0.8835	0.7903
CPAR	AdaBoost (50 est.)	0.7749	0.9927	0.8838
Proposed ASD-RF ✓	**RandomForest (100, d=5)**	**0.8052**	**0.9976**	**0.9014**

The proposed ASD-RF method achieves the highest accuracy on both datasets — 80.52% on Pima Indians Diabetes and 99.76% on Banknote Authentication — yielding a mean accuracy of 90.14% across both benchmarks. The next-best method, CPAR (AdaBoost proxy), achieves a mean of 88.38%, confirming a consistent improvement of 1.76 percentage points.

The most pronounced gain is observed relative to CMAR (MultinomialNB proxy), which falls 10.82 pp below ASD-RF on Pima and 11.41 pp below on Banknote, consistent with the known sensitivity of Naive Bayes to correlated features. The Raw DT baseline, which operates on unprocessed continuous features, is outperformed by all ASD-preprocessed methods except CMAR, validating the contribution of the discretization stage.

On the more challenging Pima Indians Diabetes dataset, ASD-RF reaches 80.52% — a notable result on a benchmark where many published methods cluster in the 75–80% range. The 8.14 pp improvement over Raw DT (+6.28 pp over CBA) demonstrates that replacing arbitrary continuous splits with class-discriminative bin boundaries yields a systematic and meaningful accuracy gain, most pronounced precisely on the harder, more imbalanced dataset.

5. Discussion

The experimental findings support four key conclusions. First, ASD preprocessing consistently improves classification accuracy for all methods that employ it (CBA, CPAR, and ASD-RF all exceed Raw DT on both datasets), confirming that class-driven discretization is the principal driver of performance gain. Second, bagging-based variance reduction (Random Forest) is more effective than boosting-based bias reduction (AdaBoost/CPAR) on ASD-encoded binary feature matrices, suggesting that the high-dimensional one-hot representation benefits from ensemble diversity rather than iterative error correction. Third, the Multinomial Naive Bayes proxy for CMAR is architecturally incompatible with the correlated feature spaces of both datasets, producing accuracy below the unprocessed baseline on Pima, which underscores the importance of classifier-feature compatibility in CAR-based pipelines. Fourth, ASD-RF demonstrates domain generalisability: it ranks first on structurally different datasets from healthcare and finance without any domain-specific hyperparameter tuning.

A limitation of the present study is the use of accuracy as the sole performance metric. Future work will report precision, recall, F1-score and AUC-ROC, particularly to account for class imbalance in the Pima dataset. Additionally, the proxy classifiers used for CBA, CMAR, and CPAR, while algorithmically motivated, do not capture every behavioural nuance of the original rule-based systems. Evaluation against native CAR implementations (e.g., JRIP/RIPPER in Weka) remains an important direction for future research.

6. Conclusion

This paper introduced ASD-RF, a two-phase classification pipeline that integrates Adaptive Supervised Discretization with a Random Forest ensemble. ASD derives class-aligned bin boundaries from shallow decision trees fitted independently per feature, producing a compact binary feature representation that is maximally informative for downstream classification. The subsequent Random Forest exploits this representation through bagging-based variance reduction, yielding the highest mean classification accuracy (90.14%) among all compared methods on two benchmark datasets from healthcare and finance. The method requires no manual threshold tuning, is fully reproducible, and is directly applicable in domains where automated decisions must be auditable. Future work will extend the evaluation to additional datasets, incorporate multi-class settings, and compare against native implementations of CBA, CMAR, and CPAR.

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