Integrating Conflict Analysis and Rule-Based Systems for Dispersed Data Classification

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Abstract. The classification of dispersed data poses challenges due to inconsistencies and conflicts arising from independently collected sources. This study introduces a coalition-based classification framework that integrates conflict analysis and rule-based learning. The approach employs four decision rule induction methods – exhaustive search, genetic algorithms, covering algorithms, and LEM2 – combined with three decision-making strategies: first rule approach, all rules approach, and weighted rules approach. Experiments were conducted on datasets from the UCI Machine Learning Repository. The theoretical contribution of the paper is a novel classification structure for dispersed data, which utilizes conflict analysis to identify consistent sources and form coalitions. The practical contribution involves the development of an interpretable method that enables the generation of transparent rules and allows comparison of different approaches in the context of dispersed data. Results indicate that the covering algorithm with weighted rules approach achieves the highest classification performance across all metrics. The limitations of the study include the poor performance of the LEM2 method, which often fails to generate covering rules, leading to random classifications, as well as aspects of scalability that may need further attention for large datasets.

Keywords: Dispersed data classification · Decision rule induction · Conflict analysis · Coalition-based learning · Hierarchical classification · Interpretable machine learning · Rough set theory.

1 Introduction

The rapid expansion of data collection in various fields has led to an increasing occurrence of dispersed datasets, where data is stored across multiple independent sources. Handling such fragmented data poses significant challenges – not only in achieving high classification accuracy but also in ensuring interpretability and transparency in decision-making. Traditional aggregation methods often fail due to inconsistencies and conflicts arising from heterogeneous sources. Instead of simple data merging, a more structured approach is required to consolidate knowledge while preserving local data integrity.

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The aim of this study is to introduce a novel framework for classification based on dispersed decision tables. Our method focuses on identifying coalitions, i.e., groups of data sources exhibiting a sufficient level of consistency. By applying conflict analysis, we categorize data attributes and form coalitions that enable effective knowledge extraction while maintaining data integrity. Unlike centralized approaches, where all data is combined into a single model, our method operates in a hierarchical manner, ensuring that only compatible information is aggregated. The key advantage of this framework is its ability to generate interpretable decision rules, making it particularly suitable for applications where explainability is crucial.

Machine learning techniques can generally be classified into two categories: highly interpretable models, such as rule-based classifiers and decision trees [8], and black-box models, such as deep learning and neural networks, which offer high accuracy but lack explainability [10]. In many real-world applications, the ability to justify predictions is as important as achieving high classification performance. The problem of classification based on dispersed data has been explored in various domains, with different methodologies aimed at handling fragmented and independently collected datasets. Traditional approaches include ensemble learning [21], where multiple classifiers are trained separately and combined through voting or weighted averaging, as seen in bagging, boosting, and stacking techniques. However, these methods focus on improving accuracy rather than integrating knowledge from dispersed sources. Federated learning offers an alternative by allowing decentralized model training without direct data exchange, preserving privacy but limiting interpretability [13]. Some studies have proposed hierarchical classification frameworks, where local models are combined at different levels, yet they often lack explicit conflict resolution mechanisms. Pawlak's conflict analysis model [12] has been widely used for addressing inconsistencies in decision-making, particularly in rough set-based learning and three-way decision theory [23]. Prior research has also explored data fusion techniques, where statistical and mathematical measures are used to reconcile inconsistencies [22], but these approaches typically do not generate human-readable patterns such as decision rules. The proposed study builds on these foundations and bridges the gap by introducing a coalition-based method for dispersed data classification, integrating conflict analysis with rule-based learning to enhance interpretability while maintaining classification performance. Thus, the proposed method delivers an explicit mechanism for identifying consistent sources and generating transparent decision rules – an aspect that distinguishes it from existing classification approaches.

A core aspect of this study is the application of conflict analysis, originally introduced by Pawlak [12] and extended by other authors [6, 18], to dispersed datasets. By assigning categorical values -1, 0, 1 to attribute characteristics, we quantify differences across data sources and establish coalition. Unlike prior paper [14, 15] that applies conflict analysis in combination with decision trees, our approach directly incorporates it into the decision-rule generation process.

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The proposed methodology emphasizes rule-based knowledge extraction – a fundamental aspect of interpretable AI. Decision rules, structured as Horn clauses, are derived using four different rule-generation techniques: exhaustive search, genetic algorithms, covering algorithms, and the LEM2 algorithm. We introduce and compare three decision-making strategies for classification based on rule sets generated for coalitions: first rule approach, all rules approach and weighted rules approach.

Considering the objective of this study, the following key research questions are addressed:

– How can decision rules be integrated into a classification system based on dispersed data, combined with a hierarchical coalition framework using conflict analysis?
– Which decision-making strategies are most effective for rule-based classification within coalitions?
– How effective are different decision rule induction methods in generating transparent and meaningful classification rules?

By structuring the problem through conflict-aware coalitions and rule-based decision-making, this study provides an interpretable, dispersed classification framework that balances accuracy with explainability – addressing a critical need in modern machine learning applications.

The structure of this paper is organized as follows. Section 2 presents the proposed framework for dispersed data classification, including conflict analysis, coalition formation, and rule induction. Section 3 describes the dataset, experimental setup and the experimental results, analyzing the performance of different rule induction methods and decision-making approaches. Finally, Section 4 provides the conclusion and future work.

2 Methods and models – decision rules for dispersed data

In the study, we adopt a dispersed data approach to classification, emphasizing the interpretability of results and the transparency of decision-making within each local unit. To achieve this, we propose the use of decision rules. The model follows a hierarchical structure, using data similarity within local units to form consistent groups. Integrating coherent datasets allows the generation of reliable decision rules. Furthermore, this approach enables the creation of shared rules across multiple local units, improving overall interpretability. The model for combining local units into coalitions was first used in the papers [14, 15]. However, it has never been applied in conjunction with decision rules created using rough set theory. The formal definition of a framework for dispersed data is presented below.

We consider dispersed data in tabular form, so let us assume that a set of local decision tables with the same conditional attributes are given $D_i = (U_i, A, d), i \in \{1, \ldots, n\}$, where U_i is the universe, a set of objects; A is a set of conditional attributes; d is a decision attribute. Local decision tables managed by local units

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are collected independently and can be found in separate locations. Local tables can also be inconsistent. The proposed approach is dedicated to both qualitative, quantitative and mixed types of attributes stored in local tables. We recognize coalitions based on data stored in local tables, using statistical characteristics of attribute values in tables and Pawlak's conflict analysis model [12]. In Pawlak model an information system is defined $S = (LD, A)$, where LD is a set of local decision tables

$$LD = \{D_i : i \in \{1, \ldots, n\}\}$$

and A is a set of conditional attributes (qualitative and quantitative) occurring in local tables D_i. This information system contains the characteristics of a given attribute values' $a \in A$ in a given local table D_i stored in the form of trisection – only three values are used $\{-1, 0, 1\}$. For each attribute $a \in A$ a function $a : LD \to \{-1, 0, 1\}$ is defined. The interpretation of the values stored in the system S is as follows. If $a(D_i) = 0$ it means that the values stored in the local table D_i for attribute a are in the area of typical values of attribute a among all local tables LD. The value $a(D_i) = 1$ means that the values stored in the local table D_i for attribute a are above average/typical. Conversely, $a(D_i) = -1$ means that the values stored in the local table D_i for attribute a are below average/typical. To determine the value in the system S, we proceed differently for qualitative and quantitative attributes.

For each quantitative attribute $a_{quan} \in A$, we compute the average of its values within each local table D_i for $i \in \{1, \ldots, n\}$. Let this average be denoted as $\overline{Val}^i_{a_{quan}}$. Additionally, we calculate the global average and the global standard deviation across all local tables, denoted as $\overline{Val}_{a_{quan}}$ and $SD_{a_{quan}}$, respectively. Next, we define a function $a_{quan} : LD \to \{-1, 0, 1\}$ that categorizes each local table based on its average attribute value:

$$a_{quan}(D_i) = \begin{cases} 1 & \text{if} \quad \overline{Val}_{a_{quan}} + SD_{a_{quan}} < \overline{Val}^i_{a_{quan}} \\ 0 & \text{if} \quad \overline{Val}_{a_{quan}} - SD_{a_{quan}} \leq \overline{Val}^i_{a_{quan}} \leq \overline{Val}_{a_{quan}} + SD_{a_{quan}} \\ -1 & \text{if} \quad \overline{Val}^i_{a_{quan}} < \overline{Val}_{a_{quan}} - SD_{a_{quan}} \end{cases} \tag{1}$$

For each qualitative attribute $a_{qual} \in A$, we construct a frequency vector representing the distribution of its values. Suppose a_{qual} has c values denoted as $val_1, \ldots, val_c$. For each local table D_i, we define the vector $Val^i_{a_{qual}} = (n^i_1, \ldots, n^i_c)$, where n^i_j is the number of occurrences of val_j in D_i. To categorize local tables based on attribute distribution, we use the $3-$means clustering algorithm using Euclidean distance on the vectors $Val^i_{a_{qual}}$ for $i \in \{1, \ldots, n\}$. This clustering groups tables with similar distributions into three clusters. Each table is then assigned a category:

- $a_{qual}(D_i) = 1$ for tables D_i in the first cluster,
- $a_{qual}(D_i) = 0$ for those D_i in the second cluster,
- $a_{qual}(D_i) = -1$ for those D_i in the third cluster,

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Once the information system defining the conflict situation is established, we quantify the intensity of conflict between pairs of decision tables using the function $\rho : LD \times LD \to [0,1]$:

$$\rho(D_i, D_j) = \frac{card\{a \in A : a(D_i) \neq a(D_j)\}}{card\{A\}}.$$

This function measures the proportion of attributes in which two tables D_i and D_j differ. A higher value of $\rho(D_i, D_j)$ indicates greater disagreement between the tables. Next, coalitions are formed as groups of decision tables that exhibit a low level of conflict. Specifically, a coalition is defined as a set of tables in which every pair (D_i, D_j) satisfies $\rho(D_i, D_j) < 0.5$, meaning that at least half of their attributes share the same classification. This threshold ensures a sufficient level of similarity within each coalition while still allowing for some variation. For each coalition, an aggregated decision table is constructed, consolidating the information from its members. For the $j-$th coalition, the aggregated decision table is denoted as:

$$D_j^{aggr} = (U_j^{aggr}, A, d)$$

where: U_j^{aggr} represents the union of all objects from the local tables in the $j-$th coalition, A is the set of attributes, which remains the same as in the original local tables, d is the decision attribute, which also remains unchanged. The attribute values in the aggregated table are inherited directly from the corresponding local tables. Specifically, for each object $x \in U_i$, the value of attribute a in the aggregated table is the same as in the local table D_i from which x originates. This aggregation process effectively combines data from multiple local sources without explicitly recognizing whether there are overlapping objects between different local tables. This assumption is based on the lack of direct identifiers linking objects across tables (tables are independently stored), making it impossible to detect duplicates or shared instances.

Once the aggregated local decision tables are constructed, rule induction is performed separately for each table to derive a set of local decision rules. Conflict analysis assumes an important role in this process. It ensures that only tables with sufficient similarity are combined, allowing rule induction to be based on a uniform set of information. As a result, classification decisions are influenced not only by the rules themselves, but also by the quality of collaboration between sources established during coalition formation. In the literature, various methods for extracting decision rules have been proposed [5, 16]. Traditional brute-force approaches systematically explore all possible rule combinations but are computationally infeasible for datasets with a large number of attributes. To overcome this limitation, heuristic-based algorithms have been developed, using optimization techniques such as ant colony systems [9], approximation methods [11], and other innovative approaches [19, 20] to generate decision rules efficiently. In this study, we apply four rough set-based rule induction methods:

– Exhaustive search algorithm (Exh) [1]
– Genetic algorithm (Gen) [3]

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- Covering algorithm (Cov) [2]
- LEM2 algorithm (LEM2) [7]

These four methods were chosen due to their diverse mechanisms for rule generation and their sensitivity to different aspects of rough set-based classification. The exhaustive search algorithm systematically explores all possible object-oriented reducts (or local reducts) within the dataset. By performing a brute-force search, it guarantees the discovery of the optimal set of decision rules. However, this approach is computationally expensive and impractical for high-dimensional datasets due to its exponential complexity. Despite its limitations, exhaustive search serves as a benchmark for evaluating the performance of heuristic algorithms. The genetic algorithm is a metaheuristic optimization technique designed to efficiently explore large search spaces and uncover patterns in multi-dimensional data. Unlike exhaustive search, genetic algorithm does not guarantee an optimal solution but aims to find high-quality reducts within a feasible time. Each candidate solution (individual) represents a potential subset of attributes (reduct), and evolutionary operations such as mutation, crossover, and roulette wheel selection drive the search for an optimal rule set. The covering algorithm constructs decision rules incrementally by identifying minimal – or near minimal – rule sets that comprehensively cover all objects in the dataset. This method focuses on interpretability by generating concise rule sets with the most relevant conditions. The LEM2 algorithm effectively handles datasets containing inconsistencies or uncertainty by deriving rules that maximize class discernibility. The algorithm operates iteratively. It initializes an empty rule set and systematically generates new rules to cover instances within the dataset. For each attribute, it evaluates potential conditions that can best partition the data into meaningful subsets. The selected conditions aim to minimize impurity (entropy), ensuring that the resulting rules accurately separate different decision classes. Rules are further refined using support and confidence measures, and a pruning strategy is applied to enhance generalization. By addressing uncertainty and noise in data, LEM2 provides a robust mechanism for identifying reliable patterns even when the dataset is imprecise. The four selected methods represent a broad spectrum of strategies, from exhaustive search to heuristic optimization and rule refinement. In the context of dispersed data classification, employing such a diverse set of methods allows for evaluating their robustness to inconsistencies across sources and for flexibly adapting the rule generation process to the local characteristics of the data. The covering algorithm and the LEM2 algorithm, which operate more locally and tolerate uncertainty, may be particularly useful when analyzing tables with high variability. In contrast, the exhaustive search algorithm and the genetic algorithm enable exploration of a broader pattern space, which may increase the likelihood of identifying meaningful generalizations across sources.

In the proposed classification approach for dispersed data, for each coalition a separate set of local decision rules are generated, forming local models that collectively contribute to global decision. The final classification is determined through a majority voting mechanism. In cases where a tie occurs, the decision is drawn from the set of decision classes that received the highest number of

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votes from the local models. The study explores three different strategies for determining the classification outcome of local models for a given test object.

- First rule approach (FRA) – The classification is determined by the decision class of the first rule in the given rule set that covers the test object. If no rule covers the object, the decision class is randomly selected from the set of all possible classes. Consequently, the classification outcome of the local model is influenced by the order in which decision rules appear within the set.
- All rules approach (ARA) – The classification is determined by the decision class that receives the highest number of votes among the rules covering the test object. In the event of a tie, the decision class is randomly selected from the set of tied classes. If no rule covers the object, the decision class is chosen at random from all possible classes.
- Weighted rules approach (WRA) – Each rule covering a given object is assigned a weight, calculated as the ratio of the rule's match count to the total number of objects in the aggregated table associated with the coalition's rule set. The weights are then summed for each decision class, and the class with the highest total weight is selected as the final decision. In the event of a tie, the decision class is randomly chosen from those with the highest summed weight. If no rule covers the object, the decision class is randomly drawn from the set of all possible classes.

The selection of three decision-making strategies allows for examining how different aggregation mechanisms influence classification outcomes in the context of dispersed data. In such settings, where local models may vary in quality and completeness, the FRA strategy enables rapid decision-making, ARA aggregates knowledge from multiple rules, and WRA introduces a mechanism for weighting rules based on their representativeness. This combination makes it possible to assess which approach performs best in environments characterized by fragmented and inconsistent information.

Figure 1 illustrates the structure of the proposed hierarchical framework with conflict analysis and decision rules. As was described above, we start with local decision tables (D_i), which represent individual data sources with identical attributes. The conflict analysis step categorizes attributes into -1, 0, 1 and measures table differences. Next, coalition formation groups tables with low conflict, ensuring that coalitions are not necessarily disjoint. These coalitions are then merged into aggregated decision tables, consolidating information from each group. The decision rule induction phase applies four rule extraction methods to generate classification rules for each coalition. Finally, the classification process determines the outcome using three approaches: First Rule Approach, All Rules Approach, or Weighted Rules Approach. The framework emphasizes structured data integration, rule-based learning, and collective voting for improved classification based on dispersed datasets.

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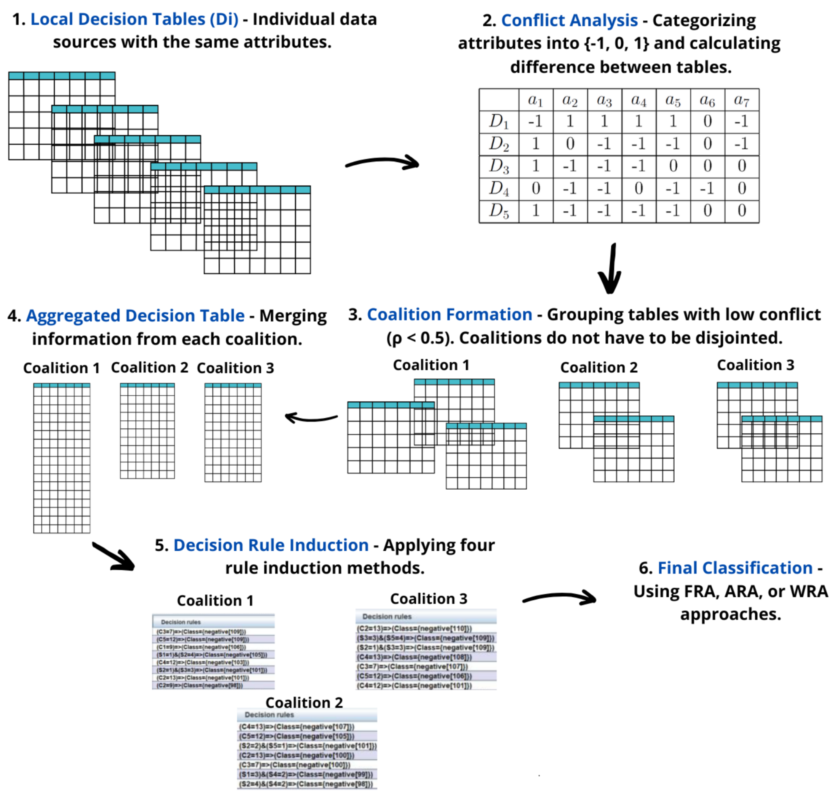

Fig. 1. Structure of the proposed framework with conflict analysis and decision rules for dispersed data classification

3 Dataset, Experimental Setup, and Evaluation Protocol

The proposed classification approach for dispersed data was tested on two datasets from the UC Irvine Machine Learning Repository [17, 4]. Vehicle Silhouettes dataset aims to classify vehicle into one of four categories based on features extracted from images taken from various angles. It includes eighteen quantitative conditional attributes and four decision classes, with a total of 846 objects. Car Evaluation dataset is designed for evaluating car acceptability based on six categorical attributes: buying price, maintenance cost, number of doors, passenger capacity, luggage boot size, and safety. The target variable represents the acceptability of the car, categorized into four decision classes: unacceptable, acceptable, good, and very good. The dataset consists of 1,728 instances. The datasets were randomly split into two disjoint subsets using stratified sampling: a training set containing 70% of the instances and a test set comprising the remaining 30%.

Each dataset was then transformed into multiple dispersed versions to simulate real-world scenarios where data is collected independently across different

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locations. Specifically, four dispersed versions were generated for each dataset, using 5, 7, 9, and 11 local tables. This process followed a stratified approach, ensuring that each local table retained the full set of attributes while containing only a subset of the original objects. Notably, since the data was dispersed in a manner that reflects independent collection, it was not possible to trace or match individual objects across different local tables. Consequently, a total of 8 dispersed datasets were created.

The classification quality was evaluated using the test set. To ensure a comprehensive comparison of results, multiple performance metrics were used: classification accuracy (*acc*); balanced accuracy (*bacc*); recall; precision (Prec.); F-measure (F-m.); geometric mean (G-mean). F-measure is a harmonic mean of Precision and Recall, assessing the classifier's ability to maintain a balance between both metrics. While G-mean evaluates the classifier's ability to maintain high recall across all classes, avoiding overfitting to the majority class while ensuring accurate classification of minority classes.

Since one of the key advantages of the proposed approach is its interpretability, Tables 1 and 2 present three decision rules with the highest number of matches, generated by each of the four algorithms, based on one of the aggregated tables for the Vehicle Silhouettes and Car Evaluation datasets (version with 5 local tables).

Table 1. Top-matching decision rules generated by each induction method for the Vehicle Silhouettes dataset (5 local tables).

Method	Rules	No. of matches
Exh	$(a_6 = 11) \wedge (a_9 = 20) \Rightarrow (\text{class} = \text{van})$	8
	$(a_1 = 86) \wedge (a_9 = 19) \Rightarrow (\text{class} = \text{bus})$	7
	$(a_9 = 19) \wedge (a_{18} = 182) \Rightarrow (\text{class} = \text{bus})$	7
Gen	$(a_6 = 11) \wedge (a_9 = 20) \Rightarrow (\text{class} = \text{van})$	8
	$(a_9 = 19) \wedge (a_{18} = 182) \Rightarrow (\text{class} = \text{bus})$	7
	$(a_1 = 86) \wedge (a_9 = 19) \Rightarrow (\text{class} = \text{bus})$	7
Cov	$(a_7 = 139) \Rightarrow (\text{class} = \text{van})$	5
	$(a_{11} = 229) \Rightarrow (\text{class} = \text{saab})$	4
	$(a_1 = 80) \Rightarrow (\text{class} = \text{opel})$	3
LEM2	$(a_9 = 20) \wedge (a_6 = 11) \Rightarrow (\text{class} = \text{van})$	8
	$(a_9 = 19) \wedge (a_6 = 9) \Rightarrow (\text{class} = \text{van})$	6
	$(a_9 = 19) \wedge (a_8 = 46) \wedge (a_{11} = 169) \Rightarrow (\text{class} = \text{bus})$	5

Table 2. Top-matching decision rules generated by each induction method for the Car Evaluation dataset (5 local tables).

Method	Rules	No. of matches
Exh	$(a_6 = 0) \Rightarrow (\text{class} = \text{unacc})$	160
	$(a_1 = 1) \wedge (a_2 = 0) \Rightarrow (\text{class} = \text{unacc})$	36
	$(a_3 = 2) \wedge (a_4 = 2) \wedge (a_5 = 0) \Rightarrow (\text{class} = \text{unacc})$	33
Gen	$(a_6 = 0) \Rightarrow (\text{class} = \text{unacc})$	160
	$(a_1 = 1) \wedge (a_2 = 0) \Rightarrow (\text{class} = \text{unacc})$	36
	$(a_3 = 2) \wedge (a_4 = 2) \wedge (a_5 = 0) \Rightarrow (\text{class} = \text{unacc})$	33
Cov	$(a_6 = 0) \Rightarrow (\text{class} = \text{unacc})$	160
LEM2	$(a_4 = 2) \wedge (a_3 = 3) \wedge (a_6 = 0) \Rightarrow (\text{class} = \text{unacc})$	63
	$(a_4 = 4) \wedge (a_6 = 0) \Rightarrow (\text{class} = \text{unacc})$	45
	$(a_4 = 4) \wedge (a_3 = 3) \wedge (a_6 = 0) \Rightarrow (\text{class} = \text{unacc})$	27

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As shown, all the presented rules contain between one and at most three conditions, which makes them particularly easy to interpret. The number of matches indicates how many training instances satisfy the given rule. This representation allows for direct tracing of the decision-making process and identification of the most influential attributes contributing to the classification.

The experiments were carried out according to the following scheme:

- Generate coalitions of local decision tables.
- Generate decision rules for aggregate coalitions' tables using one of four rough set-based rule induction methods: exhaustive search algorithm, genetic algorithm, covering algorithm, LEM2 algorithm.
- Classification of objects from the test set, based on decision rules using one of three different approaches: first rule approach, all rules approachweighted rules approach.

Tables 3 and 4 presents the measures' values for all dispersed datasets. The table uses the following designations for the tested approaches: exhaustive search algorithm (Exh), genetic algorithm (Gen), covering algorithm (Cov), LEM2 algorithm (LEM2) and first rule approach (FRA), all rules approach (ARA)weighted rules approach (WRA). During the experiments, different values of the parameter, number of reducts in the genetic algorithm, were tested: 10; 100; 1000. The tables below show the results obtained for a parameter equal to 100, since for a parameter equal to 10 the quality was much lower, while for a parameter equal to 1000 no more improvement was noticed. For Vehicle Silhouettes dataset, the best result is indicated in blue.

Based on the presented results, it can be concluded that the impact of different decision rule generation methods and voting approaches on classification quality varies across datasets. Not all datasets respond equally to these variations, indicating that the effectiveness of a particular method depends on the specific characteristics of the data. The Vehicle Silhouettes dataset showed a wider variation on efficiency measures across different methods. The Car Evaluation dataset exhibited more stable performance across most methods, except for LEM2-based approaches, which had significantly lower scores.

As can also be seen, the covering algorithm (Cov) with weighted rules approach (WRA) consistently outperforms other methods across all evaluation metrics. This suggests that the combination of covering-based rule generation and weighted voting is particularly effective in handling dispersed data classification, ensuring both strong predictive performance and robustness across different datasets. The exhaustive search (Exh) and genetic algorithm (Gen) methods also achieve competitive results, often ranking just below Cov_WRA. While these methods exhibit solid classification accuracy and recall, they tend to perform slightly worse in precision and balanced accuracy. This indicates that while they effectively capture patterns in the data, they may be more prone to misclassifications in certain classes, particularly in datasets with a more complex decision boundary.

On the other hand, the LEM2 algorithm proves to be unsuitable for these datasets, delivering extremely poor performance across all metrics. After a thor-

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Table 3. Results of classification accuracy (Acc), balanced accuracy (BAcc), precision (Prec.), Recall, F-measure (F-m.), geometric mean (G-mean) for the Vehicle Silhouettes dataset. LT means local table.

Data, no. of tables	Method	Acc	BAacc	Prec.	Recall	F-m.	G-mean
Vehicle, 5LT	Exh_FRA	0.480	0.480	0.486	0.480	0.478	0.631
	Exh_ARA	0.508	0.513	0.518	0.508	0.507	0.654
	Exh_WRA	0.516	0.519	0.523	0.516	0.511	0.659
	Gen_FRA	0.480	0.480	0.486	0.480	0.478	0.631
	Gen_ARA	0.512	0.516	0.521	0.512	0.510	0.657
	Gen_WRA	0.516	0.519	0.523	0.516	0.511	0.659
	Cov_FRA	0.504	0.503	0.513	0.504	0.503	0.650
	Cov_ARA	0.512	0.518	0.526	0.512	0.511	0.658
	Cov_WRA	**0.535**	**0.539**	**0.545**	**0.535**	**0.532**	**0.675**
	LEM2_FRA	0.264	0.250	0.070	0.264	0.110	0.441
	LEM2_ARA	0.264	0.250	0.070	0.264	0.110	0.441
	LEM2_WRA	0.264	0.250	0.070	0.264	0.110	0.441
Vehicle, 7LT	Exh_FRA	0.449	0.446	0.449	0.449	0.443	0.605
	Exh_ARA	0.508	0.505	0.511	0.508	0.505	0.652
	Exh_WRA	0.500	0.494	0.499	0.500	0.496	0.645
	Gen_FRA	0.449	0.446	0.447	0.449	0.443	0.605
	Gen_ARA	0.504	0.501	0.506	0.504	0.500	0.649
	Gen_WRA	0.500	0.494	0.499	0.500	0.495	0.645
	Cov_FRA	0.476	0.475	0.480	0.476	0.473	0.628
	Cov_ARA	**0.528**	**0.526**	**0.532**	**0.528**	**0.526**	**0.667**
	Cov_WRA	0.516	0.512	0.517	0.516	0.513	0.657
	LEM2_FRA	0.295	0.278	0.354	0.295	0.197	0.470
	LEM2_ARA	0.287	0.270	0.377	0.287	0.178	0.463
	LEM2_WRA	0.287	0.270	0.377	0.287	0.178	0.463
Vehicle, 9LT	**Exh_FRA**	**0.508**	**0.496**	**0.526**	**0.508**	**0.508**	**0.648**
	Exh_ARA	0.484	0.475	0.497	0.484	0.488	0.632
	Exh_WRA	0.496	0.485	0.505	0.496	0.497	0.640
	Gen_FRA	**0.508**	**0.496**	**0.526**	**0.508**	**0.508**	**0.648**
	Gen_ARA	0.484	0.475	0.497	0.484	0.488	0.632
	Gen_WRA	0.496	0.485	0.505	0.496	0.497	0.640
	Cov_FRA	0.504	0.492	0.517	0.504	0.505	0.646
	Cov_ARA	0.480	0.470	0.490	0.480	0.483	0.629
	Cov_WRA	0.492	0.479	0.499	0.492	0.493	0.637
	LEM2_FRA	0.256	0.243	0.069	0.256	0.109	0.433
	LEM2_ARA	0.256	0.243	0.069	0.256	0.109	0.433
	LEM2_WRA	0.256	0.243	0.069	0.256	0.109	0.433
Vehicle, 11LT	Exh_FRA	0.453	0.452	0.449	0.453	0.449	0.608
	Exh_ARA	0.469	0.467	0.468	0.469	0.467	0.620
	Exh_WRA	0.484	0.485	0.483	0.484	0.481	0.633
	Gen_FRA	0.445	0.445	0.442	0.445	0.441	0.602
	Gen_ARA	0.457	0.456	0.458	0.457	0.455	0.611
	Gen_WRA	0.472	0.474	0.472	0.472	0.469	0.624
	Cov_FRA	**0.539**	**0.535**	**0.540**	**0.539**	**0.530**	**0.676**
	Cov_ARA	0.504	0.503	0.501	0.504	0.500	0.648
	Cov_WRA	0.512	0.513	0.513	0.512	0.507	0.655
	LEM2_FRA	0.276	0.262	0.233	0.276	0.217	0.452
	LEM2_ARA	0.252	0.240	0.215	0.252	0.200	0.430
	LEM2_WRA	0.252	0.240	0.215	0.252	0.200	0.430

ough analysis of this issue, it was found that in many cases, the LEM2 algorithm failed to generate any rules covering certain objects from the test set. Since the proposed classification approaches rely on the presence of covering decision rules for object classification, the absence of such rules results in a random assignment of class labels for uncovered objects. Naturally, this significantly degrades classification quality, leading to poor performance across all evaluation metrics. This limitation suggests that LEM2 struggles to generalize effectively in the dispersed data setting, likely due to its sensitivity to inconsistencies and the way it formulates decision rules. In future work, the coverage requirements will be relaxed to allow classification based on partial rule coverage. Instead of requiring a rule to fully match an object, classification will be determined even if a rule partially covers the object. This adjustment aims to increase the number of classified instances, reducing the number of cases where no matching rule is found and minimizing the need for random assignment, ultimately improving classification quality.

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Table 4. Results of classification accuracy (Acc), balanced accuracy (BAcc), precision (Prec.), Recall, F-measure (F-m.), geometric mean (G-mean) for the Car Evaluation dataset. LT means local table.

Data, no. of tables	Method	Acc	BAacc	Prec.	Recall	F-m.	G-mean
	Exh_FRA	0.362	0.365	0.702	0.362	0.445	0.594
	Exh_ARA	0.362	0.365	0.702	0.362	0.445	0.594
	Exh_WRA	0.362	0.365	0.702	0.362	0.445	0.594
	Gen_FRA	0.362	0.365	0.702	0.362	0.445	0.594
	Gen_ARA	0.362	0.365	0.702	0.362	0.445	0.594
Car, 5LT	Gen_WRA	0.362	0.365	0.702	0.362	0.445	0.594
	Cov_FRA	0.362	0.365	0.702	0.362	0.445	0.594
	Cov_ARA	0.362	0.365	0.702	0.362	0.445	0.594
	Cov_WRA	0.362	0.365	0.702	0.362	0.445	0.594
	LEM2_FRA	0.040	0.250	0.002	0.040	0.003	0.197
	LEM2_ARA	0.040	0.250	0.002	0.040	0.003	0.197
	LEM2_WRA	0.040	0.250	0.002	0.040	0.003	0.197
	Exh_FRA	0.362	0.365	0.702	0.362	0.445	0.594
	Exh_ARA	0.362	0.365	0.702	0.362	0.445	0.594
	Exh_WRA	0.362	0.365	0.702	0.362	0.445	0.594
	Gen_FRA	0.362	0.365	0.702	0.362	0.445	0.594
	Gen_ARA	0.362	0.365	0.702	0.362	0.445	0.594
Car, 7LT	Gen_WRA	0.362	0.365	0.702	0.362	0.445	0.594
	Cov_FRA	0.362	0.365	0.702	0.362	0.445	0.594
	Cov_ARA	0.362	0.365	0.702	0.362	0.445	0.594
	Cov_WRA	0.362	0.365	0.702	0.362	0.445	0.594
	LEM2_FRA	0.040	0.250	0.002	0.040	0.003	0.197
	LEM2_ARA	0.040	0.250	0.002	0.040	0.003	0.197
	LEM2_WRA	0.040	0.250	0.002	0.040	0.003	0.197
	Exh_FRA	0.699	0.250	0.489	0.699	0.576	0.459
	Exh_ARA	0.699	0.250	0.489	0.699	0.576	0.459
	Exh_WRA	0.699	0.250	0.489	0.699	0.576	0.459
	Gen_FRA	0.699	0.250	0.489	0.699	0.576	0.459
	Gen_ARA	0.699	0.250	0.489	0.699	0.576	0.459
Car, 9LT	Gen_WRA	0.699	0.250	0.489	0.699	0.576	0.459
	Cov_FRA	0.699	0.250	0.489	0.699	0.576	0.459
	Cov_ARA	0.699	0.250	0.489	0.699	0.576	0.459
	Cov_WRA	0.699	0.250	0.489	0.699	0.576	0.459
	LEM2_FRA	0.699	0.250	0.489	0.699	0.576	0.459
	LEM2_ARA	0.699	0.250	0.489	0.699	0.576	0.459
	LEM2_WRA	0.699	0.250	0.489	0.699	0.576	0.459
	Exh_FRA	0.699	0.250	0.489	0.699	0.576	0.459
	Exh_ARA	0.699	0.250	0.489	0.699	0.576	0.459
	Exh_WRA	0.699	0.250	0.489	0.699	0.576	0.459
	Gen_FRA	0.699	0.250	0.489	0.699	0.576	0.459
	Gen_ARA	0.699	0.250	0.489	0.699	0.576	0.459
Car, 11LT	Gen_WRA	0.699	0.250	0.489	0.699	0.576	0.459
	Cov_FRA	0.699	0.250	0.489	0.699	0.576	0.459
	Cov_ARA	0.699	0.250	0.489	0.699	0.576	0.459
	Cov_WRA	0.699	0.250	0.489	0.699	0.576	0.459
	LEM2_FRA	0.699	0.250	0.489	0.699	0.576	0.459
	LEM2_ARA	0.699	0.250	0.489	0.699	0.576	0.459
	LEM2_WRA	0.699	0.250	0.489	0.699	0.576	0.459

To verify the significance of differences in the obtained results, statistical tests were conducted. The F-measure values were grouped based on the rule generation method and the final decision-making approach, forming twelve dependent groups, each containing eight observations. The Friedman test confirmed the presence of statistically significant differences in the F-measure results across the evaluated approaches, with $\chi^2(7, 11) = 47, 89, p = 0.000001$. Comparative box-whiskers charts for the results with three values of stop criterion were created (Fig. 2). Based on the charts, we can see that exhaustive search (Exh), genetic algorithm (Gen), and covering algorithm (Cov) exhibit similar and stable performance, with medians around 0.5. LEM2-based methods perform significantly worse, with medians below 0.3, indicating poor classification performance. Exh, Gen, and Cov methods show compact interquartile ranges, meaning they are consistent in performance with relatively few variations. LEM2-based methods exhibit the widest IQR and range, showing high variability in classification quality. Weighted rules approach (WRA) tends to produce slightly better results than first rule approach (FRA) and all rules approach (ARA) across Exh, Gen, and

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Cov. In conclusion, we can say that the WRA method generally provides the most consistent improvements in classification performance.

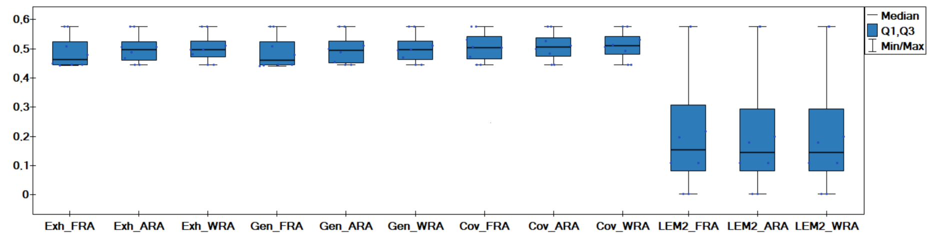

Fig. 2. Comparison of F-measure obtained for the proposed approaches.

4 Conclusions

This study introduced a coalition-based classification framework that integrates conflict analysis and rule-based learning to address the challenges of classifying dispersed data. By forming coalitions based on consistency across data sources and employing four rule induction methods – exhaustive search, genetic algorithms, covering algorithms, and LEM2 – alongside three decision-making strategies (FRA, ARA, WRA), the proposed approach effectively balances classification performance and interpretability.

Experimental results on the Vehicle Silhouettes and Car Evaluation datasets demonstrated that the covering algorithm with weighted rules approach consistently outperformed other methods, achieving the highest accuracy, balanced accuracy, precision, recall, F-measure, and G-mean. In contrast, the LEM2 algorithm performed poorly, often failing to classify objects due to missing covering rules. Statistical validation using the Friedman test confirmed significant differences between methods, reinforcing the importance of selecting appropriate rule induction and decision-making approaches for dispersed data classification.

The proposed framework has potential applications in fields such as medicine, where it can support the integration of diagnostic results collected from various healthcare facilities; finance, where it can assist in analyzing client data originating from distributed branches; and expert systems within decentralized organizations, where interpretability and decision transparency are of key importance. The coalition-based structure enables the preservation of local data context, which increases trust in classification outcomes.

A limitation of the study lies in the sensitivity of the LEM2 algorithm to the absence of rules covering the majority of test objects, which leads to random classifications and reduced result quality. Furthermore, scaling the approach to datasets with a very large number of sources or features may introduce computational challenges and reduce the effectiveness of coalition formation.

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Future research will focus on relaxing rule coverage constraints to reduce misclassification rates and further improve classification robustness in highly fragmented datasets. Additionally, extending this approach to more diverse datasets and real-world applications will provide further validation of its effectiveness.

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