

Article

Noise Resilience on Supervised Classification of Shortest-Length and Coarsest-Granularity Reducts and Constructs [†]

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Abstract

This study evaluates noise resilience in supervised classification using shortest-length and coarsest-granularity reducts and constructs under a common evaluation framework. We analyze original datasets and training sets distorted by random attribute-value noise across 20 real-world datasets and four supervised classifiers. Experimental results, validated with the Wilcoxon signed-rank test, indicate no statistically significant difference in classification accuracy between reducts and constructs across the evaluated noise levels. These findings suggest that, for the considered random-noise model, the choice between shortest-length and coarsest-granularity subsets has limited impact on supervised classification accuracy.

Keywords: rough sets; shortest reducts; shortest constructs; supervised classification; random noise

MSC: 68Q32; 15A21; 03E05

1. Introduction

Rough set theory has become a well-established framework for data preprocessing and feature selection, particularly because it allows the identification of attribute subsets that preserve relevant classification information without requiring additional assumptions about the data distribution. Recent advancements in rough-set-based feature selection have witnessed significant diversification across multiple theoretical frameworks to address complex data challenges. Specifically, researchers have heavily leveraged discernibility and consistency matrices to construct elegant algebraic structures for tracking feature relevance and scaling down large datasets [1,2]. To handle continuous and real-valued attributes effectively without prior discretization, neighborhood rough sets have been extensively explored, introducing adaptive thresholds, margin optimizations, and neighborhood-aware models [1,3–6]. Concurrently, fuzzy rough sets have been widely adopted to handle vagueness and uncertainty, particularly by integrating hybrid neural networks, label-modification learning, and robust weighting mechanisms in noisy environments [1,7–9]. Furthermore, to capture hierarchical data structures at varying levels of abstraction, multi-granularity criteria, rough subspace ensembles, and granular-ball computing models have been successfully deployed [4,10–13]. Beyond these foundational paradigms, tailored attribute



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reduction techniques have emerged to address specialized domains, including incomplete decision systems, ordered data relations, formal concept analysis, and supervised text classification [14–17]. These works provide the methodological background for using rough-set-based attribute subsets in supervised classification tasks.

Within this context, reducts and constructs represent two related but distinct strategies for selecting informative attributes. According to rough set theory [18], constructs [19] are irreducible subsets of attributes that capture the essential information necessary for distinguishing objects from different classes while preserving the similarity of objects within the same class. Meanwhile, reducts [20] are defined as irreducible subsets of attributes that retain the same level of discriminatory power between classes as the whole set of attributes. Both constructs and reducts play a crucial role in supervised classification by enabling a streamlined selection of relevant attributes. However, they serve slightly different purposes: reducts focus on achieving class differentiation with minimal attribute redundancy, whereas constructs emphasize the retention of intra-class coherence.

Recent studies on shortest-length and coarsest-granularity criteria have shown that different representative subsets can be selected from the potentially large family of admissible reducts or constructs. However, less attention has been given to whether these selection criteria lead to different classification behavior when the training data are affected by random attribute-value noise. This gap motivates the present empirical comparison.

Although constructs may theoretically preserve class structure better, Susmaga [19] reported that using all constructs can outperform using all reducts in noisy environments. However, that comparison did not isolate selection criteria such as shortest-length and coarsest-granularity. In practice, the large number of possible reducts and constructs in real datasets makes using all of them computationally impractical, so practical selection criteria are needed.

This paper evaluates the noise resilience of shortest-length and coarsest-granularity reducts and constructs under controlled random attribute-value noise. We examine 1%, 2%, and 3% noise levels across 20 real-world datasets and validate the results with four supervised classifiers. While [21] analyzes shortest-length and coarsest-granularity reducts and constructs as attribute-subset selection criteria, the present work focuses on their behavior in supervised classification under controlled random attribute-value noise. Therefore, the current contribution is complementary to [21], with emphasis on noise resilience and statistical comparison of classification accuracy rather than primarily on subset generation or computational efficiency.

The structure of the article is as follows: Section 2 introduces the fundamental concepts pertinent to this study. Section 3 provides a comprehensive account of the experimental evaluation, including discretization, noise generation, voting-based classification, and statistical testing. Finally, Section 4 summarizes our study's key findings, conclusions and future work.

2. Basic Definitions

In this work, we will consider the data represented through the so-called decision table (DT), which is a common way to represent data in rough set theory (RST) [18]. It is a matrix representation where the rows correspond to the objects and the columns to the attributes that describe them. Each cell contains the value that the attribute corresponding to that column takes in the object corresponding to the row. We will denote by $\mathcal{O}$ the set of all objects and by $\mathcal{A}^*$ the set of all attributes. Among the attributes, we will highlight the so-called decision attribute or class attribute, denoted by d . Thus, $\mathcal{A}^* = \mathcal{A} \cup \{d\}$, with $\mathcal{A}$ being the set of descriptive or condition attributes. The set of possible values for

the attribute $a \in \mathcal{A}$ will be denoted by V_a . Thus, $a(o)$ means the value corresponding to object o for the attribute a , and $d(o)$ is the class to which o belongs.

A decision table is said to be consistent if every combination of values from the set of condition attributes uniquely determines the value of the decision attribute; otherwise, it is considered inconsistent.

To express the fact that a set of attributes cannot discern objects in a DS , the *indiscernibility relation* [18] is defined for a non-empty set of attributes $\mathcal{A} \subseteq \mathcal{A}^*$ as follows:

$$IND(\mathcal{A}) = \{(x, y) \in \mathcal{O} \times \mathcal{O} : \forall_{a \in \mathcal{A}} I_a(x) = I_a(y)\}$$

If a pair of objects belongs to $IND(\mathcal{A})$, the objects cannot be differentiated from each other given the attributes of the subset $\mathcal{A}$.

Before defining the notions of reducts and constructs, it is essential to introduce two key relations: the *discernibility relation* and the *similarity relation*, as described by Susmaga [19].

The *discernibility relation*, denoted as $DIS(\mathcal{A}) \subseteq \mathcal{O} \times \mathcal{O}$, is defined as follows:

$$DIS(\mathcal{A}) = \{(x, y) \in \mathcal{O} \times \mathcal{O} : (x, y) \notin IND(\mathcal{A})\}$$

This means that if a pair of objects (x, y) belongs to $DIS(\mathcal{A})$, then x and y differ from each other by at least one attribute from the set $\mathcal{A}$.

On the other hand, the *similarity relation*, denoted as $SIM(\mathcal{A}) \subseteq \mathcal{O} \times \mathcal{O}$, is defined for a set of attributes $\mathcal{A} \subseteq \mathcal{A}^*$ as follows:

$$SIM(\mathcal{A}) = \{(x, y) \in \mathcal{O} \times \mathcal{O} : \exists_{a \in \mathcal{A}} I_a(x) = I_a(y)\}$$

If a pair of objects (x, y) belongs to $SIM(\mathcal{A})$, then these two objects are similar in at least one attribute from the set $\mathcal{A}$.

We focus on two types of subsets of attributes, distinguished by the similarity and discernibility they induce in a decision table. Both reducts and constructs are irreducible subsets of attributes, meaning that no proper subset preserves the required property. Pawlak [18] introduced reducts, and Susmaga later introduced constructs [19]. The properties that define them are formally stated below.

Definition 1. Given a decision table, let $\mathcal{C} \subseteq \mathcal{A}$ be a subset of attributes, and let the following conditions be as follows:

$$\forall_{p \in \mathcal{O} \times \mathcal{O}} \{[p \in DIS(\{d\}) \wedge p \in DIS(\mathcal{A})] \rightarrow p \in DIS(\mathcal{C})\} \quad (1)$$

$$\forall_{p \in \mathcal{O} \times \mathcal{O}} \{[p \in SIM(\{d\}) \wedge p \in SIM(\mathcal{A})] \rightarrow p \in SIM(\mathcal{C})\} \quad (2)$$

Then,

- $\mathcal{C}$ is a *reduct* if it satisfies condition (1) and no proper subset of $\mathcal{C}$ also satisfies it.
- $\mathcal{C}$ is a *construct* if it satisfies conditions (1) and (2) and no proper subset of $\mathcal{C}$ satisfies them simultaneously.

Thus, according to condition (1), a reduct preserves the discernibility of any pair of objects belonging to different classes whenever that pair is discernible using the complete set of condition attributes. A construct, additionally, according to condition (2), preserves intra-class similarity by ensuring that any two objects in the same class that share at least one value in the complete condition-attribute set also share at least one value in the selected subset. This preservation of intra-class similarity is the defining characteristic of constructs.

In both cases, irreducibility means that all attributes in the subset are indispensable. This inclusion-based minimality should not be confused with having the smallest number of attributes, which corresponds to the shortest-length criterion discussed below.

Real-world decision tables often contain a considerable number of reducts and/or constructs, so various criteria have been defined to select a practical subset of them. One of the most widely used is to consider those reducts/constructs with the fewest number of attributes, i.e., the shortest ones [22–24]. This criterion is useful because it may reduce model complexity, improve interpretability, and simplify subsequent classification tasks.

Another selection criterion considers those reducts/constructs that induce a partition in the decision table with the coarsest granularity [21,25,26]. Each reduct/construct induces a partition on the decision table which, because of condition (1) in Definition 1, is always a refinement of the partition determined by the class attribute. The elements of that partition are known as granules. A partition is coarser to the extent that its granules more closely resemble the classes determined by d , which is why reducts/constructs of the coarsest granularity have received attention recently.

3. Experimental Evaluation

The objective of this paper is to evaluate noise resilience on supervised classification of shortest-length and coarsest-granularity reducts and constructs under the same evaluation framework.

Given the similarity between the concepts of constructs and reducts, algorithms designed for computing irreducible subsets from binary matrices can be used to obtain either type. The search procedure is the same; the critical difference lies in how the input binary matrix is constructed [27]. For reducts, the matrix encodes the constraints associated with preserving discernibility between objects from different decision classes. For constructs, the matrix additionally encodes the constraints associated with preserving intra-class similarity. Therefore, the algorithm may compute reducts or constructs depending on the binary matrix provided as input. There are several algorithms that can be used for this purpose. However, the objective of this study is not to guide the selection of an algorithm for computing reducts or constructs, but to assess which concept is better to select features for supervised classification under noise conditions. Therefore, any algorithm could be used. In our study, we employed the algorithm described in [28], following the methodology outlined in [27]. This approach was used to compute both constructs and reducts, each from its corresponding binary matrix.

As in previous works, the experimental analysis was conducted using real-world datasets sourced from two well-known repositories: the UCI Machine Learning Repository [29] and the OpenML Repository [30]. These datasets have been widely employed in various research studies and experiments, including those focused on the calculation of reducts and constructs.

For our study, only discrete condition attributes allow the calculation of the shortest and coarsest-granularity reducts/constructs. Consequently, the continuous attributes in the datasets required discretization. To solve this, we utilized the discretization technique implemented in Weka [31], which was applied with the following setup:

- `weka.filters.unsupervised.attribute.Discretize -B 10 -M -1.0 -R first-last -precision 6.`

The discretizer was fitted using only the training split, and the learned bin boundaries were then applied to the corresponding test split to avoid information leakage.

The datasets and their characteristics are presented in Table 1. The datasets are listed alphabetically based on the “Name” column. The number of condition attributes (attributes excluding the decision attribute) is shown in the “#Cond. Attr.” column. The “#Objects” column contains the number of instances, while the number of classes (distinct values of

the decision attribute) is listed in the “#Classes” column. The source from which each dataset was extracted is provided in the final column.

Table 1. Characteristics of the datasets used in the experiments.

No.	Dataset	#Cond. Attr.	#Objects	#Classes	Source
1	Anneal	38	898	5	OpenML [30]
2	Chess-Kr-vs-kp	36	3196	2	OpenML [30]
3	Credit-g	20	1000	2	OpenML [30]
4	Cylinder-Bands	39	540	2	OpenML [30]
5	Eucalyptus	19	736	5	OpenML [30]
6	Flags	29	194	2	UCI [29]
7	German-credit	20	1000	2	UCI [29]
8	Hypothyroid	27	3772	4	UCI [29]
9	Ilpd	10	583	2	UCI [29]
10	Led24	10	3200	2	UCI [29]
11	Loan	24	614	10	OpenML [30]
12	Lymphography	18	148	4	UCI [29]
13	Mushroom	21	8124	2	UCI [29]
14	Primary-tumor	17	339	22	UCI [29]
R15	RShuttle	R9	R58000	R7	UCI [29]
16	Soybean	35	683	19	UCI [29]
17	Thyroid	21	3772	3	UCI [29]
18	Titanic	12	1309	2	OpenML [30]
19	Vote	16	435	2	OpenML [30]
20	Zoo	16	101	7	UCI [29]

An overview of the experimental workflow is presented in Figure 1. Each dataset was randomly split into training and testing sets, with 90% of the data used for training and 10% reserved for testing. Using a fixed split between training and testing with controlled random seeding ensures that all reductions and constructs being compared are evaluated under the same reproducible partition for each dataset. Modified versions of the training sets were created to assess the impact of noise by introducing different levels of controlled random attribute-value noise. For each noise level $N \in \{1\%, 2\%, 3\%\}$, $N\%$ of the training cells were selected uniformly at random and resampled from the corresponding attribute domain; therefore, in some cases, the sampled value could coincide with the original one. Here, the domain of an attribute refers to the set of valid values observed or defined for that attribute in the processed decision table. For nominal attributes, this domain corresponds to the observed categories; for previously discretized continuous attributes, it corresponds to the discrete values or bins obtained after discretization.

Using three increasing noise levels allows us to examine whether the observed behavior of the evaluated subsets remains stable as the intensity of random attribute-value perturbation increases. For instance, for the dataset “Anneal-train”, modified versions such as “Anneal-train-0.01”, “Anneal-train-0.02”, and “Anneal-train-0.03” were generated, corresponding to 1%, 2%, and 3% of random attribute-value noise, respectively. This procedure produces controlled, independent corruption and limits the conclusions of this paper to the random-noise model.

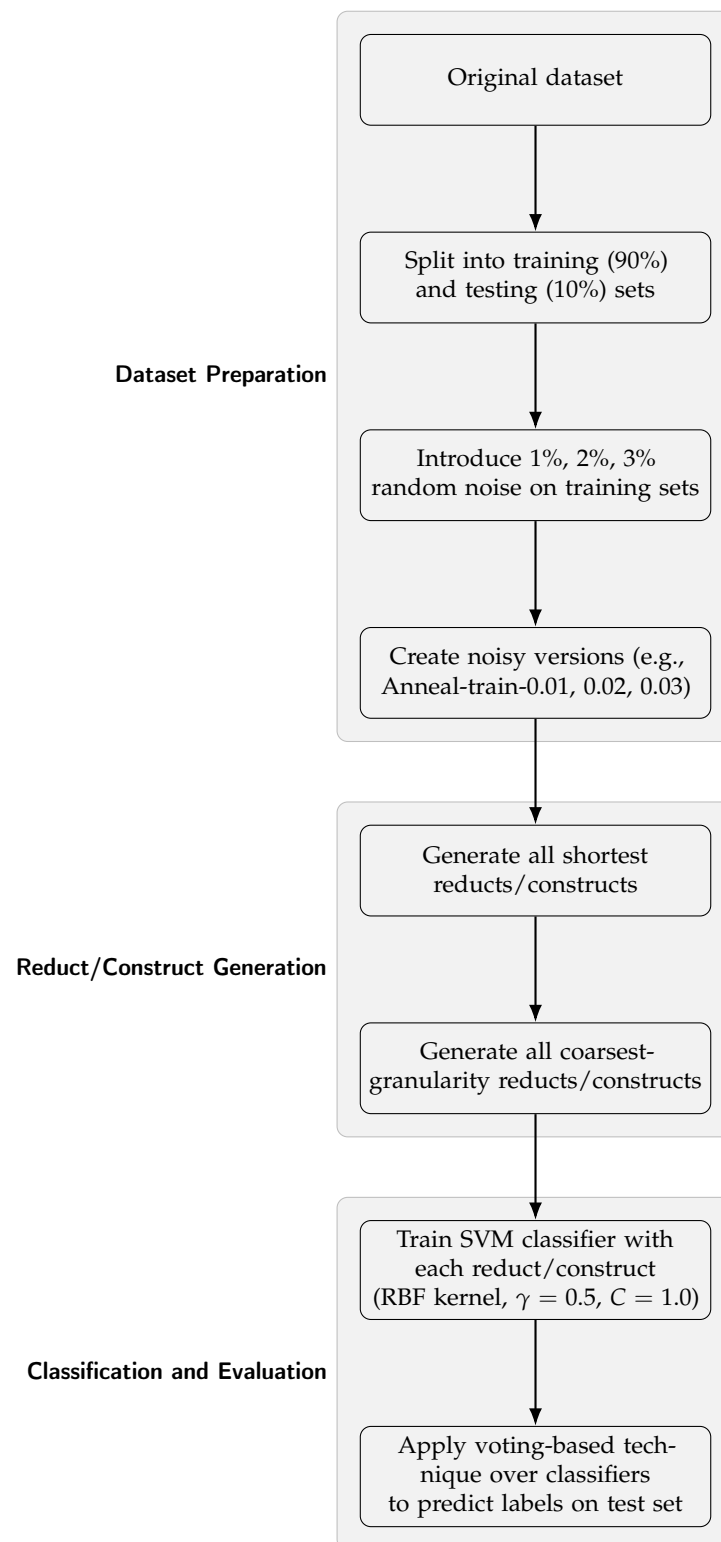


Figure 1. Experimental workflow involving noise addition, attribute reduction, and classification using largest number of votes.

For each training set, all shortest reducts/constructs and coarsest-granularity reducts/constructs were computed. The shortest reducts/constructs were computed using the algorithm proposed in [32], employing the methodology outlined in [27] to compute all possible reducts/constructs and subsequently select the shortest ones. Similarly, the coarsest-granularity reducts/constructs were obtained by first generating all reducts/constructs and then applying the principle described in [21] to determine the coarsest-granularity

solutions. Each shortest and coarsest-granularity reduct/construct was then individually applied to select the attributes considered for training and testing the classifier.

A Support Vector Machine (SVM) was employed for the experiments, configured with the same settings as in [33]: kernel = rbf, gamma = 0.5, and C = 1.0. Since several shortest-length or coarsest-granularity reducts/constructs may be obtained for a given dataset, classification is not based on a single attribute subset. Instead, an individual classifier was trained using each selected subset of attributes. For each test object, each classifier trained on a selected reduct or construct produces one predicted class label. The final prediction is assigned to the class receiving the largest number of votes among these classifiers.

Three additional classifiers (Decision Tree, Hist Gradient Boosting, and Random Forest) were also used as complementary models to examine whether the behavior observed with SVM remained consistent across different learning paradigms. These classifiers represent diverse machine learning paradigms and are well-suited for handling datasets with varying characteristics, such as non-linear relationships, feature interactions, and different dimensionalities. Although the accuracy results for these classifiers are included in the corresponding tables, the statistical results presented in the main text focus on the SVM Classifier to keep the discussion concise. The complete results and statistical tests for all classifiers are available at <https://github.com/ygdiaz1202/ReductsVsConstructs.git> (accessed on 10 July 2026).

Although the use of a single 90/10 train-test split may increase variability, particularly for small datasets, the split was fixed using `random_state=45` to ensure reproducibility. This means that all compared reducts and constructs were evaluated under the same data partition for each dataset. The paired Wilcoxon signed-rank test was then applied across the 20 datasets under this fixed experimental protocol. Therefore, the statistical results should be interpreted as evidence obtained under a reproducible fixed-split design, rather than as a repeated-resampling estimate of performance variability within each dataset. Repeated random splits, stratified cross-validation, and confidence intervals are left as future work, especially for small datasets such as Zoo, Lymphography, and Flags.

3.1. Experiments with Data Sets Without Noise

The initial experiments were conducted on datasets without added noise to determine whether significant differences exist between using shortest-length and coarsest-granularity constructs or reducts in supervised classification tasks. Table 2a–d presents the classification accuracy obtained using the shortest and coarsest-granularity reducts and constructs with the SVM, Decision Tree, Hist Gradient Boosting, and Random Forest Classifiers.

Table 2a–d indicates no significant difference in classification accuracy between the shortest and coarsest-granularity reducts/constructs. This observation is supported by the Wilcoxon test, with *p*-values for the SVM Classifier presented in Table 6a. With *p*-values greater than the conventional significance level of 0.05, we fail to reject the null hypothesis, indicating no statistically significant difference in accuracy between using shortest or coarsest-granularity reducts/constructs for attribute selection.

In conclusion, despite minor differences, neither the shortest nor coarsest-granularity reducts/constructs demonstrate a notable advantage over the other. These baseline results indicate that, in clean data, neither criterion provides an inherent advantage. Consequently, any later difference under noise would need to arise from the noise model itself rather than from the baseline selection criterion.

Table 2. (a) Accuracy of the SVM Classifier without including noise in the datasets. (b) Accuracy of the Decision Tree Classifier without including noise in the datasets. (c) Accuracy of the Hist Gradient Boosting Classifier without including noise in the datasets. (d) Accuracy of the Random Forest Classifier without including noise in the datasets.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
(a)					
1	Anneal	0.96	0.96	1.00	1.00
2	Chess-Kr-vs-kp	0.99	0.99	0.99	0.99
3	Credit-g	0.72	0.72	0.65	0.73
4	Cylinder-Bands	0.65	0.65	0.78	0.78
5	Eucalyptus	0.54	0.41	0.61	0.41
6	Flags	0.65	0.55	0.80	0.80
7	German-credit	0.67	0.67	0.70	0.67
8	Hypothyroid	0.94	0.94	0.97	0.97
9	Ilpd	0.69	0.69	0.73	0.69
10	Led24	0.74	0.74	0.73	0.73
11	Loan	0.61	0.61	0.65	0.61
12	Lymphography	0.53	0.47	0.60	0.67
13	Mushroom	0.97	0.97	0.99	0.99
14	Primary-tumor	0.50	0.50	0.50	0.50
15	Shuttle	0.94	0.94	0.94	0.94
16	Soybean	0.67	0.67	0.80	0.80
17	Thyroid	0.96	0.96	0.96	0.96
18	Titanic	0.86	0.78	0.86	0.82
19	Vote	0.98	0.98	0.98	0.98
20	Zoo	1.00	1.00	1.00	1.00
(b)					
1	Anneal	1.00	1.00	1.00	1.00
2	Chess-Kr-vs-kp	0.98	0.98	0.99	0.99
3	Credit-g	0.58	0.67	0.62	0.66
4	Cylinder-Bands	0.69	0.70	0.59	0.59
5	Eucalyptus	0.51	0.58	0.59	0.61
6	Flags	0.60	0.60	0.70	0.70
7	German-credit	0.66	0.71	0.69	0.61
8	Hypothyroid	0.96	0.96	0.96	0.96
9	Ilpd	0.61	0.63	0.69	0.64
10	Led24	0.65	0.66	0.58	0.60
11	Loan	0.50	0.76	0.58	0.74
12	Lymphography	0.67	0.67	0.60	0.60
13	Mushroom	0.99	0.99	0.99	0.99
14	Primary-tumor	0.32	0.32	0.32	0.32
15	Shuttle	0.94	0.94	0.94	0.94
16	Soybean	0.88	0.88	0.83	0.83
17	Thyroid	0.93	0.93	0.94	0.93
18	Titanic	0.96	0.94	0.96	0.95
19	Vote	0.95	0.93	0.95	0.91
20	Zoo	1.00	1.00	1.00	1.00

Table 2. Cont.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
(c)					
1	Anneal	0.98	0.98	1.00	1.00
2	Chess-Kr-vs-kp	0.98	0.98	0.98	0.98
3	Credit-g	0.70	0.75	0.69	0.75
4	Cylinder-Bands	0.76	0.76	0.70	0.70
5	Eucalyptus	0.51	0.70	0.61	0.70
6	Flags	0.60	0.70	0.75	0.75
7	German-credit	0.66	0.73	0.73	0.72
8	Hypothyroid	0.97	0.97	0.96	0.96
9	Ilpd	0.64	0.63	0.63	0.63
10	Led24	0.73	0.73	0.72	0.72
11	Loan	0.55	0.77	0.74	0.77
12	Lymphography	0.60	0.53	0.67	0.67
13	Mushroom	1.00	0.99	1.00	1.00
14	Primary-tumor	0.38	0.38	0.38	0.38
15	Shuttle	0.94	0.94	0.93	0.94
16	Soybean	0.83	0.83	0.86	0.86
17	Thyroid	0.95	0.95	0.95	0.95
18	Titanic	0.95	0.93	0.95	0.93
19	Vote	0.93	0.95	0.93	0.95
20	Zoo	1.00	0.91	0.91	0.91
(d)					
1	Anneal	0.98	1.00	1.00	1.00
2	Chess-Kr-vs-kp	0.97	0.97	0.98	0.98
3	Credit-g	0.63	0.76	0.68	0.80
4	Cylinder-Bands	0.72	0.76	0.72	0.70
5	Eucalyptus	0.57	0.65	0.61	0.64
6	Flags	0.60	0.70	0.60	0.60
7	German-credit	0.69	0.76	0.71	0.72
8	Hypothyroid	0.97	0.97	0.97	0.97
9	Ilpd	0.66	0.58	0.69	0.61
10	Led24	0.75	0.75	0.73	0.74
11	Loan	0.58	0.77	0.69	0.76
12	Lymphography	0.67	0.60	0.67	0.67
13	Mushroom	0.99	0.99	0.99	1.00
14	Primary-tumor	0.44	0.41	0.41	0.41
15	Shuttle	0.94	0.94	0.94	0.94
16	Soybean	0.84	0.84	0.87	0.87
17	Thyroid	0.95	0.95	0.95	0.95
18	Titanic	0.96	0.95	0.97	0.95
19	Vote	0.98	0.98	0.98	0.98
20	Zoo	1.00	1.00	1.00	1.00

3.2. Experiments with Noise-Distorted Data Sets

The second set of experiments assesses whether certain feature subsets derived from the shortest-length reducts/constructs or the coarsest-granularity reducts/constructs are less noise-sensitive when used in supervised classification tasks.

The results of these experiments, which report the classifier's accuracy using the shortest and coarsest-granularity reducts and constructs, are presented in Table 3a–d for 1% noise, Table 4a–d for 2% noise, and Table 5a–d for 3% noise.

Table 3. (a) Accuracy of the SVM Classifier after adding 1% noise. (b) Accuracy of the Decision Tree Classifier after adding 1% noise. (c) Accuracy of the Hist Gradient Boosting Classifier after adding 1% noise. (d) Accuracy of the Random Forest Classifier after adding 1% noise.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
(a)					
1	Anneal-0.01	0.76	0.72	0.81	0.81
2	Chess-Kr-vs-kp-0.01	0.96	0.96	0.96	0.96
3	Credit-g-0.01	0.72	0.72	0.69	0.72
4	Cylinder-Bands-0.01	0.61	0.61	0.76	0.76
5	Eucalyptus-0.01	0.46	0.34	0.47	0.34
6	Flags-0.01	0.80	0.80	0.75	0.60
7	German-credit-0.01	0.67	0.67	0.66	0.67
8	Hypothyroid-0.01	0.94	0.94	0.94	0.94
9	Ilpd-0.01	0.69	0.69	0.69	0.69
10	Led24-0.01	0.43	0.63	0.51	0.51
11	Loan-0.01	0.61	0.63	0.63	0.63
12	Lymphography-0.01	0.60	0.60	0.53	0.67
13	Mushroom-0.01	0.93	0.93	0.93	0.93
14	Primary-tumor-0.01	0.50	0.50	0.50	0.50
15	Shuttle-0.01	0.94	0.94	0.94	0.94
16	Soybean-0.01	0.65	0.61	0.71	0.71
17	Thyroid-0.01	0.96	0.96	0.96	0.96
18	Titanic-0.01	0.68	0.66	0.72	0.66
19	Vote-0.01	0.93	0.93	0.93	0.93
20	Zoo-0.01	1.00	1.00	1.00	1.00
(b)					
1	Anneal-0.01	0.90	0.84	0.84	0.84
2	Chess-Kr-vs-kp-0.01	0.88	0.89	0.88	0.89
3	Credit-g-0.01	0.55	0.56	0.65	0.58
4	Cylinder-Bands-0.01	0.69	0.70	0.78	0.81
5	Eucalyptus-0.01	0.49	0.53	0.57	0.53
6	Flags-0.01	0.55	0.80	0.55	0.60
7	German-credit-0.01	0.57	0.59	0.58	0.62
8	Hypothyroid-0.01	0.88	0.89	0.88	0.88
9	Ilpd-0.01	0.66	0.63	0.63	0.59
10	Led24-0.01	0.28	0.57	0.38	0.38
11	Loan-0.01	0.48	0.66	0.71	0.68
12	Lymphography-0.01	0.40	0.60	0.53	0.67
13	Mushroom-0.01	0.94	0.94	0.94	0.95
14	Primary-tumor-0.01	0.38	0.35	0.38	0.38
15	Shuttle-0.01	0.94	0.94	0.94	0.94
16	Soybean-0.01	0.74	0.78	0.80	0.83
17	Thyroid-0.01	0.89	0.88	0.89	0.89
18	Titanic-0.01	0.89	0.92	0.92	0.92
19	Vote-0.01	0.95	0.89	0.93	0.89
20	Zoo-0.01	0.91	0.91	0.91	0.91
(c)					
1	Anneal-0.01	0.92	0.90	0.82	0.90

Table 3. Cont.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
2	Chess-Kr-vs-kp-0.01	0.98	0.98	0.98	0.98
3	Credit-g-0.01	0.63	0.60	0.70	0.70
4	Cylinder-Bands-0.01	0.74	0.67	0.74	0.67
5	Eucalyptus-0.01	0.47	0.57	0.73	0.73
6	Flags-0.01	0.60	0.65	0.65	0.75
7	German-credit-0.01	0.62	0.60	0.69	0.69
8	Hypothyroid-0.01	0.97	0.96	0.97	0.96
9	Ilpd-0.01	0.66	0.64	0.64	0.64
10	Led24-0.01	0.43	0.51	0.63	0.51
11	Loan-0.01	0.58	0.76	0.69	0.69
12	Lymphography-0.01	0.60	0.60	0.53	0.60
13	Mushroom-0.01	0.99	0.99	0.99	0.99
14	Primary-tumor-0.01	0.35	0.35	0.35	0.35
15	Shuttle-0.01	0.94	0.94	0.94	0.94
16	Soybean-0.01	0.83	0.80	0.84	0.80
17	Thyroid-0.01	0.95	0.95	0.95	0.95
18	Titanic-0.01	0.92	0.95	0.96	0.96
19	Vote-0.01	0.96	0.95	0.98	0.98
20	Zoo-0.01	1.00	0.91	1.00	0.91
(d)					
1	Anneal-0.01	0.96	0.84	0.89	0.92
2	Chess-Kr-vs-kp-0.01	0.95	0.96	0.96	0.95
3	Credit-g-0.01	0.64	0.70	0.64	0.72
4	Cylinder-Bands-0.01	0.78	0.76	0.63	0.63
5	Eucalyptus-0.01	0.54	0.69	0.57	0.69
6	Flags-0.01	0.65	0.70	0.65	0.55
7	German-credit-0.01	0.65	0.71	0.62	0.70
8	Hypothyroid-0.01	0.98	0.98	0.96	0.96
9	Ilpd-0.01	0.66	0.68	0.68	0.64
10	Led24-0.01	0.41	0.63	0.54	0.50
11	Loan-0.01	0.56	0.69	0.74	0.71
12	Lymphography-0.01	0.67	0.60	0.53	0.60
13	Mushroom-0.01	0.99	0.99	0.99	0.99
14	Primary-tumor-0.01	0.41	0.41	0.41	0.38
15	Shuttle-0.01	0.94	0.94	0.94	0.94
16	Soybean-0.01	0.84	0.86	0.84	0.86
17	Thyroid-0.01	0.95	0.94	0.96	0.95
18	Titanic-0.01	0.94	0.95	0.95	0.95
19	Vote-0.01	0.98	0.95	0.95	0.95
20	Zoo-0.01	0.91	0.91	0.91	0.91

Table 4. (a) Accuracy of the SVM Classifier after adding 2% noise. (b) Accuracy of the Decision Tree Classifier after adding 2% noise. (c) Accuracy of the Hist Gradient Boosting Classifier after adding 2% noise. (d) Accuracy of the Random Forest Classifier after adding 2% noise.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
(a)					
1	Anneal-0.02	0.83	0.80	0.88	0.88
2	Chess-Kr-vs-kp-0.02	0.95	0.95	0.95	0.95

Table 4. Cont.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
3	Credit-g-0.02	0.72	0.72	0.70	0.72
4	Cylinder-Bands-0.02	0.61	0.61	0.70	0.70
5	Eucalyptus-0.02	0.45	0.35	0.47	0.35
6	Flags-0.02	0.50	0.70	0.55	0.55
7	German-credit-0.02	0.67	0.64	0.64	0.64
8	Hypothyroid-0.02	0.93	0.93	0.93	0.93
9	Ilpd-0.02	0.71	0.69	0.68	0.69
10	Led24-0.02	0.60	0.60	0.73	0.73
11	Loan-0.02	0.61	0.61	0.63	0.61
12	Lymphography-0.02	0.47	0.53	0.40	0.60
13	Mushroom-0.02	0.93	0.92	0.94	0.93
14	Primary-tumor-0.02	0.50	0.50	0.50	0.50
15	Shuttle-0.02	0.94	0.94	0.94	0.94
16	Soybean-0.02	0.59	0.57	0.68	0.68
17	Thyroid-0.02	0.96	0.96	0.96	0.96
18	Titanic-0.02	0.66	0.62	0.67	0.62
19	Vote-0.02	0.95	0.95	0.95	0.95
20	Zoo-0.02	1.00	1.00	1.00	1.00
(b)					
1	Anneal-0.02	0.91	0.92	0.83	0.83
2	Chess-Kr-vs-kp-0.02	0.89	0.90	0.88	0.87
3	Credit-g-0.02	0.51	0.68	0.66	0.68
4	Cylinder-Bands-0.02	0.67	0.69	0.63	0.65
5	Eucalyptus-0.02	0.49	0.49	0.58	0.50
6	Flags-0.02	0.70	0.70	0.60	0.55
7	German-credit-0.02	0.58	0.63	0.54	0.65
8	Hypothyroid-0.02	0.96	0.96	0.82	0.81
9	Ilpd-0.02	0.59	0.53	0.66	0.54
10	Led24-0.02	0.40	0.38	0.53	0.50
11	Loan-0.02	0.65	0.61	0.65	0.63
12	Lymphography-0.02	0.67	0.47	0.40	0.33
13	Mushroom-0.02	0.95	0.94	0.94	0.95
14	Primary-tumor-0.02	0.38	0.35	0.38	0.35
15	Shuttle-0.02	0.94	0.94	0.94	0.94
16	Soybean-0.02	0.68	0.67	0.83	0.83
17	Thyroid-0.02	0.88	0.89	0.88	0.89
18	Titanic-0.02	0.77	0.85	0.85	0.85
19	Vote-0.02	0.95	0.89	0.95	0.91
20	Zoo-0.02	0.82	0.82	0.82	0.91
(c)					
1	Anneal-0.02	0.93	0.93	0.90	0.90
2	Chess-Kr-vs-kp-0.02	0.96	0.96	0.95	0.95
3	Credit-g-0.02	0.63	0.72	0.65	0.72
4	Cylinder-Bands-0.02	0.80	0.80	0.72	0.72
5	Eucalyptus-0.02	0.51	0.62	0.61	0.62
6	Flags-0.02	0.55	0.50	0.60	0.60
7	German-credit-0.02	0.70	0.73	0.61	0.73
8	Hypothyroid-0.02	0.95	0.95	0.92	0.92
9	Ilpd-0.02	0.56	0.56	0.61	0.56
10	Led24-0.02	0.58	0.58	0.66	0.66
11	Loan-0.02	0.58	0.76	0.76	0.76

Table 4. Cont.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
12	Lymphography-0.02	0.53	0.47	0.60	0.47
13	Mushroom-0.02	0.99	0.99	0.99	0.99
14	Primary-tumor-0.02	0.38	0.38	0.38	0.38
15	Shuttle-0.02	0.94	0.94	0.94	0.94
16	Soybean-0.02	0.74	0.74	0.86	0.86
17	Thyroid-0.02	0.95	0.95	0.95	0.95
18	Titanic-0.02	0.79	0.95	0.94	0.95
19	Vote-0.02	0.98	0.95	0.98	0.95
20	Zoo-0.02	0.91	0.91	0.91	0.91
(d)					
1	Anneal-0.02	0.96	0.93	0.94	0.94
2	Chess-Kr-vs-kp-0.02	0.95	0.94	0.94	0.94
3	Credit-g-0.02	0.67	0.73	0.71	0.69
4	Cylinder-Bands-0.02	0.74	0.74	0.80	0.76
5	Eucalyptus-0.02	0.57	0.68	0.64	0.64
6	Flags-0.02	0.65	0.55	0.65	0.70
7	German-credit-0.02	0.61	0.71	0.66	0.70
8	Hypothyroid-0.02	0.95	0.96	0.93	0.92
9	Ilpd-0.02	0.64	0.63	0.63	0.63
10	Led24-0.02	0.60	0.58	0.69	0.69
11	Loan-0.02	0.61	0.71	0.65	0.74
12	Lymphography-0.02	0.60	0.67	0.67	0.47
13	Mushroom-0.02	0.98	0.99	0.98	0.99
14	Primary-tumor-0.02	0.38	0.38	0.38	0.38
15	Shuttle-0.02	0.94	0.94	0.94	0.94
16	Soybean-0.02	0.84	0.81	0.90	0.88
17	Thyroid-0.02	0.95	0.94	0.95	0.94
18	Titanic-0.02	0.80	0.94	0.88	0.93
19	Vote-0.02	0.95	0.95	0.95	0.95
20	Zoo-0.02	0.82	0.82	0.82	0.91

Table 5. (a) Accuracy of the SVM Classifier after adding 3% noise. (b) Accuracy of the Decision Tree Classifier after adding 3% noise. (c) Accuracy of the Hist Gradient Boosting Classifier after adding 3% noise. (d) Accuracy of the Random Forest Classifier after adding 3% noise.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
(a)					
1	Anneal-0.03	0.82	0.81	0.77	0.77
2	Chess-Kr-vs-kp-0.03	0.98	0.98	0.98	0.98
3	Credit-g-0.03	0.72	0.72	0.71	0.72
4	Cylinder-Bands-0.03	0.65	0.65	0.67	0.67
5	Eucalyptus-0.03	0.42	0.36	0.42	0.36
6	Flags-0.03	0.70	0.60	0.65	0.60
7	German-credit-0.03	0.67	0.67	0.67	0.67
8	Hypothyroid-0.03	0.93	0.93	0.93	0.93
9	Ilpd-0.03	0.69	0.69	0.68	0.69
10	Led24-0.03	0.64	0.64	0.62	0.62
11	Loan-0.03	0.61	0.61	0.61	0.61
12	Lymphography-0.03	0.60	0.67	0.60	0.60

Table 5. Cont.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
13	Mushroom-0.03	0.93	0.93	0.94	0.93
14	Primary-tumor-0.03	0.44	0.44	0.44	0.44
15	Shuttle-0.03	0.94	0.94	0.94	0.94
16	Soybean-0.03	0.62	0.62	0.67	0.67
17	Thyroid-0.03	0.96	0.96	0.96	0.96
18	Titanic-0.03	0.70	0.63	0.70	0.63
19	Vote-0.03	0.93	0.93	0.93	0.93
20	Zoo-0.03	0.91	0.91	0.91	0.91
(b)					
1	Anneal-0.03	0.93	0.93	0.80	0.81
2	Chess-Kr-vs-kp-0.03	0.90	0.89	0.89	0.90
3	Credit-g-0.03	0.58	0.65	0.67	0.65
4	Cylinder-Bands-0.03	0.69	0.67	0.74	0.74
5	Eucalyptus-0.03	0.32	0.54	0.53	0.58
6	Flags-0.03	0.60	0.60	0.65	0.50
7	German-credit-0.03	0.61	0.59	0.68	0.60
8	Hypothyroid-0.03	0.94	0.94	0.80	0.79
9	Ilpd-0.03	0.66	0.59	0.61	0.59
10	Led24-0.03	0.57	0.56	0.52	0.50
11	Loan-0.03	0.61	0.61	0.65	0.58
12	Lymphography-0.03	0.53	0.73	0.67	0.67
13	Mushroom-0.03	0.94	0.95	0.95	0.95
14	Primary-tumor-0.03	0.32	0.29	0.35	0.35
15	Shuttle-0.03	0.94	0.94	0.94	0.94
16	Soybean-0.03	0.54	0.59	0.72	0.68
17	Thyroid-0.03	0.89	0.88	0.89	0.89
18	Titanic-0.03	0.88	0.85	0.88	0.85
19	Vote-0.03	0.93	0.89	0.91	0.89
20	Zoo-0.03	0.91	0.91	0.91	0.91
(c)					
1	Anneal-0.03	0.96	0.96	0.82	0.82
2	Chess-Kr-vs-kp-0.03	0.97	0.97	0.97	0.97
3	Credit-g-0.03	0.67	0.72	0.80	0.72
4	Cylinder-Bands-0.03	0.76	0.76	0.65	0.65
5	Eucalyptus-0.03	0.43	0.70	0.62	0.70
6	Flags-0.03	0.65	0.60	0.65	0.65
7	German-credit-0.03	0.63	0.69	0.66	0.69
8	Hypothyroid-0.03	0.96	0.96	0.92	0.92
9	Ilpd-0.03	0.64	0.59	0.59	0.59
10	Led24-0.03	0.63	0.63	0.58	0.58
11	Loan-0.03	0.58	0.69	0.76	0.69
12	Lymphography-0.03	0.60	0.67	0.73	0.73
13	Mushroom-0.03	0.99	0.99	0.99	0.99
14	Primary-tumor-0.03	0.38	0.38	0.38	0.38
15	Shuttle-0.03	0.94	0.94	0.94	0.94
16	Soybean-0.03	0.72	0.72	0.84	0.84
17	Thyroid-0.03	0.95	0.95	0.95	0.95
18	Titanic-0.03	0.96	0.94	0.96	0.94
19	Vote-0.03	0.95	0.93	0.95	0.93
20	Zoo-0.03	0.91	0.91	0.91	0.91

Table 5. Cont.

No.	Name	Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
(d)					
1	Anneal-0.03	0.97	0.97	0.86	0.83
2	Chess-Kr-vs-kp-0.03	0.97	0.97	0.97	0.96
3	Credit-g-0.03	0.67	0.71	0.74	0.70
4	Cylinder-Bands-0.03	0.81	0.85	0.72	0.76
5	Eucalyptus-0.03	0.43	0.72	0.64	0.72
6	Flags-0.03	0.65	0.55	0.70	0.60
7	German-credit-0.03	0.63	0.69	0.72	0.75
8	Hypothyroid-0.03	0.95	0.95	0.91	0.92
9	Ilpd-0.03	0.73	0.69	0.66	0.63
10	Led24-0.03	0.65	0.63	0.61	0.63
11	Loan-0.03	0.63	0.71	0.68	0.73
12	Lymphography-0.03	0.67	0.67	0.67	0.67
13	Mushroom-0.03	0.98	0.99	0.99	1.00
14	Primary-tumor-0.03	0.38	0.38	0.38	0.35
15	Shuttle-0.03	0.94	0.94	0.94	0.94
16	Soybean-0.03	0.68	0.74	0.81	0.83
17	Thyroid-0.03	0.95	0.95	0.94	0.95
18	Titanic-0.03	0.95	0.95	0.95	0.95
19	Vote-0.03	0.91	0.89	0.91	0.91
20	Zoo-0.03	0.91	0.91	0.91	0.91

Based on the classification accuracy reported in Tables 3a–d–5a–d, numerical differences can be observed for some individual datasets. However, these differences do not reveal a consistent pattern favoring either shortest-length or coarsest-granularity reducts/constructs across the evaluated noise levels (1%, 2%, or 3%). For this reason, the Wilcoxon signed-rank test was used to assess whether the paired accuracy differences reflected a statistically significant systematic tendency across datasets, rather than relying only on raw accuracy percentages.

We validated this finding by applying the Wilcoxon test across all noise levels (1%, 2%, and 3%) (see Table 6a–d), which consistently showed no significant difference in accuracy between the shortest and coarsest-granularity reducts or constructs.

Table 6. (a) Wilcoxon-test p -values for SVM without noise. (b) Wilcoxon-test p -values for SVM with 1% of noise. (c) Wilcoxon-test p -values for SVM with 2% of noise. (d) Wilcoxon-test p -values for SVM with 3% of noise.

		Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
(a)					
Reducts	Shortest-Length				
	Coarsest-Granularity	0.99			
Constructs	Shortest-Length	0.23	0.99		
	Coarsest-Granularity	0.96	0.30	0.99	
(b)					
Reducts	Shortest-Length				
	Coarsest-Granularity	0.93			
Constructs	Shortest-Length	0.16	0.89		
	Coarsest-Granularity	0.85	0.43	0.75	

Table 6. *Cont.*

		Reducts		Constructs	
		Shortest-Length	Coarsest-Granularity	Shortest-Length	Coarsest-Granularity
(c)					
Reducts	Shortest-Length				
	Coarsest-Granularity	0.90			
Constructs	Shortest-Length	0.22	0.78		
	Coarsest-Granularity	0.87	0.50	0.88	
(d)					
Reducts	Shortest-Length				
	Coarsest-Granularity	0.42			
Constructs	Shortest-Length	0.15	0.84		
	Coarsest-Granularity	0.22	0.19	0.54	

Across all evaluated conditions, the Wilcoxon test consistently produced p -values greater than the significance threshold of $\alpha = 0.05$. This means that the null hypothesis of no significant difference could not be rejected in the pairwise comparisons analyzed. Specifically, the results did not show statistically significant differences between shortest-length and coarsest-granularity reducts, between shortest-length and coarsest-granularity constructs, or between the corresponding reduct- and construct-based alternatives.

These results suggest that all evaluated attribute subsets perform similarly in the presence of noise in supervised classification tasks.

Importantly, the noise model used here is random attribute-value corruption; therefore, these conclusions should not be generalized to systematic, correlated, or class-dependent noise. The similar behavior across 1%, 2%, and 3% levels indicates that both criteria are comparably robust under this specific model.

In summary, our experiments did not rely solely on raw accuracy percentages for our interpretation. The accuracy values in Tables 3–5 provide a descriptive view of classifier performance, but they do not show whether the paired differences reflect a systematic tendency across datasets. The paired Wilcoxon signed-rank test was used as a nonparametric procedure to compare all evaluated attribute subsets. Since the resulting p -values were greater than 0.05, the null hypothesis of no significant difference could not be rejected. Accordingly, we conclude that under the specific experimental conditions considered, shortest-length and coarsest-granularity reducts/constructs did not exhibit systematically different classification performance under random attribute-value noise.

To position the present study with respect to recent rough-set research and a relevant historical antecedent, Table 7 compares our contribution with representative related works. For each study, we indicate the type of attribute subset or feature selection strategy considered, the learning task, the datasets or evaluation environment, whether noise was explicitly analyzed, and the authors' main conclusions. This comparison provides a clearer context for this paper. Recent studies have examined attribute selection, reduct calculation, rough-set-based methods, and supervised classification from different perspectives. Our paper addresses a more specific question: how do shorter, coarser-grained reducts and constructs perform in supervised classification when controlled random noise is introduced into the attribute values of the training data? Under the experimental conditions considered in this study, and based on the results presented earlier, we conclude that the analyzed selection criteria did not show statistically significant differences in classification accuracy.

Table 7. Comparison with representative and recent related papers.

Year	First Author	Method Focus	Noise Type	Key Finding	Relation to Current Work
2024	Lazo-Cortés [21]	Shortest vs. coarsest selection criteria	None	Computational costs vary by criterion	Extends with noise resilience analysis
2025	Chen [1]	Fuzzy/matrix reducts	None	Discernibility matrices remain effective	Related theoretical foundation
2024	Kumar [7]	Fuzzy rough sets + neural network	None	Scales to high-dimensional data	Alternative feature selection approach
2025	An [5]	Neighborhood rough sets	None	Robust to multi-density data	Related RST variant
2025	Yang [9]	Weighted fuzzy rough sets	Implicit noisy data	Adaptive selection is beneficial	Noise-handling comparison
2003	Susmaga [19]	Reducts vs. constructs	Real-world inherent noise	Constructs outperform reducts in noise	Historical antecedent for the present comparison

4. Conclusions

Processing large datasets with numerous reducts/constructs can be time-consuming, making the use of a representative subset more practical than using all possible solutions. In this study, we compared shortest-length and coarsest-granularity reducts/constructs across 20 real-world datasets and four supervised classifiers.

Experiments without added noise and experiments with 1%, 2%, and 3% random attribute-value noise did not show statistically significant differences between the two selection criteria. The Wilcoxon test consistently produced p -values above 0.05, so we failed to reject the null hypothesis. These results did not provide statistical evidence that, for the considered random-noise model, the choice between shortest-length and coarsest-granularity subsets systematically affects classification accuracy.

These findings should also be interpreted in relation to previous studies reporting different behavior between reducts and constructs in noisy environments. The apparent discrepancy may be explained by differences in the experimental protocol. In particular, previous works considered broader comparisons between reducts and constructs, whereas the present study focuses specifically on shortest-length and coarsest-granularity subsets selected as representative solutions. In addition, the perturbation model used here corresponds to controlled random attribute-value noise introduced into the training data at relatively low levels. Other perturbation mechanisms, such as targeted, correlated, systematic, or class-dependent noise, may affect the selected subsets differently. Dataset selection, classifier choice, the voting-based classification procedure, and the use of a fixed train–test split may also influence the observed results. Therefore, the present findings should be seen as complementary to previous evidence rather than contradictory: under the specific protocol evaluated in this study, no statistically significant accuracy differences were observed between the evaluated selection criteria.

From a practical perspective, when accuracy is statistically comparable, shortest-length subsets may be preferable when compactness and interpretability are priorities, since they typically use fewer attributes. Conversely, coarsest-granularity subsets may remain relevant when preserving the structure of the induced partition is a priority. However, these practical considerations should be read with two limitations in mind. First, the added noise was random and independent, so the findings should not be generalized to structured or non-random perturbation mechanisms, such as targeted, correlated, systematic, or class-dependent noise. Second, runtime, memory usage, the number of generated reducts/constructs, and the overhead associated with the voting-based procedure were not directly evaluated in this study. Therefore, future work should analyze computational cost more systematically, including runtime, memory use, the number of generated subsets, and the cost of training and aggregating classifiers, alongside classification accuracy. Future

studies should also examine whether structured or non-random noise mechanisms can favor one type of subset or selection criterion over another.

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Abbreviations

The following abbreviations are used in this manuscript:

RST	Rough Set Theory
DT	Decision Table
SVM	Support Vector Machine
SECIHTI	Secretaría de Ciencia, Humanidades, Tecnología e Innovación

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