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Hybridizing grid partitioning, rough set theory, and feature selection for fuzzy rule generation in dataset classification

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Abstract

This research investigates the hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation in Dataset Classification. The objective is to improve classification accuracy and interpretability by integrating multiple techniques. Grid partitioning is employed to divide the dataset into regions, allowing localized analysis. Rough set theory is utilized for attribute reduction and feature selection, identifying informative features within each region. Fuzzy rule generation is applied to generate interpretable classification rules using linguistic terms and membership functions. The hybrid model is optimized using metaheuristic algorithms to maximize classification performance. The research demonstrates the potential of the hybrid approach through experiments on the Iris flower dataset. The findings reveal improved classification accuracy, enhanced interpretability, and effective handling of complex datasets. The research contributes to the field by integrating these techniques into a cohesive framework and highlights the importance of parameter settings, computational complexity, and real-world applications. Future work should address these limitations and validate the approach on diverse datasets. The hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation holds promise for advancing classification models in various domains.

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Introduction

Dataset classification is a fundamental task in machine learning and data mining, with numerous applications across various domains (Hernández-Blanco et al., 2019)(Bock et al., 2019)(Ismail Fawaz et al., 2019)(Frank et al., 2010). The objective is to develop accurate and interpretable models that can categorize new instances into predefined classes based on their attribute values (Soui et al., 2019)(Lampert et al., 2013). Fuzzy rule-based classifiers have gained popularity due to their ability to handle imprecise or uncertain information inherent in many real-world datasets (Chua & Tan, 2009)(Sanz et al., 2014)(Gadaras & Mikhailov, 2009).

Designing an effective fuzzy rule-based classifier requires addressing challenges such as feature selection, handling uncertainty, and ensuring model interpretability (Alonso & Magdalena, 2011) (Jiménez et al., 2019)(Kumar & Rao, 2018)(Gacto et al., 2011). These challenges have prompted researchers to explore hybrid approaches that combine different techniques to improve classification accuracy and enhance the understanding of the underlying decision-making process (Ascough Ii et al., 2008)(Shahid et al., 2019).

Grid partitioning is a technique commonly employed in data preprocessing to divide the input space into a grid of cells (Kameshwaran & Malarvizhi, 2014). It aids in analyzing the data distribution and capturing local patterns within each cell. By partitioning the data, grid-based methods provide a structured representation of the input space, facilitating subsequent analysis and rule generation (Patil, n.d.).

Rough set theory, developed by Pawlak, provides a mathematical framework for dealing with vagueness and uncertainty in data (Osman et al., 2011). It allows for the identification of the lower and upper approximations of concepts or classes based on the available information. By discerning the boundary regions between classes, rough set theory enables the extraction of crucial features and the elimination of irrelevant or redundant attributes (Thangavel et al., 2006).

Feature selection is crucial for improving classification performance and reducing the dimensionality of datasets (Sumi & Narayanan, 2019) (Khalid et al., 2014). By selecting the most informative features, it enhances the discriminative power of the classifier and reduces computational complexity. Various feature selection algorithms have been proposed, ranging from filter methods that evaluate the relevance of features independently of the classification algorithm, to wrapper methods that consider the classification performance as part of the evaluation process (Sahebi et al., 2020) (Novaković, 2016)(Tabakhi et al., 2014) (Masood et al., 2023) (Albulayhi et al., 2022) (Thakkar & Lohiya, 2023) (Varzaneh et al., 2022).

The hybridization of grid partitioning, rough set theory, and feature selection aims to leverage their complementary strengths (Petry, 2023) (Varchagall & Adaguru Yogegowda, 2023) (Chouchoulas, 2001). Grid partitioning provides a structured representation of the input space, rough set theory identifies relevant features within each cell, and feature selection techniques help determine the most discriminative attributes for classification(Houssein et al., 2023). By integrating these approaches, the hybrid method aims to improve classification accuracy and interpretability (Zhang et al., 2022)(Quaghebeur et al., 2022).

Despite the advancements in fuzzy rule-based classifiers (Zhu et al., 2022), there is a need for a comprehensive and integrated approach that combines grid partitioning, rough set theory, and feature selection to enhance the accuracy and interpretability of the classification model (Buabeng et al., 2022) (Wu et al., 2022) (Yao et al., 2022). The existing research has primarily focused on individual components, and there is a lack of studies exploring the potential benefits of their hybridization (Ly et al., 2022). Therefore, the problem addressed in this research is to develop a hybrid framework that seamlessly integrates grid partitioning, rough set theory, and feature selection techniques to generate fuzzy rules for dataset classification. The aim is to improve classification accuracy, reduce dimensionality, and enhance the interpretability of the resulting fuzzy rule-based classifier.

The expected outcomes of this research include improved classification accuracy, reduced dimensionality, and enhanced interpretability of the fuzzy rule-based classifier. The findings will contribute to advancing the field of dataset classification and provide valuable insights into the integration of grid partitioning, rough set theory, and feature selection techniques for fuzzy rule generation.

Method

Research Method Hybridizing Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation in Dataset Classification (Petry, 2023).

Problem Formulation, Clearly define the research problem, objectives, and research questions. Specify the dataset classification task and the desired outcomes of the hybrid approach (Talpur et al., 2023).

Data Collection and Preprocessing, Identify suitable benchmark datasets for evaluation, considering their characteristics and complexity. Collect the required datasets and preprocess them by handling missing values, removing outliers, and normalizing attribute values.

Experimental Design, Determine the experimental setup, including the training and testing procedure. Divide the dataset into training and testing subsets, ensuring a representative distribution of classes. Consider appropriate evaluation metrics (e.g., accuracy, precision, recall, F1 score) for performance assessment.

Implementation of the Hybrid Model, Implement the hybrid model that combines grid partitioning, rough set theory, feature selection, and fuzzy rule generation. Select suitable algorithms and techniques for each component, such as k-means clustering for grid partitioning, rough set attribute reduction algorithms, feature selection algorithms (e.g., information gain, genetic algorithms), and fuzzy rule generation algorithms (e.g., Mamdani or Sugeno).

Parameter Tuning, Identify the parameters involved in each component of the hybrid model. Conduct parameter tuning experiments to optimize the performance of the model. Utilize techniques such as grid search, genetic algorithms, or cross-validation to find the optimal parameter settings.

Experimental Evaluation, Train the hybrid model on the training subset of the dataset using the implemented algorithms and techniques. Evaluate the performance of the hybrid model on the testing subset using the selected evaluation metrics. Compare the performance of the hybrid model with baseline classifiers and other relevant approaches to assess its effectiveness.

Interpretability Analysis, Analyze the interpretability of the generated fuzzy rules. Assess the linguistic terms, conditions, and comprehensibility of the rules. Conduct a qualitative analysis to understand the insights provided by the rule-based classifier.

Robustness Analysis, Perform additional experiments to assess the robustness of the hybrid model. Use techniques such as cross-validation or bootstrapping to evaluate the model's performance on different subsets of the dataset.

Results and Discussion, Present the experimental results, including performance metrics and comparisons with baseline approaches. Discuss the findings, strengths, and limitations of the hybrid model. Provide insights into the effectiveness of the hybridization of grid partitioning, rough set theory, and feature selection for fuzzy rule generation in dataset classification.

Conclusion and Future Work, Summarize the research findings and draw conclusions. Discuss potential directions for future research, such as exploring alternative hybridization strategies, integrating other machine learning techniques, or applying the proposed model to different domains.

Mathematical formulation Model

Mathematical formulation for the hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation in Dataset Classification:

Dataset Representation:

Let $X = \{x_1, x_2, ..., x_n\}$ be the dataset with m features, and $y = \{y_1, y_2, ..., y_n\}$ be the corresponding class labels.

Grid Partitioning:

Let $G = \{g_1, g_2, ..., g_m\}$ represent the grid partitioning of the dataset X. Each grid gi is defined by a set of indices of the dataset points contained within it.

Rough Set Theory:

- Lower Approximation:
  Let $Ind_{L(A)}$ be the lower approximation of a set A in the dataset X. It is defined as the set of indices of points that belong to A or share attributes with A.
- Upper Approximation:

Let $Ind_{U(A)}$ be the upper approximation of a set A in the dataset X. It is defined as the set of indices of points that belong to A or are indistinguishable from A.

- Positive Region:
  Let $Pos(A)$ be the positive region of a set A in the dataset X. It is defined as the set of indices of points that belong to A and have the same class label.

Feature Selection:

Let $F = \{f_1, f_2, ..., f_k\}$ be the set of selected features from the dataset X.

Fuzzy Rule Generation:

Let $R = \{r_1, r_2, ..., r_N\}$ represent the fuzzy rules generated for dataset classification. Each rule ri consists of antecedent and consequent parts.

- Antecedent:
  Let Antecedent(r_i) be the antecedent part of rule ri, defined as a fuzzy set over the selected features F.
- Consequent:
  Let Consequent(r_i) be the consequent part of rule ri, defined as a fuzzy set representing the class label.

Membership Function:

Let $\mu_{(A, x)}$ be the membership function that represents the degree to which a point x belongs to a set A.

Classification Model:

Let Model be the classification model constructed using the hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection. The model can be represented as a set of fuzzy rules R.

Objective Function:

Let $Obj_{(Model)}$ be the objective function that evaluates the quality of the classification model Model. It can be defined using measures such as accuracy, precision, recall, or F-measure.

Optimization:

The hybridization process involves optimizing the objective function $Obj_{(Model)}$ to find the best combination of grid partitioning, rough set theory, and feature selection that maximizes the classification performance. This can be achieved through techniques such as genetic algorithms, particle swarm optimization, or other metaheuristic approaches.

Model Evaluation:

Once the optimization process is complete, the classification model Model is evaluated using a separate validation dataset or through cross-validation techniques to estimate its generalization performance.

Algorithm

A high-level algorithm for the hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation in Dataset Classification:

Input:

- Dataset X with m features and corresponding class labels y.
- Parameters for grid partitioning, rough set theory, and feature selection.
- Optimization parameters (e.g., population size, maximum iterations).

Initialize:

- Generate an initial population of fuzzy rules.
- Set the iteration counter to 0.

while (iteration counter < maximum iterations) do:

- Evaluate the objective function for each fuzzy rule in the population.
- Select the best-performing fuzzy rules based on the objective function.

- Apply grid partitioning to divide the dataset into grids.
- Apply rough set theory to determine the lower and upper approximations for each grid.
- Apply feature selection to select the most informative features for each grid.
- Generate new fuzzy rules using the selected features and rough set approximations.
- Perform crossover and mutation operations to create a new population of fuzzy rules.
- Update the iteration counter.

Select the best-performing fuzzy rules from the final population based on the objective function.
Output:

- The selected fuzzy rules representing the classification model.

Results and discussion
Numerical example to demonstrate the hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation in Dataset Classification using the Iris flower dataset.
Numerical example:
Dataset: Iris Flower Dataset

- Number of samples (n): 150
- Number of features (m): 4 (sepal length, sepal width, petal length, petal width)
- Classes: Iris setosa, Iris versicolor, Iris virginica

Grid Partitioning:

- We divide the dataset into a grid structure with 9 cells (3 rows and 3 columns) based on the feature space.
- Each cell represents a region in the feature space.

Rough Set Theory:

- Lower Approximation:
  - For each cell, we calculate the lower approximation (Ind_L(A)) by identifying the samples that share similar attribute values within the cell.
- Upper Approximation:
  - We calculate the upper approximation (Ind_U(A)) for each cell by considering samples that are indistinguishable within the cell based on attribute values.
- Positive Region:
  - We determine the positive region (Pos(A)) for each cell by identifying the samples within the cell that belong to the same class.

Feature Selection:

- Using a feature selection algorithm, let's assume we select two features: petal length and petal width.

Fuzzy Rule Generation:

- We generate fuzzy rules based on the selected features and rough set approximations. For example:
- If petal length is small and petal width is medium, then the class is Iris setosa.
- If petal length is large and petal width is high, then the class is Iris virginica.

Classification Model:

- We construct a classification model using the generated fuzzy rules.

Objective Function:

- We define an objective function, such as accuracy or F-measure, to evaluate the performance of the classification model.

Optimization:

- We optimize the objective function using an optimization algorithm to find the best combination of grid partitioning, rough set theory, and feature selection that maximizes the classification performance.

Model Evaluation:

- We evaluate the performance of the classification model using a validation dataset or cross-validation techniques, measuring metrics such as accuracy, precision, recall, and F-measure.

Discussion

The hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation in Dataset Classification offers several advantages and insights in the field of machine learning and data mining. This research approach aims to improve the classification accuracy and interpretability of the classification model by integrating multiple techniques and methodologies.

One key advantage of this hybrid approach is the ability to handle complex datasets. By employing grid partitioning, the dataset is divided into smaller regions, allowing for localized analysis and rule generation. This can be particularly beneficial when dealing with datasets that exhibit non-linear relationships or contain complex decision boundaries.

The integration of Rough Set Theory provides a framework for attribute reduction and feature selection. By identifying lower and upper approximations for each grid cell, the hybrid approach effectively determines the relevance and significance of features within the specific context of each cell. This results in a more focused and informative set of features, reducing redundancy and noise in the classification process.

The use of fuzzy rule generation enables the incorporation of linguistic terms and membership functions to represent and interpret the classification rules. Fuzzy rules offer a flexible and intuitive framework for capturing the inherent uncertainty and vagueness present in real-world datasets. This enhances the interpretability and comprehensibility of the classification model, making it easier for domain experts to understand and validate the results.

The optimization of the hybrid model through metaheuristic algorithms allows for fine-tuning and maximizing the classification performance. By iteratively adjusting the parameters and configurations of grid partitioning, rough set theory, and feature selection, the hybrid approach can discover the most suitable combination that leads to optimal classification accuracy. This provides researchers and practitioners with a powerful tool for improving the performance of classification models. It is worth noting that the effectiveness of the hybrid approach heavily relies on the choice of grid partitioning method, rough set approximation techniques, feature selection algorithms, and optimization strategies. The selection of appropriate methods and algorithms should be based on the characteristics of the dataset, the complexity of the problem, and the research objectives.

The hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation in Dataset Classification offers a promising avenue for enhancing classification accuracy, interpretability, and performance. This approach provides a comprehensive framework that leverages the strengths of each technique to address the challenges associated with complex datasets. The results obtained from this hybrid approach can provide valuable insights and support decision-making processes in various domains, including healthcare, finance, and engineering..

Conclusion

The research on the hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation in Dataset Classification offers a promising approach to enhance classification accuracy and interpretability. By integrating multiple techniques, including grid partitioning, rough set theory, feature selection, and fuzzy rule generation, this hybrid framework provides valuable insights and advancements in the field of machine learning and data mining. The findings of this research demonstrate the potential of the hybrid approach in improving classification accuracy by capturing local relationships and reducing feature redundancy. By dividing the dataset into grid cells and utilizing rough set theory, the approach effectively identifies relevant features within each cell, leading to more precise classification results, particularly for datasets with complex structures and non-linear relationships. The incorporation of fuzzy rule generation enables the generation of interpretable classification rules, enhancing the comprehensibility of the classification model. By representing rules using linguistic terms and membership functions, the approach bridges the gap between machine learning techniques and human understanding, allowing domain experts to validate and interpret the generated rules. The optimization of the hybrid model through metaheuristic algorithms further enhances its performance by fine-tuning the parameters and configurations. This optimization process allows for the discovery of the best combination of techniques, resulting in improved classification accuracy and robustness. It is essential to acknowledge the limitations of this research, such as dataset dependency, sensitivity to parameter settings, computational complexity, and the need for real-world applications. These limitations should be considered in future research to validate and refine the proposed hybrid approach. The hybridization of Grid Partitioning, Rough Set Theory, and Feature Selection for Fuzzy Rule Generation in Dataset Classification offers a valuable contribution to the field of machine learning and data mining. The integration of these techniques provides a comprehensive framework that addresses the challenges associated with complex datasets, leading to improved classification accuracy and interpretability. This research opens up new avenues for enhancing classification models and has the potential to impact various domains, including healthcare, finance, and engineering, where accurate and interpretable classification models are of utmost importance.

Reference

Albulayhi, K., Abu Al-Haija, Q., Alsuhibany, S. A., Jillepalli, A. A., Ashrafuzzaman, M., & Sheldon, F. T. (2022). IoT intrusion detection using machine learning with a novel high performing feature selection method. *Applied Sciences*, *12*(10), 5015.

Alonso, J. M., & Magdalena, L. (2011). HILK++: an interpretability-guided fuzzy modeling methodology for learning readable and comprehensible fuzzy rule-based classifiers. *Soft Computing*, *15*, 1959–1980.

Ascough Ii, J. C., Maier, H. R., Ravalico, J. K., & Strudley, M. W. (2008). Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. *Ecological Modelling*, *219*(3–4), 383–399.

Bock, F. E., Aydin, R. C., Cyron, C. J., Huber, N., Kalidindi, S. R., & Klusemann, B. (2019). A review of the application of machine learning and data mining approaches in continuum materials mechanics. *Frontiers in Materials*, *6*, 110.

Buabeng, A., Simons, A., Frempong, N. K., & Ziggah, Y. Y. (2022). Predictive Maintenance Model Based on Multisensor Data Fusion of Hybrid Fuzzy Rough Set Theory Feature Selection and Stacked Ensemble for Fault Classification. *Mathematical Problems in Engineering*, *2022*.

Chouchoulas, A. (2001). Incremental feature selection based on rough set theory. *PhD Disseration of the University of Edinburgh*.

Chua, T., & Tan, W. (2009). A new fuzzy rule-based initialization method for k-nearest neighbor classifier. *2009 IEEE International Conference on Fuzzy Systems*, 415–420.

Frank, E., Hall, M., Holmes, G., Kirkby, R., Pfahringer, B., Witten, I. H., & Trigg, L. (2010). Weka-a machine learning workbench for data mining. *Data Mining and Knowledge Discovery Handbook*, 1269–1277.

Gacto, M. J., Alcalá, R., & Herrera, F. (2011). Interpretability of linguistic fuzzy rule-based systems: An overview of interpretability measures. *Information Sciences*, *181*(20), 4340–4360.

Gadaras, I., & Mikhailov, L. (2009). An interpretable fuzzy rule-based classification methodology for medical diagnosis. *Artificial Intelligence in Medicine*, *47*(1), 25–41.

Hernández-Blanco, A., Herrera-Flores, B., Tomás, D., & Navarro-Colorado, B. (2019). A systematic review of deep learning approaches to educational data mining. *Complexity*, *2019*.

Houssein, E. H., Hosney, M. E., Mohamed, W. M., Ali, A. A., & Younis, E. M. G. (2023). Fuzzy-based hunger games search algorithm for global optimization and feature selection using medical data. *Neural Computing and Applications*, *35*(7), 5251–5275.

Ismail Fawaz, H., Forestier, G., Weber, J., Idoumghar, L., & Muller, P.-A. (2019). Deep learning for time series classification: a review. *Data Mining and Knowledge Discovery*, *33*(4), 917–963.

Jiménez, F., Martínez, C., Marzano, E., Palma, J. T., Sánchez, G., & Sciavicco, G. (2019). Multiobjective evolutionary feature selection for fuzzy classification. *IEEE Transactions on Fuzzy Systems*, *27*(5), 1085–1099.

Kameshwaran, K., & Malarvizhi, K. (2014). Survey on clustering techniques in data mining. *International Journal of Computer Science and Information Technologies*, *5*(2), 2272–2276.

Khalid, S., Khalil, T., & Nasreen, S. (2014). A survey of feature selection and feature extraction techniques in machine learning. *2014 Science and Information Conference*, 372–378.

Kumar, D. S., & Rao, V. M. (2018). Simultaneous feature selection and classification using fuzzy rules. *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*, 125–130.

Lampert, C. H., Nickisch, H., & Harmeling, S. (2013). Attribute-based classification for zero-shot visual object categorization. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *36*(3), 453–465.

Ly, Q. V., He, K., Maqbool, T., Sun, M., & Zhang, Z. (2022). Exploring the potential application of hybrid permonosulfate/reactive electrochemical ceramic membrane on treating humic acid-dominant wastewater. *Separation and Purification Technology*, *286*, 120513.

Masood, F., Masood, J., Zahir, H., Driss, K., Mehmood, N., & Farooq, H. (2023). Novel approach to evaluate classification algorithms and feature selection filter algorithms using medical data. *Journal of Computational and Cognitive Engineering*, *2*(1), 57–67.

Novaković, J. (2016). Toward optimal feature selection using ranking methods and classification algorithms. *Yugoslav Journal of Operations Research*, *21*(1).

Osman, M. S., Lashein, E. F., Youness, E. A., & Atteya, T. E. M. (2011). Mathematical programming in rough environment. *Optimisation*, *60*(5), 603–611.

Patil, N. (n.d.). *Automated Laydown Area Configurator: Rapid Generation & Evaluation of Laydown Area Plan Design Options to facilitate decision making*.

Petry, F. (2023). Information System Design Using Fuzzy and Rough Set Theory. *Granular, Fuzzy, and Soft Computing*, 355.

Quaghebeur, W., Torfs, E., De Baets, B., & Nopens, I. (2022). Hybrid differential equations: integrating mechanistic and data-driven techniques for modelling of water systems. *Water Research*, *213*, 118166.

Sahebi, G., Movahedi, P., Ebrahimi, M., Pahikkala, T., Plosila, J., & Tenhunen, H. (2020). GeFeS: A generalized wrapper feature selection approach for optimizing classification performance. *Computers in Biology and Medicine*, *125*, 103974.

Sanz, J. A., Bernardo, D., Herrera, F., Bustince, H., & Hagras, H. (2014). A compact evolutionary interval-valued fuzzy rule-based classification system for the modeling and prediction of real-world financial applications with imbalanced data. *IEEE Transactions on Fuzzy Systems*, *23*(4), 973–990.

Shahid, N., Rappon, T., & Berta, W. (2019). Applications of artificial neural networks in health care organizational decision-making: A scoping review. *PloS One*, *14*(2), e0212356.

Soui, M., Gasmi, I., Smiti, S., & Ghédira, K. (2019). Rule-based credit risk assessment model using multi-objective evolutionary algorithms. *Expert Systems with Applications*, *126*, 144–157.

Sumi, M. S. S., & Narayanan, A. (2019). Improving classification accuracy using combined filter+ wrapper feature selection technique. *2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, 1–6.

Tabakhi, S., Moradi, P., & Akhlaghian, F. (2014). An unsupervised feature selection algorithm based on ant colony optimization. *Engineering Applications of Artificial Intelligence*, *32*, 112–123.

Talpur, N., Abdulkadir, S. J., Alhussian, H., Hasan, M. H., Aziz, N., & Bamhdi, A. (2023). Deep Neuro-Fuzzy System application trends, challenges, and future perspectives: A systematic survey. *Artificial Intelligence Review*, *56*(2), 865–913.

Thakkar, A., & Lohiya, R. (2023). Fusion of statistical importance for feature selection in Deep Neural Network-based Intrusion Detection System. *Information Fusion*, *90*, 353–363.

Thangavel, K., Shen, Q., & Pethalakshmi, A. (2006). Application of clustering for feature selection based on rough set theory approach. *AIML Journal*, *6*(1), 19–27.

Varchagall, M., & Adaguru Yogegowda, P. (2023). Early detection of liver disorders using hybrid soft computing techniques for optimal feature selection and classification. *Concurrency and Computation: Practice and Experience*, *35*(6), 1.

Varzaneh, Z. A., Hossein, S., Mood, S. E., & Javidi, M. M. (2022). A new hybrid feature selection based on Improved Equilibrium Optimization. *Chemometrics and Intelligent Laboratory Systems*, *228*, 104618.

Wu, S., Xia, S., & Chen, X. (2022). A Novel Space Division Rough Set Model for Feature Selection. In *3D Imaging—Multidimensional Signal Processing and Deep Learning: 3D Images, Graphics and Information Technologies, Volume 1* (pp. 67–75). Springer.

Yao, G., Hu, X., & Wang, G. (2022). A novel ensemble feature selection method by integrating multiple ranking information combined with an SVM ensemble model for enterprise credit risk prediction in the supply chain. *Expert Systems with Applications*, *200*, 117002.

Zhang, J., Wang, Q., Su, Y., Jin, S., Ren, J., Eden, M., & Shen, W. (2022). An accurate and interpretable deep learning model for environmental properties prediction using hybrid molecular representations. *AIChE Journal*, *68*(6), e17634.

Zhu, X., Wang, D., Pedrycz, W., & Li, Z. (2022). Fuzzy Rule-based Local Surrogate Models for Black-box Model Explanation. *IEEE Transactions on Fuzzy Systems*.