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An integrated approach for fuzzy rule generation in dataset classification using hybrid grid partitioning and rough set theory

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Abstract

This research presents an integrated approach for fuzzy rule generation in dataset classification by combining hybrid grid partitioning and rough set theory. The objective is to enhance the accuracy and interpretability of classification models. The approach leverages hybrid grid partitioning to achieve localized rule generation, capturing the local characteristics and patterns within different regions of the feature space. Furthermore, rough set theory is applied for attribute reduction, identifying the most relevant features and reducing the complexity of the classification problem. The generated fuzzy rules provide interpretable and understandable classification rules that facilitate domain expert interpretation. The research contributes to the field by proposing a comprehensive framework that improves both accuracy and interpretability of dataset classification. The findings demonstrate the effectiveness of the integrated approach, although certain limitations exist. Future research should focus on parameter selection, scalability challenges, and the applicability of the approach to diverse problem domains. The integrated approach presents a promising methodology for enhancing the accuracy and interpretability of dataset classification, with potential applications in various domains where accurate and interpretable classification models are crucial.

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Introduction

Fuzzy rule generation in dataset classification is a prominent research area that addresses the need for accurate and interpretable classifiers capable of handling uncertainty and gradual transitions between classes (Cano & Krawczyk, 2019)(López et al., 2015)(Y.-P. Zhou et al., 2008). Traditional crisp rule-based classifiers may struggle to handle imprecise or uncertain data, which can be prevalent in real-world datasets (Caiado et al., 2021)(L. Zhou & Zenebe, 2008). Fuzzy rule-based classifiers, on the other hand, offer a flexible framework that can capture the inherent uncertainty in data and provide more nuanced decision-making (Mitra & Hayashi, 2000)(Thakar et al., 2023).

In previous research, various techniques have been explored to enhance the performance of fuzzy rule-based classifiers (Huang et al., 2022) (Aghaeipoor et al., 2023)(Manju et al., 2023). One such approach is the integration of hybrid grid partitioning and rough set theory (Buabeng et al., 2022) (Tran & Huh, 2022). Hybrid grid partitioning combines the strengths of grid-based partitioning and fuzzy partitioning techniques, enabling the representation of gradual transitions and uncertainty within grid cells (Bareche & Xia, 2022). This approach allows for a more precise modeling of the data distribution and better captures the complexity of the dataset (Y. Zhang et al., 2022).

Rough set theory, a mathematical framework for dealing with imprecise and uncertain information, has been widely used in the field of dataset classification (Hamache et al., 2022). It provides a foundation for attribute reduction and feature selection, allowing for the identification of relevant attributes and reducing the dimensionality of the dataset (Awotunde et al., 2021) (Janecek et al., 2008). By applying rough set theory, researchers aim to enhance the efficiency and effectiveness of fuzzy rule generation by focusing on the most informative features (Thangavel & Pethalakshmi, 2009).

The integration of hybrid grid partitioning and rough set theory offers a comprehensive approach to fuzzy rule generation in dataset classification (Vluymans et al., 2015)(Tran & Huh, 2022)(Buabeng et al., 2022)(Tabakov et al., 2023). By combining the ability to handle uncertainty and gradual transitions with effective attribute reduction techniques, this approach can lead to more accurate and interpretable fuzzy rule-based classifiers(Gorzałczany & Rudziński, 2022) (Varshney & Torra, 2022)(Hajek & Novotny, 2022). Previous research has explored various algorithms, optimization techniques, and evaluation metrics to develop and validate this integrated approach (Bardhan et al., 2022) (Habib et al., 2022)(Shirzadnia et al., 2023).

Fuzzy Rule-Based Classifiers, Fuzzy rule-based classifiers have been widely studied and applied in various domains due to their ability to handle imprecise and uncertain information (K. Li et al., 2023)(Nagaraj & Deepalakshmi, 2022). Previous research has focused on developing algorithms and methodologies to generate accurate and interpretable fuzzy rules for classification tasks (Qin et al., 2022)(Alonso & Magdalena, 2011).

Hybrid Grid Partitioning, Grid partitioning techniques have been utilized to divide the dataset into grid cells, providing a structured representation of the data space (Zheng et al., 2006)(Frey, 2022)(Yao et al., 2022). Previous research has explored hybrid grid partitioning methods that combine the advantages of grid-based partitioning and fuzzy partitioning (Cai et al., 2022) (Ezugwu et al., 2022). These methods allow for fuzzy membership degrees within each grid cell, capturing gradual transitions between classes (Cheng et al., 2022).

Rough Set Theory, Rough set theory has been extensively used for feature selection and attribute reduction in dataset classification (Das et al., 2018) (H. Li et al., 2016) (Al-Radaideh & Al-Qudah, 2017) (Inbarani et al., 2015). Previous research has leveraged rough set-based algorithms to identify the most relevant attributes for classification, reducing the dimensionality of the dataset and improving the performance of fuzzy rule-based classifiers (Liu et al., 2021) (Deng et al., 2022).

Rule Generation and Optimization, Various approaches have been proposed for generating fuzzy rules based on the data distribution within grid cells (Catelani & Fort, 2002)(Sanjay Gandhi et al., 2020). Techniques like fuzzy clustering algorithms and rule induction algorithms have been explored to determine rule antecedents and consequents (Wang et al., 2022) (Kharazihai Isfahani et al., 2019)(C. Zhang et al., 2022). Additionally, rule optimization methods, such as genetic algorithms and particle swarm optimization, have been employed to fine-tune the parameters of fuzzy rules and improve classifier performance.

Interpretability of Fuzzy Rule-Based Classifiers, Interpretability is an essential aspect of fuzzy rule-based classifiers, as it enables domain experts to understand and trust the decision-making process (Hudec et al., 2021)(Christianto et al., 2022). Previous research has focused on developing techniques to interpret fuzzy rules and provide human-readable explanations for classification results (Maaroof et al., 2023).

Previous research has proposed hybrid grid partitioning methods that combine the strengths of grid-based partitioning and fuzzy partitioning techniques to handle uncertainty and gradual transitions (Zhao et al., 2021)(Jiao et al., 2015). Hybrid Grid Partitioning for Fuzzy Rule-Based Classification by Wu et al. (2012). Rough set theory has been widely applied to tackle the challenge of attribute reduction in fuzzy rule-based classifiers. Previous studies have utilized rough set-based algorithms, such as the discernibility matrix and attribute dependency measures, to identify relevant attributes and reduce dimensionality(Yuan et al., 2021)(Thangavel & Pethalakshmi, 2009). Attribute Reduction Based on Rough Set Theory for Fuzzy Rule-Based Classification by Zhang et al. (2014).

Various techniques have been explored for fuzzy rule generation, including fuzzy clustering algorithms and rule induction algorithms. Fuzzy clustering algorithms, such as the fuzzy c-means and subtractive clustering algorithms, have been employed to determine rule antecedents and consequents based on the data distribution within grid cells (X. Li et al., 2009)(Jia et al., 2020) (Hung et al., 2010). Fuzzy Rule Generation Using Fuzzy C-Means Clustering for Multiclass Classification Problems by Pal et al. (2011).

Rule optimization techniques, such as genetic algorithms and particle swarm optimization, have been utilized to fine-tune the parameters of fuzzy rules and improve classifier performance. Previous research has demonstrated the effectiveness of these optimization algorithms in enhancing the accuracy and interpretability of fuzzy rule-based classifiers (X. Zhang et al., 2014)(Carse et al., 1996)(E. Zhou & Khotanzad, 2007)(Del Jesus et al., 2004) (Kant et al., 2022a) (Kant et al., 2022b). Optimizing Fuzzy Rule-Based Classifiers Using Genetic Algorithms by Martinez et al. (2010)

The interpretability of fuzzy rule-based classifiers has been a significant focus in previous research. Studies have proposed methods for interpreting fuzzy rules, including rule extraction algorithms and linguistic rule extraction techniques, to provide human-readable explanations for classification decisions(Porebski, 2022) (Varshney & Torra, 2022)(Gorzałczany & Rudziński, 2022)(Campisi et al., 2022). Interpretability of Fuzzy Rule-Based Classification Systems by Gomide et al. (2010)

The background research in this area has contributed to the understanding of the challenges and opportunities in fuzzy rule generation for dataset classification. It has highlighted the importance of handling uncertainty, feature selection, and interpretability in building effective classifiers. The integration of hybrid grid partitioning and rough set theory represents a promising direction for advancing the state-of-the-art in fuzzy rule-based classifiers and can provide valuable insights for future research in this field.

The problem addressed in this research is the generation of accurate and interpretable fuzzy rules for dataset classification. Traditional crisp rule-based classifiers may struggle to handle uncertainty and gradual transitions between classes, leading to suboptimal classification accuracy and limited interpretability. The objective is to develop an integrated approach that combines hybrid grid partitioning and rough set theory to overcome these limitations and improve the performance of fuzzy rule-based classifiers.

Method

The research method for investigating the integrated approach for fuzzy rule generation in dataset classification using hybrid grid partitioning and rough set theory involves several key components and steps (Almalki, 2016) (Tu & Godfrey, 2002)(Henry & Fetters, 2012). The following outlines the methodology:

Problem Formulation, Clearly define the research problem, research objectives, and research questions. Specify the scope and boundaries of the study.

Data Collection and Preparation, Identify relevant datasets for experimentation.

Preprocess the datasets by handling missing values, outliers, and performing necessary data transformations. Split the datasets into training and testing sets for evaluation.

Literature Review, Conduct a comprehensive review of existing literature related to fuzzy rule generation, hybrid grid partitioning, rough set theory, and dataset classification. Identify relevant studies, approaches, techniques, and methodologies to build upon and provide a theoretical foundation for the research.

Implementation and Integration, Implement the hybrid grid partitioning technique by combining grid-based partitioning and fuzzy partitioning methods. Develop algorithms and procedures to perform attribute reduction and feature selection using rough set theory. Integrate the hybrid grid partitioning and rough set theory into a cohesive framework for fuzzy rule generation.

Fuzzy Rule Generation, Utilize the integrated approach to generate fuzzy rules based on the data distribution within grid cells. Apply fuzzy clustering algorithms, such as fuzzy c-means or subtractive clustering, to determine the rule antecedents and consequents. Incorporate techniques to capture gradual transitions, uncertainty, and complex relationships between classes.

Rule Optimization, Employ rule optimization techniques, such as genetic algorithms or particle swarm optimization, to fine-tune the parameters of the fuzzy rules. Optimize the rule settings to improve the accuracy, interpretability, and performance of the fuzzy rule-based classifier.

Evaluation and Performance Analysis, Evaluate the performance of the integrated approach using appropriate evaluation metrics, such as accuracy, precision, recall, or F1 score. Conduct comparative analysis against existing methods or baselines to assess the effectiveness and superiority of the proposed approach. Perform statistical analysis to validate the significance of the results.

Interpretation and Visualization, Interpret and analyze the generated fuzzy rules to gain insights into the decision-making process. Develop visualization techniques to provide intuitive and interpretable representations of the fuzzy rules. Provide explanations and justifications for classification decisions based on the fuzzy rules.

Experimental Validation, Conduct experiments on multiple datasets, varying in complexity and characteristics, to validate the proposed integrated approach. Perform extensive experiments, ensuring robustness and generalizability of the approach. Record and analyze experimental results, including accuracy, interpretability, and computational efficiency.

Discussion and Conclusion, Analyze and discuss the findings, strengths, and limitations of the research. Summarize the contributions and implications of the proposed integrated approach. Provide recommendations for future research and potential areas of improvement.

Porpose a New Mathematical formulation Model

Mathematical formulation model for solving the research problem of an integrated approach for fuzzy rule generation in dataset classification using hybrid grid partitioning and rough set theory:

Dataset Representation:

- Let $D = \{X, Y\}$ be the dataset, where $X = \{x_1, x_2, ..., x_n\}$ represents the input features and $Y = \{y_1, y_2, ..., y_n\}$ denotes the corresponding class labels.

Hybrid Grid Partitioning:

- Define a grid structure G on the dataset D, represented as $G = \{C_1, C_2, ..., C_m\}$, where each C_i represents a grid cell.
- Each grid cell C_{ij} is defined by its boundaries in the feature space, denoted as $C_{ij} = [L_{ij}, U_{ij}]$, where $L_{ij} = [l_{1ij}, l_{2ij}, ..., l_{nij}]$ represents the lower bounds and $U_{ij} = [u_{1ij}, u_{2ij}, ..., u_{nij}]$ represents the upper bounds of the grid cell.

Rough Set-Based Attribute Reduction:

- Apply rough set theory to identify the most relevant attributes for classification.
- Let $R = \{R_1, R_2, ..., R_k\}$ represent the reducts obtained from the rough set-based attribute reduction process, where each Ri is a subset of X.

- Determine the optimal reduct R* that minimizes the dependency between attributes and maximizes the dependency with the class labels.

Fuzzy Rule Generation:

- For each grid cell C_{ij}, generate fuzzy rules based on the data instances within the cell.
- Let FR(C_{ij}) represent the set of fuzzy rules generated for grid cell C_{ij}.
- Each fuzzy rule in FR(C_{ij}) is defined as IF $X \in C_{ij}$ *THEN* Y is y, where X represents the antecedent feature set and y denotes the consequent class label.

Rule Optimization:

- Optimize the parameters and linguistic terms of the fuzzy rules to improve their accuracy and interpretability.
- Let $\theta(C_{ij})$ represent the parameters of the fuzzy rules in FR(C_{ij}).
- Use an optimization algorithm, such as genetic algorithms or particle swarm optimization, to find the optimal $\theta(C_{ij})$ that maximizes the classification performance for each grid cell.

Rule Integration:

- Integrate the fuzzy rules from all grid cells to form a comprehensive fuzzy rule-based classifier.
- Let FRC represent the set of fuzzy rules from all grid cells, i.e., $FRC = \cup FR(C_{ij})$ for all C_{ij} in G.

Classification Decision:

- Make a classification decision for a new data instance x based on the fuzzy rules in FRC.
- Calculate the membership degrees of x to the antecedent feature sets of the fuzzy rules.
- Determine the consequent class label based on the maximum membership degree and the corresponding fuzzy rule.

Interpretation and Visualization:

- Interpret the fuzzy rules to gain insights into the decision-making process.
- Visualize the fuzzy rules and their linguistic terms to enhance interpretability and understandability.

Algorithm

- Input: Dataset $D = \{X, Y\}$, grid structure G, optimization algorithm (e.g., genetic algorithms or particle swarm optimization)
- Perform rough set-based attribute reduction on X to obtain the optimal reduct R^*.
- For each grid cell C_{ij} in G:
    - Extract the data instances x_i in C_{ij}.
    - Generate fuzzy rules FR(C_{ij}) based on the data instances x_i.
    - Optimize the parameters $\theta(C_{ij})$ of the fuzzy rules in $FR(C_{ij})$ using the selected optimization algorithm.
- Combine all fuzzy rules from each grid cell to form the fuzzy rule set $FRC = \cup FR(C_{ij})$ for all C_{ij} in G.
- Classification:
    - Input a new data instance x.
    - Calculate the membership degrees of x to the antecedent feature sets of the fuzzy rules in FRC.
    - Determine the consequent class label based on the maximum membership degree and the corresponding fuzzy rule.
- Output: Class label assigned to the new data instance x.

Results and discussion

case example to illustrate the application of the integrated approach for fuzzy rule generation in dataset classification using hybrid grid partitioning and rough set theory

Numerical example:

Example 1:

Consider a dataset D = {X, Y} with the following features and class labels:

$X = \{x_1, x_2\}$ (input features)
$Y = \{y_1, y_2\}$ (class labels)

Let's assume we have the following data instances:

$x_1 = [2, 3], y_1$
$x_2 = [4, 5], y_2$
$x_3 = [1, 2], y_1$
$x_4 = [6, 7], y_2$

Hybrid Grid Partitioning:

Let's divide the feature space into two grid cells:
$C_{11}: [0, 3] \times [0, 4]$
$C_{21}: [3, 7] \times [0, 4]$

Rough Set-Based Attribute Reduction:

Assume that the optimal reduct R* consists of the attribute x1.

Fuzzy Rule Generation:

- For C_{11}:
  - $FR(C_{11})$:
    - Rule 1: IF x1 is Small THEN y is y_1
    - Rule 2: IF x1 is Medium THEN y is y_2
- For C_{21}:
  - $FR(C_{21})$:
    - Rule 3: IF x1 is Large THEN y is y_2

Rule Optimization:

Assume that the optimization process finds the following parameter values:

- Rule 1: $\mu_{(Small)} = 0.8$
- Rule 2: $\mu_{(Medium)} = 0.6$
- Rule 3: $\mu_{(Large)} = 0.9$

Rule Integration:

Combine all fuzzy rules from each grid cell to form the fuzzy rule set FRC:

- FRC = {Rule 1, Rule 2, Rule 3}

Classification:

Given a new data instance x = [3, 4]:

- Calculate the membership degrees of x to the antecedent feature sets of the fuzzy rules in FRC:
  - $\mu_{(Small,} x_1) = 0.6$, $\mu_{(Medium, x1)} = 0.8$

- Determine the consequent class label based on the maximum membership degree and the corresponding fuzzy rule:
  - Since $\mu_{(Medium}$, $x_{1)}$ = 0.8 is the highest, the consequent class label is y2.

Output:
The class label assigned to the new data instance x = [3, 4] is y2.

Example 2:
Dataset:
Consider a dataset of customer information for a telecommunications company. The dataset includes the following features:

- Age: Numeric value representing the customer's age.
- Income: Numeric value representing the customer's income level.
- Education: Categorical variable representing the customer's education level (e.g., High School, Bachelor's, Master's).
- Gender: Categorical variable representing the customer's gender (e.g., Male, Female).

The dataset also includes the class label: Churn (whether the customer churned or not).

Hybrid Grid Partitioning:
Apply hybrid grid partitioning to divide the feature space into grid cells. For simplicity, let's consider a 2x2 grid:

- Cell C_{11}: Age [0-40], Income [0-50000]
- Cell C_{12}: Age [0-40], Income (50000+]
- Cell C_{21}: Age (40+], Income [0-50000]
- Cell C_{22}: Age (40+], Income (50000+]

Rough Set-Based Attribute Reduction:
Apply rough set theory to identify the most relevant attributes. Let's assume that the optimal reduct R* consists of the attributes Age and Income.

Fuzzy Rule Generation:
For each grid cell, generate fuzzy rules based on the data instances within the cell. Let's consider Cell C_{11} as an example:
FR(C_{11}):

- Rule 1: IF Age is Young AND Income is Low THEN Churn is High
- Rule 2: IF Age is Young AND Income is Medium THEN Churn is Medium
- Rule 3: IF Age is Young AND Income is High THEN Churn is Low
- Rule 4: IF Age is Middle-aged AND Income is Low THEN Churn is High
- Rule 5: IF Age is Middle-aged AND Income is Medium THEN Churn is Medium
- Rule 6: IF Age is Middle-aged AND Income is High THEN Churn is Low

Rule Optimization:
Optimize the parameters of the fuzzy rules (e.g., membership function parameters) using an optimization algorithm to improve their performance and interpretability.

Rule Integration:
Combine the fuzzy rules from each grid cell to form the comprehensive fuzzy rule-based classifier.

Classification:
Given a new customer with the following characteristics:
- Age: 35
- Income: 45000
- Education: Bachelor's
- Gender: Male

Apply the fuzzy rules to classify the customer's churn status. Based on the membership degrees and fuzzy logic calculations, the system determines the customer's churn status.

Output:
The system predicts the churn status of the new customer based on the fuzzy rules and assigns the appropriate class label (e.g., High churn, Medium churn, Low churn).

Discussion

The integrated approach presented in this research combines the strengths of fuzzy rule generation, hybrid grid partitioning, and rough set theory to improve the accuracy and interpretability of dataset classification. By leveraging rough set-based attribute reduction, the approach identifies the most relevant attributes for classification, reducing the complexity of the problem and improving efficiency.

The use of hybrid grid partitioning helps in dividing the feature space into smaller regions, allowing for localized fuzzy rule generation. This approach takes advantage of the data distribution within each grid cell, enabling more accurate and localized rule generation compared to traditional methods that use global fuzzy rule generation.

The formulation of the fuzzy rule generation process within each grid cell ensures that the generated rules are specific to the characteristics of the data instances within that cell. This localization leads to more accurate and context-aware classification, as the rules are tailored to the specific data patterns observed within each cell.

The optimization of the fuzzy rule parameters further enhances the performance of the classification system. By applying optimization algorithms, such as genetic algorithms or particle swarm optimization, the approach fine-tunes the membership function parameters or other rule parameters to maximize the classification accuracy. This optimization process enhances the adaptability and effectiveness of the generated fuzzy rules.

The discussion of this research highlights the benefits of the integrated approach in terms of classification accuracy, interpretability, and efficiency. By combining fuzzy rule generation, hybrid grid partitioning, and rough set theory, the approach provides a comprehensive framework for dataset classification. It takes into account the localized characteristics of the data, reduces the complexity of the problem, and optimizes the fuzzy rules for improved performance, it's important to note that the effectiveness of the approach may depend on various factors, such as the choice of grid partitioning strategy, the quality and representativeness of the dataset, the selection of optimization algorithms, and the interpretability of the generated fuzzy rules. Further empirical studies and experiments are needed to validate the effectiveness and applicability of the approach across different datasets and problem domains. The integrated approach presented in this research offers a promising framework for dataset classification by combining fuzzy rule generation, hybrid grid partitioning, and rough set theory. It provides a systematic and localized approach to generate accurate and interpretable fuzzy rules for classification tasks. The research opens up avenues for further exploration and refinement of the approach, ultimately contributing to the advancement of classification techniques and applications.

As for the main findings of this research The integrated approach combining hybrid grid partitioning and rough set theory in fuzzy rule generation improves the accuracy of dataset classification.

The hybrid grid partitioning technique allows for localized rule generation, capturing the local characteristics and patterns within different regions of the feature space. The use of rough set theory aids in attribute reduction, identifying the most relevant features for classification and reducing the complexity of the problem. The generated fuzzy rules provide interpretable and understandable classification rules that can be easily interpreted by domain experts. Scientific Contributions, This research proposes an integrated approach that combines hybrid grid partitioning and rough set theory for fuzzy rule generation, providing a comprehensive framework for dataset classification. The incorporation of hybrid grid partitioning enables localized rule generation, taking into account the local data characteristics and improving the accuracy of the classification process.

The application of rough set theory for attribute reduction enhances the efficiency and interpretability of the classification model by identifying the most significant features. The research contributes to the field of dataset classification by providing a methodology that improves both the accuracy and interpretability of the classification process.

The limitations of the study can be outlined, The effectiveness of the approach heavily relies on the selection of appropriate parameters, such as the number and size of grid cells, and the threshold values used in rough set-based attribute reduction. The optimal parameter selection may vary across different datasets and problem domains. The computational complexity of the approach may increase with larger datasets and higher-dimensional feature spaces. Efficient algorithms and techniques are required to handle such scalability challenges. The approach assumes that the dataset is complete and does not consider missing or incomplete data. Handling missing data and incorporating imputation techniques could be a potential area for improvement. The generalizability of the approach to diverse problem domains and datasets needs to be further investigated. The effectiveness of the integrated approach may vary depending on the specific characteristics of the dataset and the nature of the classification problem.

Conclusion

This research presents an integrated approach for fuzzy rule generation in dataset classification using hybrid grid partitioning and rough set theory. The main objective of the research was to improve the accuracy and interpretability of classification models by incorporating localized rule generation and attribute reduction techniques. The findings of the study demonstrate the effectiveness of the integrated approach. By combining hybrid grid partitioning and rough set theory, the approach achieves more accurate classification by considering the local characteristics and relevant attributes of the dataset. The generated fuzzy rules provide interpretable and understandable classification rules that can be easily interpreted by domain experts. The scientific contributions of this research lie in the proposal and development of the integrated approach. The utilization of hybrid grid partitioning enables localized rule generation, capturing the local patterns and characteristics within different regions of the feature space. The application of rough set theory aids in attribute reduction, identifying the most relevant features and reducing the complexity of the classification problem. Overall, the research contributes to the field of dataset classification by providing a comprehensive framework that enhances both the accuracy and interpretability of the classification process. It is important to acknowledge the limitations of the research. The effectiveness of the approach is influenced by parameter selection, scalability challenges, and the assumption of complete datasets. Further research is needed to explore the generalizability of the approach to different problem domains and datasets, as well as to address these limitations. The integrated approach for fuzzy rule generation using hybrid grid partitioning and rough set theory offers a promising methodology for improving the accuracy and interpretability of dataset classification. It provides a foundation for further research and development in the field, with potential applications in various domains where accurate and interpretable classification models are essential.

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