Genetic Optimization of Fuzzy Inference Systems for Enhanced Interpretability in Machine Learning

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ACM Reference Format:
Rutvi Khamar. 2024. Genetic Optimization of Fuzzy Inference Systems for Enhanced Interpretability in Machine Learning.

1 INTRODUCTION

Interpretable artificial intelligence (AI), also known as explainable AI, is indispensable in establishing trustable AI, with substantial implications for human well-being. However, the majority of existing research in this area has centered on designing complex and sophisticated methods, regardless of their interpretability. Consequently, the main prerequisite for implementing trustworthy AI in medical domains has not been met. Scientists have developed various explanation methods for interpretable AI. Among these methods, fuzzy rules embedded in a fuzzy inference system (FIS) have emerged as a novel and powerful tool to bridge the communication gap between humans and advanced AI machines.[2]

In the realm of machine learning, there exists a trade-off between model interpretability and predictive performance. While traditional machine learning algorithms offer robust predictive capabilities, their complex structures often hinder interpretability. On the other hand, fuzzy inference systems provide transparent decision-making processes but may lack the predictive power of their counterparts.

This project aims to bridge this gap by optimizing fuzzy inference systems using genetic algorithm. The primary goal is to enhance the interpretability of traditional machine learning models while preserving or even improving their predictive accuracy. By employing genetic algorithms to optimize membership functions of fuzzy systems, the project seeks to uncover interpretable models that maintain competitive performance across various domains

2 RELATED WORK

This section presents a representative overview of related works that includes current methods for integrating fuzzy logic to achieve greater interpretability.

Towards Complex Regional Pain Syndrome (CRPS) Monitoring and Management Using an AI Powered Mobile Application: [3]
They developed a prototype mobile application, powered by an Artificial Intelligence (AI) algorithm called the Fuzzy Inference System (FIS), to track and manage the onset of CRPS symptoms for determining an appropriate exercise for the patient. The FIS was created using MATLAB's Fuzzy Logic Designer toolbox. They suggested an improvement in their model by implementing genetic algorithm to automatically tune membership functions.

A Way Towards Explainable AI Using Neuro-Fuzzy System [1]
In this paper a new model of XAI is introduced, in which a Neuro-fuzzy hybrid model is present. This new concept idea can be used to describe the working system of any ML model.The basic idea is to first solve any problem using interested machine learning model say Model1(FIS). This model takes input and produce some output also called decision in AI. Now this decision (output of model1) is used as input in ANFIS model. The role of AFIS model is to find rules which are responsible for Model1 to take any decision.

Fuzzy Inference Systems Optimization [5]
This paper outlines a study comparing optimization methods for fuzzy inference systems. The methods compared include genetic algorithms, particle swarm optimization, and simulated annealing. The study observed that the performance of each optimization technique within the fuzzy inference system classification varied depending on the context.

Fuzzy inference system with interpretable fuzzy rules: Advancing explainable artificial intelligence for disease diagnosis—A comprehensive review [2]
This research paper provides a fundamental understanding of interpretability and fuzzy rules, conducts comparative analyses of the use of fuzzy rules and other explanation methods in handling three major types of multi-modal data (i.e., sequence signals, medical images, and tabular data), and offers insights into appropriate fuzzy rule application scenarios and recommendations for future research.

3 APPROACH

3.1 Initial concrete idea

The proposed approach harnesses genetic algorithms to refine membership functions within fuzzy inference systems, offering a solution to the limitations of current techniques in machine learning interpretability. This approach focuses on the following key aspects:

Membership Function Refinement: Genetic algorithm is employed to iteratively adjust the parameters of membership functions within the fuzzy inference system. By evolving these functions, the model adapts to the underlying data distribution, enhancing both interpretability and predictive accuracy. Trade-off Optimization: The approach aims to strike a balance between model interpretability and predictive performance. Through the genetic optimization of membership functions, the fuzzy inference system is fine-tuned to generate transparent decision boundaries while maintaining competitive accuracy. By leveraging genetic algorithms to refine membership functions within fuzzy inference systems, this approach presents a viable strategy for enhancing interpretability in machine learning models. Through systematic optimization, the proposed framework strives to deliver transparent and accurate models capable of informing decision-making processes in complex real-world scenarios.

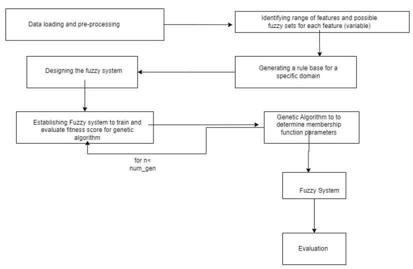

Figure 1: Methodology used

Figure.1 shows the whole methodolgy followed for buiding the algorithm. The basic Fuzzy inference system is builts using the following pseudocode[4]:
- Step 1: Develop membership functions for both input and output features, utilizing a Genetic Algorithm to explore all the possible functions and select the most optimal ones.Eg- Temperature will have 3 MF (low, mid, high)
- Step 2: Utilize an IF-Then structure to create linguistic fuzzy rules. Establish fuzzy rules based on the membership functions developed in Step 1.(Eg- If Temperature is low Then Output)
- Step 3:Fuzzifying the inputs using the fuzzy membership functions.
- Step 4: Determine firing strengths of activated rules based on the input training data
- Step 5: Defuzzify the output, using centroid of gravity.

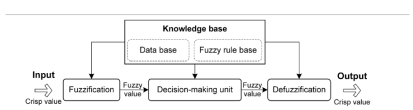

Figure 2: Fuzzy System Architecture

Genetic algorithm is employed to encode a bitstring of sufficient length to represent all membership function parameters, enabling the generation of diverse membership functions. Fitness evaluation within the population involves applying these parameter values to the fuzzy inference system and assessing their performance on the training dataset. This iterative process continues for the specified number of generations.

Pseudocode:
1. Initialize Population: - Create an initial population of candidate solutions, each represented by a chromosome encoding membership function parameters.
2. Evaluate Fitness: - Assess the fitness of each chromosome by using the fuzzy inference system.
3. Repeat for a Fixed Number of Generations:
a. Selection: - Select parents for the next generation based on their fitness.
b. Crossover: - Combine pairs of parents to produce offspring through crossover.
c. Mutation: - Introduce random changes (mutation) to the offspring.
d. Evaluate Fitness: - Assess the fitness of the mutated offspring.
4. Output: - Select the best-performing chromosome from the final population.
- Decode the chromosome to obtain optimized parameters for membership functions.Use these parameters in the fuzzy inference system for predictions.

4 EMPIRICAL EVALUATION

4.1 Evaluation criteria

The evaluation will focus on several key aspects. First, we'll compare the predictive accuracy of the optimized fuzzy inference system with neural networks. Next, we'll assess the interpretability of both models, considering the ease of understanding and transparency of their decision-making processes.

4.2 Experimental data and procedures

Two datasets were employed: the Iris dataset with four features and the Wine Quality dataset with several features.

For the Iris dataset, preprocessing involved converting string features to floats and defining feature value ranges for membership function parameters. Hypotheses for the genetic algorithm were formulated based on these ranges, with constraints applied to ensure feasibility. A rule base was established by analyzing the dataset. It has been shown that a system designed using such represented knowledge performs comparably to a system designed by experts and performs slightly better in terms of completeness of knowledge representation than a system designed using non-monotonic logic.[2]

Regarding the Wine Quality dataset, only the top four features were selected due to the computational limitations in processing lengthy hypotheses. Preprocessing included categorizing the output variable and defining feature value ranges. Hypotheses were constructed similarly to the Iris dataset.

Iris Dataset: (Feature - Fuzzy set)

- Sepal length - (short, long)
- Sepal width - (narrow, wide)
- Petal length - (short, long)
- Petal width - (narrow, wide)
- Iris (Target feature) - (Iris-Setosa, Iris-Versicolour, Iris-Virginica)

Wine Quality Dataset: (Feature - Fuzzy set)

- Alcohol - (low, high)
- Sulphates - (low, high)

- Volatile acidity - (low, high)
- Chlorides - (low, high)
- Quality (Target feature) - (Poor, Fair, Excellent)

4.3 Results and Analysis

After getting the membership functions for all the features using the genetic algorithm, as shown in Figure 3 and 4, we use those membership function paraemeters obtained, in the Fuzzy inference system for evaluation.

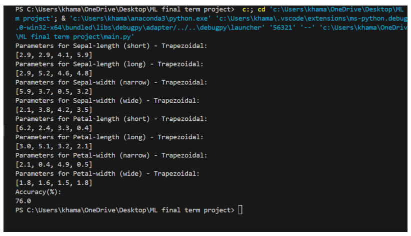

Figure 3: Membership function Parameters (Iris)

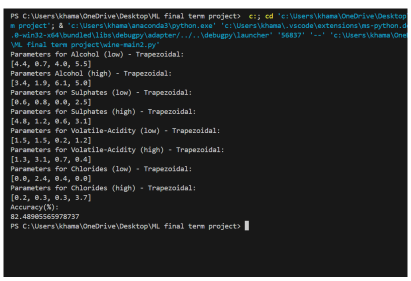

Figure 4: Membership function Parameters (Wine-quality)

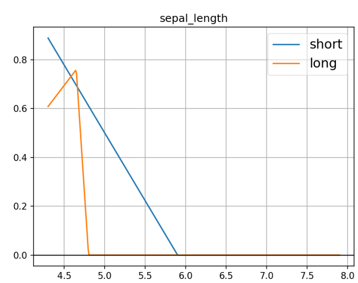

Figure 5: Membership function (f1)

The FIS optimized with genetic algorithm achieved an accuracy of 76% on the Iris dataset and 82.48% on the Wine-quality dataset. In comparison, the neural network achieved significantly higher accuracies of 99% on the Iris dataset and 82.48% on the Wine-quality dataset. Overall, the neural network outperformed the FIS optimized with genetic algorithm in terms of accuracy on the Iris dataset. However, both models achieved similar accuracies on the Wine-quality dataset. Therefore, while the neural network excels

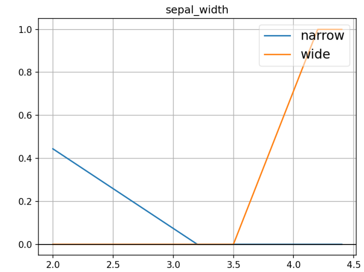

Figure 6: Membership function (f2)

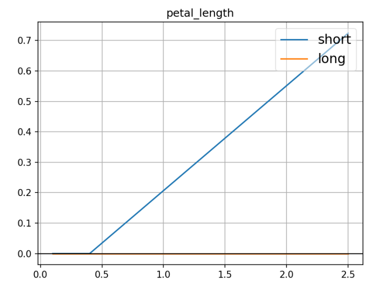

Figure 7: Membership function (f3)

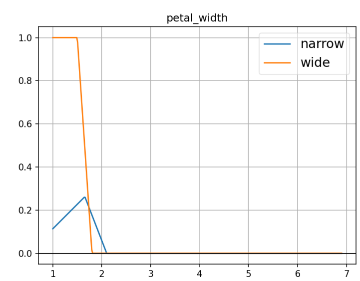

Figure 8: Membership function (f4)

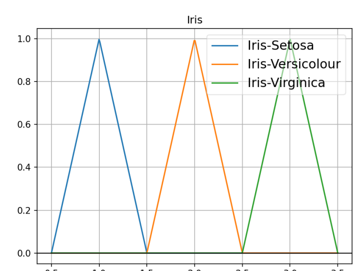

Figure 9: Membership function (Target)

in accuracy, the FIS optimized with genetic algorithm provides a

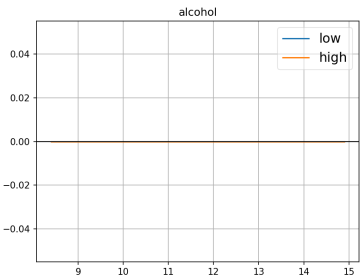

Figure 10: Membership function (f1)

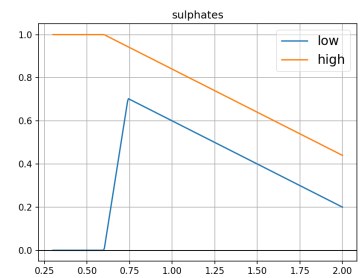

Figure 11: Membership function (f2)

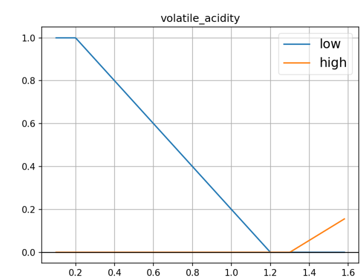

Figure 12: Membership function (f3)

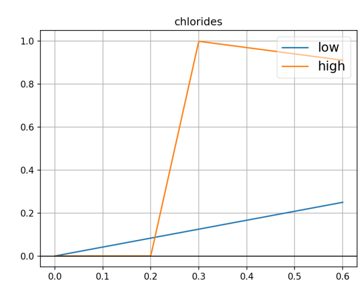

Figure 13: Membership function (f4)

competitive alternative, especially considering its interpretability and transparency.

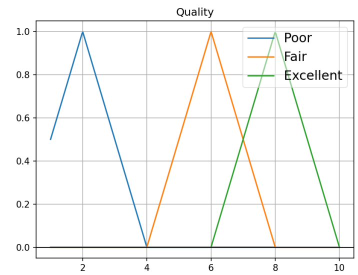

Figure 14: Membership function (Target)

FIS Optimized with Genetic Algorithm: Iris Dataset: Achieved an accuracy of 76%. Wine-quality Dataset: Achieved an accuracy of 82.48%. Neural Network: Iris Dataset: Achieved an accuracy of 99%. Wine-quality Dataset: Achieved an accuracy of 82.48%.
Considering interpretability,
FIS Optimized with Genetic Algorithm:
Fuzzy Inference Systems offer high interpretability. As membership function graphs(as shown in the figures above) provide a clear visualization of how input variables are mapped to linguistic labels and how these labels are combined to make decisions. The optimization process using genetic algorithms improves the performance of the FIS while preserving its interpretability.
Neural Network:
Neural networks are often considered black-box models, meaning they lack interpretability compared to systems like FIS. While neural networks can achieve high accuracy, understanding the decision-making process is challenging due to the complex interactions between neurons in hidden layers. Interpretability is limited, making it difficult to explain why a certain prediction was made.

Algorithm	Accuracy
FIS optimized with genetic Algorithm(Iris)	76%
FIS optimized with genetic algorithm (Wine-quality)	82.48%
Neural network(Iris)	99%
Neural network (Wine quality)m	82.48%

Table 1: Performance comparison

5 CONCLUSION

The Fuzzy Inference System optimized with genetic algorithm offers a trade-off between accuracy and interpretability. While neural networks achieve higher accuracy, they sacrifice interpretability. Depending on the specific requirements of the application, practitioners may prefer the FIS for its transparency and explainability, especially when interpretability is crucial for decision-making and understanding the model's behavior.

One limitation of the Fuzzy Inference System (FIS) optimized with genetic algorithm is the need to generate a rule base beforehand. This process requires expert advice or data analysis, which can be time-consuming and may introduce bias. This additional step adds complexity to the model development process.

An improvement to the FIS could involve implementing the ANFIS(Adaptive Neuro-Fuzzy Inference System). As it surpasses the limitations of the fuzzy inference systems by integrating neural networks with fuzzy logic. It excels in learning from data, automatically generating rules, and efficiently optimizing parameters, making it adept at handling nonlinear relationships. ANFIS's ability to adapt, learn, and optimize parameters based on data enables it to model complex systems more effectively than traditional FIS systems, thus offering improved performance and versatility in various applications.[1]

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