

OPTIMIZING EXPERT SYSTEMS USING GENETIC ALGORITHMS: A PRACTICAL AI-BASED APPROACH

Wesam M. Ahmed¹, Rabee H. Gareeb²

¹ Surman College of Science & Technology, Libya

² Sabratha University, Economy College, Libya

wesam_ahmed@scst.edu.ly¹

rabee@sabu.edu.ly²

Abstract

Expert systems are computer programs that mimic human reasoning to make decisions in complex domains. These systems rely heavily on a predefined set of rules that can be difficult to optimize manually. Genetic Algorithms (GAs), inspired by natural selection, have shown great promise in solving complex optimization problems. This study explores the integration of GAs into expert systems to automatically evolve and improve their rule base. A prototype expert system for medical diagnosis was developed, and GA was used to optimize rule weighting and selection. Results demonstrated significant improvement in decision accuracy and system robustness. The findings suggest that GAs can enhance expert systems' adaptability and performance, providing a strong basis for hybrid AI systems.

Submitted: 17/07/2025

Accepted: 26/08/2025

1. Introduction

Expert systems are one of the earliest forms of Artificial Intelligence (AI), designed to simulate the decision-making capabilities of human experts in narrow domains such as medical diagnosis, legal reasoning, or mechanical troubleshooting (Jackson, 1998). These systems consist of three main components: a knowledge base, an inference engine, and a user interface. Among these, the knowledge base—composed of rules or heuristics—plays a central role in guiding decisions. However, crafting and fine-tuning these rules is a labor-intensive and error-prone process.

Traditional rule development often depends on domain experts, which limits scalability and adaptability. Moreover, static rule sets lack the flexibility to respond to changing data or environments. This challenge has prompted researchers to explore machine learning techniques for dynamic rule generation and optimization. One such technique is the Genetic Algorithm (GA), an evolutionary algorithm that simulates the process of natural selection to evolve solutions over time (Holland, 1975).

GAs have been successfully applied in various AI subfields, including neural network training, scheduling, and optimization tasks (Mitchell, 1998). Their population-based search and stochastic behavior make them well-suited for evolving rule-based systems. In this study, we investigate how GAs can be used to enhance expert systems by automatically evolving a better-performing rule set. A practical expert system for medical diagnosis is implemented, where GA is used to optimize rule selection and weighting. The results are analyzed to evaluate the improvements in classification accuracy and inference efficiency.

2. Background and Literature Review

Expert systems gained popularity in the 1980s as a way to encapsulate expert-level knowledge in rule-based formats (Durkin, 1994). Despite their success, they often struggle with limitations in scalability and adaptability. This is where Genetic Algorithms provide a compelling alternative.

GAs was first introduced by John Holland (1975) as a method of problem solving inspired by natural evolution. A typical GA operates by encoding potential solutions as chromosomes and evolving them through selection, crossover, and mutation. These algorithms have found applications in domains such as robotics, data mining, and AI (Goldberg, 1989).

In recent years, researchers have explored the use of GAs for rule extraction, rule pruning, and optimization in expert systems. For instance, Li and Li (2011) applied a GA to improve rule selection in a fault diagnosis expert system, resulting in enhanced accuracy. Similarly, Ravi and Prasad (2010) demonstrated that using GAs to weight rules in a fuzzy expert system improved decision-making performance in medical applications.

3. Methodology

To evaluate the effectiveness of Genetic Algorithms in optimizing expert systems, we developed a prototype expert system in the medical domain, targeting basic diagnostic decisions based on patient symptoms.

3.1 System Architecture

- Knowledge Base: Initially populated with 50 rules derived from domain expert consultation and medical literature.
- Inference Engine: Forward chaining mechanism used to infer conclusions.
- Rule Encoding: Each rule is represented as a binary string where '1' indicates rule activation.
- GA Operators:
 - Selection: Roulette Wheel Selection
 - Crossover: Single-point crossover with probability 0.7
 - Mutation: Bit-flip mutation with rate 0.01
- Fitness Function: Accuracy of diagnosis based on a labeled validation dataset

3.2 Dataset

A synthetic dataset of 500 patient cases was generated based on symptom-diagnosis mappings. The dataset was divided into 70% training, 15% validation, and 15% testing.

3.3 Implementation

The system was implemented in Python using the DEAP library for GA operations. The expert system and rule base were coded manually to simulate the inference process.

4. Results

After 100 generations, the GA-optimized rule set achieved a classification accuracy of 91.2% on the test dataset, compared to 82.4% using the original manually tuned rule base. Additionally, rule redundancy was reduced by 35%, and average inference time per case improved by 18%.

The results suggest that GAs effectively prune irrelevant or conflicting rules and prioritize high-impact rules for decision-making. The optimized system showed better generalization and robustness, especially on unseen data.

5. Discussion

These findings demonstrate the practical viability of integrating GAs with expert systems. Unlike traditional tuning, which relies heavily on domain expertise, GAs automate the search for optimal rule combinations. This not only enhances accuracy but also reduces manual overhead.

However, GA performance depends on parameter tuning, such as population size, mutation rate, and crossover strategy. Moreover, the approach may not scale well with extremely large rule bases without additional improvements like parallel processing or hybrid models.

6. Conclusion and Future Work

This paper presented a practical approach for optimizing expert systems using Genetic Algorithms. The integration led to substantial improvements in accuracy, rule compactness, and inference speed. This research supports the notion that GAs can serve as powerful tools for enhancing traditional AI systems.

Future work may explore hybrid models that combine GAs with reinforcement learning or deep learning to create more adaptive expert systems. Another direction involves applying this framework to real-world datasets in more complex domains such as oncology or cardiology.

References

- [1] Durkin, J. (1994). *Expert systems: Design and development*. Macmillan Publishing Company.
- [2] Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison-Wesley.
- [3] Holland, J. H. (1975). *Adaptation in Natural and Artificial Systems*. University of Michigan Press.
- [4] Jackson, P. (1998). *Introduction to Expert Systems* (3rd ed.). Addison-Wesley.
- [5] Li, Y., & Li, X. (2011). Rule optimization in fault diagnosis expert systems using genetic algorithms. *Expert Systems with Applications*, 38(8), 10204-10210.
- [6] Mitchell, M. (1998). *An Introduction to Genetic Algorithms*. MIT Press.
- [7] Ravi, V., & Prasad, G. (2010). Decision support in healthcare using fuzzy expert systems and genetic algorithms. *Applied Soft Computing*, 10(1), 189-197.