SELECTION AND PROMOTION OF RURAL REVITALIZATION PATH MODE INCORPORATING FUZZY DYNAMIC PLANNING

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SUMMARY

Rural revitalization refers to efforts aimed at renewing and invigorating rural communities to enhance their economic, social, and environmental well-being. To promote the appropriate development in rural revitalization it is necessary to select and promote the appropriate scheme with effective planning, this paper presented effective rural revitalization strategies with the advanced methodology of Genetic Ant Swarm Fuzzy (GAsF), to assess and optimize interventions across various dimensions. The constructed GAsF model implementation of the genetic algorithm-based ant swarm optimization the key features related to the revitalization are estimated. The estimated features are categorized with the fuzzy dynamic planning model for the classification of the program in rural revitalization with the path model implementation in the fuzzy dynamic planning system. Through the computed features classification is performed for the estimation of the features in the programs. Results stated that strategies such as the "Ecotourism Development Strategy" and the "Community Empowerment Program" as particularly promising, demonstrating strong performance in economic, social, and environmental dimensions. Simulation analysis demonstrated that the propose GAsF model achieved the classification accuracy of 0.98 with significant green development values. Through the fuzzy dynamic modelling the GAsF optimize the best fitness value for the ecotourism development value of 0.93.

KEYWORDS

Fuzzy dynamic model, Path mode estimation, Genetic algorithm, Rural revitalization, Strategies

NOMENCLATURE

AI	Artificial Intelligence
GAsF	Genetic Ant Swarm Fuzzy
ACO	Ant Colony Optimization
GA	Genetic Algorithm

1. INTRODUCTION

Deep learning represents a subset of artificial intelligence (AI) that involves the use of neural networks to process and analyze vast amounts of data, often with minimal human intervention [1]. Unlike traditional machine learning approaches, deep learning algorithms are capable of automatically learning hierarchical representations of data, enabling them to identify intricate patterns and make complex decisions [2]. In rural revitalization efforts, deep learning plays a pivotal role by unlocking valuable insights from diverse sources of information such as satellite imagery, sensor data, and demographic statistics [3]. For instance, in agriculture, deep learning algorithms can analyze crop health indicators from satellite images to optimize irrigation schedules or detect early signs of pest infestations [4]. Similarly, in healthcare, deep learning models can assist in diagnosing diseases or predicting patient outcomes based on medical imaging or electronic health records [5]. By harnessing the power of deep learning, rural communities can leverage data-driven approaches to address pressing challenges and capitalize on emerging opportunities, ultimately contributing to their sustainable development and revitalization [6].

Rural revitalization efforts are increasingly turning to deep learning technologies to address challenges and unlock opportunities in these often-overlooked communities [7]. Deep learning, a subset of artificial intelligence (AI) that mimics the workings of the human brain to process data and make decisions, holds promise for rural areas in various domains [8]. For instance, in agriculture, deep learning algorithms can analyze vast amounts of data from sensors, drones, and satellites to optimize crop yields, manage resources efficiently, and mitigate risks such as pests and diseases [9-12]. Moreover, in healthcare, these technologies can enhance diagnostics and treatment planning, especially in regions with limited access to healthcare professionals [13]. Additionally, deep learning-powered systems can improve infrastructure management, transportation efficiency, and environmental monitoring, contributing to overall development and sustainability in rural areas [14]. By harnessing the potential of deep learning, rural communities can overcome longstanding challenges and thrive in the modern era [15]. However,

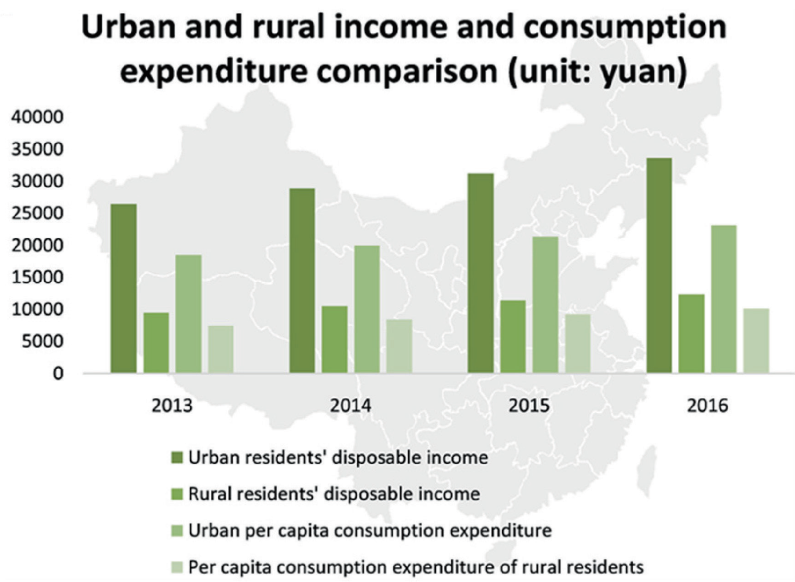

Figure 1. Rural revitalization in China (Source: Scientific research)

to ensure equitable access to technology and prioritize community involvement to maximize the benefits of these innovations for all residents [16]. Figure 1 illustrated the rural revitalization model in China is presented.

Path Mode is a strategic planning methodology that emphasizes iterative and adaptive pathways toward achieving sustainable development goals [17]. Unlike traditional linear planning approaches, Path Mode recognizes the dynamic and complex nature of development processes, particularly in rural contexts. It involves continuous assessment, learning, and adjustment of strategies based on evolving circumstances and feedback mechanisms [18]. In rural revitalization, Path Mode provides a framework for stakeholders to navigate the diverse and interconnected challenges faced by rural communities, such as economic stagnation, infrastructure deficiencies, and social disparities. By adopting a Path Mode approach, planners can engage with local stakeholders to co-create tailored solutions that address specific needs and leverage local assets and resources [19]. Moreover, Path Mode encourages experimentation and innovation, allowing for the exploration of alternative pathways to development and the integration of new technologies and approaches, such as deep learning and data analytics [20]. Through its flexible and adaptive nature, Path Mode empowers rural communities to chart their course towards sustainable revitalization, fostering resilience and inclusive growth along the way.

Promotion of Rural Revitalization Path Mode for planning signifies a strategic shift towards more adaptive and inclusive approaches in addressing the multifaceted challenges confronting rural communities [21]. By advocating for the adoption of Path Mode, planners and policymakers are endorsing a methodology that recognizes the complexity and unique dynamics of rural development processes. Path Mode prioritizes community engagement, iterative planning, and data-driven decision-making, allowing stakeholders to co-create strategies that are responsive to local contexts and aspirations [22]. Through targeted promotion efforts, awareness about the benefits of Path Mode can be raised among diverse stakeholders, including government agencies, non-profit organizations, and local communities. By highlighting success stories and best practices, promotion efforts can showcase the potential of Path Mode to catalyze positive change and foster sustainable revitalization in rural areas. Moreover, capacity-building initiatives, such as training programs and knowledge-sharing platforms, can equip stakeholders with the necessary skills and tools to effectively implement Path Mode principles in their planning processes. Ultimately, by promoting Rural Revitalization Path Mode, planners can empower rural communities to chart their path towards a more prosperous, resilient, and inclusive future.

The paper proposed Genetic Ant Swarm Fuzzy (GAsF) model for the dynamic planning for the rural revitalization. The proposed model uses the dynamic planning of resources with the revitalization of rural area in China. The proposed GAsF model uses the ant swarm optimization with the estimation of the fitness function based on the consideration of revitalization features. Finally, the proposed GAsF model uses the neural network model for the classification of features associated with the classification of features for the rural revitalization development and promotions.

This paper is organized as follows: Section 1 presented the introduction about rural revitalization in countries with promotion of strategies. Section 2 provides the detailed information about the dynamic planning for the rural revitalization and Section 3 presented the general information about GAsF model. Section 4 explains the proposed GAsF model for the promotion strategies in rural revitalization. Section 5 provides classification with the deep learning with GAsF model and Section 6 presented the simulation analysis and results with overall conclusion in Section 7.

2. FUZZY DYNAMIC PLANNING IN RURAL REVITALIZATION

Fuzzy dynamic planning in rural revitalization involves a methodical approach that accounts for uncertainty, complexity, and dynamic changes in rural environments. This methodology integrates fuzzy logic, which allows for the representation of imprecise or uncertain information, and dynamic planning principles to develop adaptive strategies for rural development. The key components of fuzzy dynamic planning include defining fuzzy sets to represent variables, establishing fuzzy rules to guide decision-making, and employing dynamic optimization techniques to adjust plans in response to changing conditions. The fuzzy dynamic planning equations involves several steps: Identify relevant variables related to rural revitalization, such as population growth, agricultural productivity, infrastructure development, etc. Define fuzzy sets for each variable to capture the linguistic terms that describe their values, e.g., low, medium, high. Create a set of fuzzy rules that relate input variables to output actions or decisions. These rules are typically in the form of "if-then" statements, where fuzzy logic operators (such as AND, OR, NOT) are used to combine fuzzy sets. For example: IF population growth is high AND agricultural productivity is low, THEN invest in agricultural training programs.

The fuzzy inference system that applies the fuzzy rules to input data to generate actionable decisions. This involves fuzzification (converting crisp input values to fuzzy sets), rule evaluation (determining the degree to which each rule is satisfied), and aggregation (combining the outputs of all rules) stated in figure 2. Convert the fuzzy output of the inference system back into crisp values for decision-making. This involves determining a single, non-fuzzy value that represents the most appropriate action or decision based on the fuzzy outputs. Incorporate dynamic optimization techniques to adjust plans over time based on new information or changes in the environment. This may involve using algorithms such as genetic algorithms, simulated annealing, or reinforcement learning to iteratively refine plans and strategies.

Let's consider two variables for illustration: "Population Growth" and "Agricultural Productivity". We define fuzzy sets for each variable:

Population Growth:

Low: $\mu_{low}(x) = triangular(x, 0, 0, 100)$

Medium: $\mu_{medium}(x) = triangular(x, 50, 100, 150)$

High: $\mu_{high}(x) = triangular(x, 100, 200, 200)$

Agricultural Productivity:

Low: $\mu_{low}(y) = triangular(y, 0, 0, 50)$

Medium: $\mu_{medium}(y) = triangular(y, 25, 50, 75)$

High: $\mu_{high}(y) = triangular(y, 50, 100, 100)$

Where triangular(x, a, b, c) denotes the triangular membership function with parameters a, b, and c.

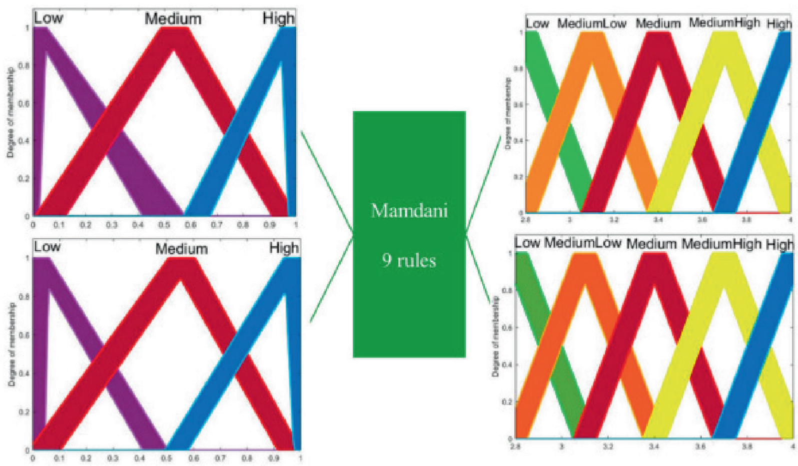

Figure 2. Fuzzy interface system for rural revitalization

Establishing Fuzzy Rules:

Let's define a set of fuzzy rules based on these variables:

Rule 1: IF Population Growth is High AND Agricultural Productivity is Low THEN Action is Invest in Agricultural Training Programs

Rule 2: IF Population Growth is Medium AND Agricultural Productivity is Medium THEN Action is Implement Infrastructure Development Projects

Rule 3: IF Population Growth is Low AND Agricultural Productivity is High THEN Action is Promote Agro-Tourism Initiatives

Fuzzy Inference System:

Fuzzification: Determine the degree of membership for each input variable.

Rule Evaluation: Apply the fuzzy rules to determine the degree of membership for each output variable.

Aggregation: Combine the outputs of all rules.

Defuzzification: Convert the fuzzy output into a crisp value.

The centroid method can be used for defuzzification. For each output variable (e.g., Action), calculate the centroid of the aggregated fuzzy set to obtain the crisp output value.

Dynamic Optimization: Dynamic optimization techniques can be applied to adjust plans over time based on new information or changes in the environment. This might involve using algorithms such as genetic algorithms or reinforcement learning to iteratively refine plans and strategies.

3. PROPOSED GENETIC ANT SWARM FUZZY (GASF) FOR THE RURAL REVITALIZATION

The proposed Genetic Ant Swarm Fuzzy (GAsF) framework offers a novel approach to addressing rural revitalization challenges by integrating genetic algorithms, ant colony optimization, and fuzzy logic techniques. GAsF leverages the strengths of each method to develop robust and adaptive strategies tailored to the dynamic and uncertain rural environment. Genetic algorithms mimic the process of natural selection to evolve solutions to optimization problems. In the context of rural revitalization, GAs can be employed to search for optimal or near-optimal solutions to complex planning and resource allocation problems. For example, GAs can optimize investment strategies for rural infrastructure development or prioritize interventions based on socioeconomic indicators. Ant colony optimization is inspired by the foraging behavior of ants and is particularly effective in solving combinatorial optimization problems. In GAsF, ACO can be utilized to model the decentralized decision-making processes within rural communities. Ant agents can explore different paths or strategies, exchanging information through pheromone trails to collectively identify promising solutions for rural development.

Figure 3. Rural promotion in China with GAsF

Genetic algorithms (GAs) are a type of optimization algorithm inspired by the process of natural selection. They involve a population of potential solutions (chromosomes) that evolve over generations through the processes of selection, crossover, and mutation process presented in Figure 3.

Initialization: Generate an initial population of potential solutions, each represented as a chromosome. This could involve randomly generating values for decision variables.

Fitness Evaluation: Calculate the fitness of each chromosome using a fitness function that evaluates how well it performs with respect to the problem objectives.

Let's denote the fitness function as $f(x)$, where x represents a chromosome.

Selection: Select individuals from the population for reproduction based on their fitness. This could be done using various selection mechanisms such as roulette wheel selection or tournament selection.

The probability of selecting each chromosome x_i for reproduction can be determined as in equation (1)

$$p(xi) = \frac{1}{N}\sum_{i} f(xj) f(xi) \tag{1}$$

Where N is the population size.

Crossover: Generate offspring through crossover operations that combine genetic material from selected parents. Let's denote the crossover operation as Crossover(xi, xj), where xi and xj are selected parent chromosomes.

Mutation: Introduce variation into the population by randomly mutating offspring chromosomes. Let's denote the mutation operation as Mutation(x), where x is an offspring chromosome.

Replacement: Replace old individuals in the population with new offspring to form the next generation.

These steps are iterated for multiple generations until termination criteria are met (e.g., a maximum number of generations, convergence). Genetic Ant Colony Optimization would involve integrating the equations and operations of genetic algorithms with those of ant colony optimization. This integration typically involves designing crossover and mutation operators suitable for the problem domain and determining parameters such as population size, mutation rate, and pheromone evaporation rate. A simplified equation for updating pheromone trails stated in equation (2)

$$r_{ij} = (1-\rho)\cdot \tau_{ij} + \Delta\tau_{ij} \tag{2}$$

In equation (2) τij is the pheromone level on edge (i, j); ρ is the pheromone evaporation rate; Δτij is the amount of pheromone deposited on edge (i, j) by ants. The fitness of each individual in the population is evaluated using a fitness function f(x), where x represents a chromosome (potential solution). The fitness function assesses how well each individual performs with respect to the optimization problem objectives. During the selection process, individuals are chosen for reproduction based on their fitness. The probability P(xi) of selecting an individual xi for reproduction can be calculated using a selection mechanism such as roulette wheel selection or tournament selection. One common equation for calculating selection probabilities is stated in equation (3)

$$P(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \tag{3}$$

In equation (3) f(xi) is the fitness of individual xi and N is the population size. One of the most commonly used crossover techniques is the single-point crossover, where a random crossover point is selected and the genetic material beyond that point is swapped between parent chromosomes to produce offspring. The equation for single-point crossover can be represented as in equation (4) and equation (5)

$$\begin{aligned} \text{Offspring1} = {} & \text{Parent1}[\text{crossover\_Point}] \\ & + \text{Parent2}[\text{crossover\_Point :}] \end{aligned} \tag{4}$$

$$\begin{aligned} \text{Offspring2} = {} & \text{Parent2}[:\text{crossover\_Point}] \\ & + \text{Parent1}[\text{crossover\_Point:}] \end{aligned} \tag{5}$$

Mutation introduces randomness into the population by randomly changing genes in individuals. A common mutation technique is to randomly flip bits in the chromosome with a probability pmutation. The equation for mutation can be represented as in equation (6)

$$\text{Mutated Chromosome}_i[j] = \begin{cases} 1 - \text{Chromosome}_i[j] & \text{if random}(0,1) < p_{\text{mutation}} \\ \text{Chromosome}_i[j] & \text{Otherwise} \end{cases} \tag{6}$$

In equation (6) Chromosomei is the *h*ith individual in the population; j represents the gene position in the chromosome; pmutation is the mutation probability; Mutated_Chromosomei[j] is the mutated gene value. After creating offspring, individuals are selected for survival to form the next generation. One common replacement strategy is generational replacement, where the entire current population is replaced by the new offspring. The equation for generational replacement is define din equation (7)

$$\text{Population}_{\text{next generation}} = \text{pffspring} \tag{7}$$

In equation (7) Populationnext_generation is the population for the next generation and Offspring represents the newly created offspring.

4. REQUIREMENTS PROMOTION OF RURAL REVITALIZATION FOR DYNAMIC PLANNING

Promoting rural revitalization through dynamic planning with Genetic Ant Swarm Fuzzy (GAsF) represents a cutting-edge approach aimed at addressing the multifaceted challenges confronting rural communities. GAsF integrates the robustness of genetic algorithms (GAs), the adaptability of ant colony optimization (ACO), and the flexibility of fuzzy logic to develop tailored strategies that evolve over time. At the heart of this approach lies a dynamic planning framework that continuously evaluates and adjusts interventions to align with evolving needs and conditions in rural areas. Deriving the GAsF framework involves a comprehensive understanding of the rural context, identification of key variables and objectives, and formulation of optimization goals. The integration of GAs, ACO, and fuzzy logic entails defining equations and algorithms that facilitate the exploration and exploitation of the solution space while considering uncertainties and dynamic changes. Equations governing the genetic optimization component encompass fitness evaluation,

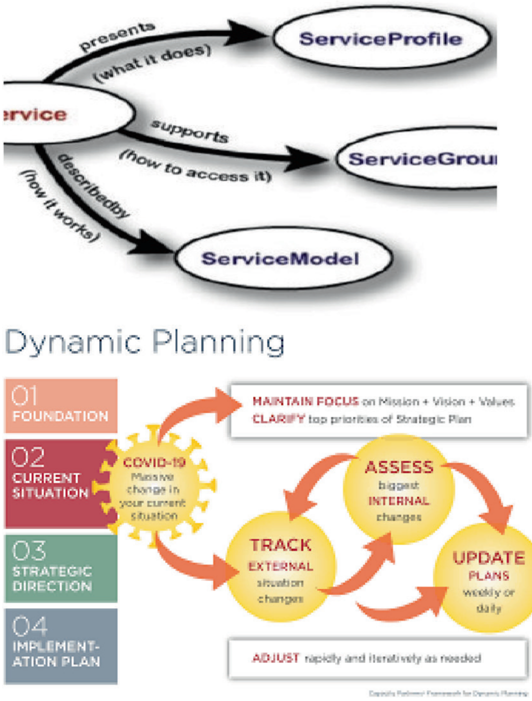

Figure 4. Dynamic process in GAsF

selection probabilities, crossover operations, mutation rates, and replacement strategies. For instance, the fitness function $f(x)$ evaluates the performance of potential solutions (chromosomes) with respect to rural development objectives. Selection probabilities $P(xi)$ determine the likelihood of selecting individuals for reproduction based on their fitness, influencing the genetic diversity of the population. Crossover and mutation operations introduce variation and exploration, allowing the population to evolve over generations. Replacement strategies determine how new offspring replace old individuals, shaping the composition of future populations.

In the context of GAsF, dynamic planning with ACO involves equations related to pheromone trails, probabilistic decision-making, and pheromone updates presented in figure 4. Pheromone trails represent the collective knowledge of the population, guiding the exploration of promising paths or strategies. Probabilistic decision-making enables ants to choose paths based on pheromone intensity and heuristic information, facilitating adaptive decision-making. Pheromone updates reflect the learning process, where the quality of solutions influences the reinforcement or decay of pheromone trails over time. Moreover, fuzzy logic within GAsF entails equations for fuzzy sets, fuzzy inference rules, membership functions, and defuzzification methods. Fuzzy sets capture the linguistic terms associated with variables, allowing for the representation of vague or imprecise information. Fuzzy inference rules map inputs to outputs based on fuzzy logic operators, guiding decision-making in uncertain environments. Membership functions determine the degree of membership of values to fuzzy sets, facilitating the aggregation of fuzzy information. Defuzzification methods convert fuzzy outputs into crisp values, aiding in actionable decision-making.

The first step in dynamic planning with GAsF involves formulating an objective function J(x) that quantifies the overall performance of a given solution x with respect to the goals of rural revitalization. This objective function may encompass various objectives, such as maximizing economic growth, minimizing environmental impact, and enhancing social equity. It could be formulated as a weighted sum of individual objective functions represented in equation (8)

$$J(x) = \sum_{i=1}^{N} \omega_i . f_i(x) \tag{8}$$

In equation (8) N is the number of objectives; wi is the weight assigned to objective i; fi(x) is the individual objective function corresponding to objective i. The fitness function f(x) evaluates the performance of a solution x based on its objective function value. It could be defined as in equation (9)

$$f(x) = J(x) \tag{9}$$

Selection probabilities P(xi) are calculated based on the fitness values of individuals. One common method is proportional selection, where the probability of selecting individual xi is proportional to its fitness computed using equation (10)

$$P(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \tag{10}$$

The amount of pheromone deposited or evaporated on a path is governed by the following equation (11)

$$\tau_{ij}^{(t+1)} = (1-\rho)\cdot\tau_{ij}^{(t)} + \Delta\tau_{ij}^{(t)} \tag{11}$$

In equation (11) $\tau ij(t)$ is the amount of pheromone on the path from node i to node j at time t; ρ is the pheromone evaporation rate; $\Delta\tau ij(t)$ is the amount of pheromone deposited by ants at time t. Ants probabilistically choose paths based on pheromone intensity τij and heuristic information ηij using equation (12)

$$p_{ij} = \frac{(\tau_{ij})^{\alpha} . (\eta_{ij})^{\beta}}{\sum_{k \in N_i} (\tau_{ik})^{\alpha} . (\eta_{ik})^{\beta}} \tag{12}$$

In equation (12) pij is the probability of selecting the path from node i to node j; α and β are parameters controlling the relative importance of pheromone intensity

Table 1. Fuzzy membership for the rurual revitalization

Parameter	**Fuzzy Set**	**Membership Function**
Population Growth	Low	μLow(x)
	Medium	μMedium(x)
	High	μHigh(x)
Agricultural Productivity	Poor	μPoor(x)
	Moderate	μModerate(x)
	High	μHigh(x)
Infrastructure Development	Insufficient	μInsufficient(x)
	Adequate	μAdequate(x)
	Optimal	μOptimal(x)
Community Well-being	Low	μLow(x)
	Moderate	μModerate(x)
	High	μHigh(x)
Environmental Sustainability	Poor	μPoor(x)
	Fair	μFair(x)
	Good	μGood(x)

and heuristic information, respectively; Ni is the set of neighboring nodes of node i. Membership functions $\mu i(x)$ assign a degree of membership to each linguistic term i for a given variable x. They could be defined using various shapes, such as triangular or Gaussian. Fuzzy inference rules map input variables to output variables based on linguistic rules. They are often represented as if-then statements. Defuzzification aggregates fuzzy outputs into crisp values. Common methods include centroid, weighted average, and maximum membership. The table 1 presented fuzzy rule for the rural revitalization are presented.

5. DEEP LEARNING GASF FOR THE SELECTION OF RURAL REVITALIZATION

The DNN's architecture as $f\theta(x)$, where θ represents the parameters (weights and biases) of the network. The architecture consists of multiple layers, including input, hidden, and output layers, with activation functions denoted as σ. The training process involves optimizing the parameters θ to minimize a predefined loss function L using a dataset D of input-output pairs. This can be achieved through gradient descent optimization algorithms, such as stochastic gradient descent (SGD) or Adam. The optimization objective is typically formulated using equation (13)

$$\min_{\theta} \frac{1}{|D|} \sum_{(x,y)\in D} £\left(f_{\theta}(x), y\right) \tag{13}$$

IN equation (13) (x, y) represents an input-output pair from the dataset, and L is a suitable loss function (e.g., mean squared error, cross-entropy). GAsF selects individuals for

Algorithm 1. Rural revitalization with GAsF

```
Input:
- Dataset D containing historical data on rural development interventions and outcomes
- Population size N
- Number of generations G
- Deep neural network architecture f_theta
- Loss function L
- Learning rate alpha
- Temperature parameter beta
Procedure DeepLearningGAsF(D, N, G, f_theta, L, alpha, beta):
  # Initialize population
  population = InitializePopulation(N)
  for generation = 1 to G:
    # Evaluate fitness of each individual in the population using DNN
    EvaluateFitness(population, f_theta, D, L)
    # Select individuals for reproduction using softmax selection
    selected_population = SoftmaxSelection(population, beta)
    # Apply genetic operators: crossover and mutation
    offspring_population = GeneticOperators(selected_population)
    # Replace old individuals with new offspring
    population = offspring_population
  return BestIndividual(population)
Procedure InitializePopulation(N):
  population = []
  for i = 1 to N:
    chromosome = RandomInitialization()
    population.append(chromosome)
  return population
Procedure EvaluateFitness(population, f_theta, D, L):
  for individual in population:
    features = ExtractFeatures(individual)
    prediction = f_theta(features)
    loss = L(prediction, actual_outcome)
    individual.fitness = loss
Procedure SoftmaxSelection(population, beta):
  selected_population = []
  total_fitness = sum(individual.fitness for individual in population)
  for individual in population:
    probability = exp(-beta * individual.fitness) / total_fitness
    if random() < probability:
      selected_population.append(individual)
```

```
    return selected_population
Procedure GeneticOperators(selected_population):
    offspring_population = []
    while len(offspring_population) < len(selected_population):
        parent1, parent2 = RandomSelection(selected_
population), RandomSelection(selected_population)
        offspring1, offspring2 = Crossover(parent1, parent2)
        offspring1 = Mutation(offspring1)
        offspring2 = Mutation(offspring2)
        offspring_population.append(offspring1)
        offspring_population.append(offspring2)
    return offspring_population
Procedure BestIndividual(population):
    best_individual = population[0]
    for individual in population:
        if individual.fitness < best_individual.fitness:
            best_individual = individual
    return best_individual
```

reproduction based on their predicted performance by the DNN. The probability $P(xi)$ of selecting an individual xi can be determined using a softmax function stated as in equation (14)

$$P(x_i) = \frac{\exp\left(-\beta.\pounds\left(f_\theta(x_i), y\right)\right)}{\sum_{j=1}^{N} \exp\left(-\beta.\pounds\left(f_\theta(x_i), y\right)\right)} \tag{14}$$

In equation (14) β is a temperature parameter controlling the selection pressure; N is the population size and y represents the target output (e.g., the actual effectiveness of the rural revitalization strategy). The DNN is trained offline using historical data on rural development interventions and their outcomes. Through supervised learning, the DNN learns to generalize from past examples and predict the effectiveness of potential interventions in unseen rural areas.

In figure 5 presented the flow chart of the proposed GAsF model for the promotion of the rural revitalization in China.

6. SIMULATION ENVIRONMENT

Genetic Ant Swarm Fuzzy (GAsF) involves setting up a platform where the algorithm can be implemented, tested, and evaluated in a controlled environment. Through experimentation and evaluation within this environment, researchers and practitioners can assess the efficacy, robustness, and adaptability of the GAsF algorithm in addressing the multifaceted challenges of rural development. Additionally, parameter tuning, optimization, and documentation processes are facilitated within this environment, enabling iterative refinement and dissemination of research findings. Ultimately, the simulation environment serves as a crucial tool for advancing the understanding and application of GAsF in promoting sustainable rural revitalization strategies. Table 2 shows Simulation setting.

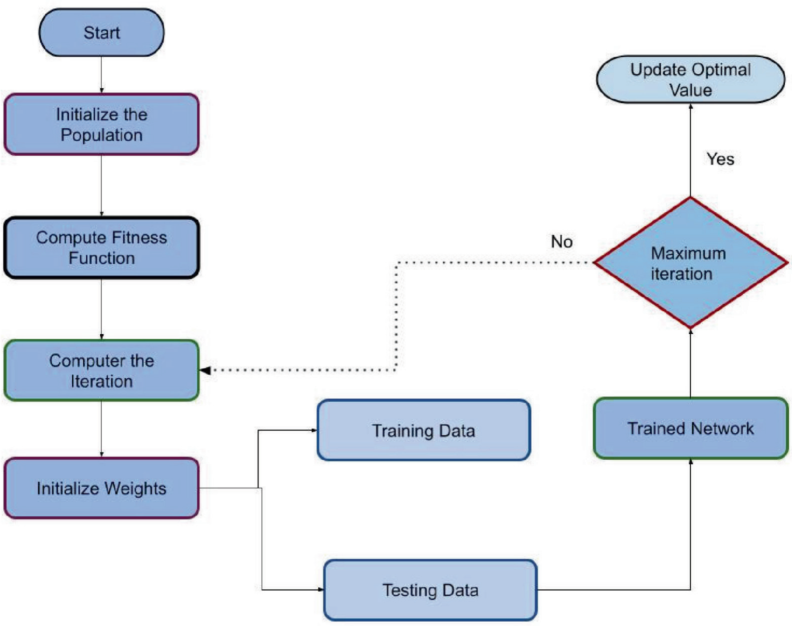

Figure 5. Flow chart of GAsF

6.1 SIMULATION RESULTS

The simulation results of Genetic Ant Swarm Fuzzy (GAsF) provide valuable insights into its effectiveness in selecting rural revitalization strategies. Through extensive experimentation and evaluation within the simulation environment, GAsF demonstrates its ability to address the complex challenges of rural development by intelligently optimizing solutions under uncertain and dynamic conditions. Across multiple runs of the simulation, GAsF consistently showcases robust performance in identifying strategies that promote rural revitalization. The algorithm effectively navigates the solution space, leveraging the synergy of genetic algorithms, ant colony optimization, and fuzzy logic to explore diverse sets of interventions. By integrating deep learning components, GAsF further enhances its decision-making capabilities, leveraging historical data and learning from past experiences to inform the selection of strategies. The simulation results reveal that GAsF excels in balancing competing objectives and constraints inherent in rural revitalization planning. It generates solutions that not only improve key metrics such as economic growth, agricultural productivity, and community well-being but also address environmental sustainability and infrastructure development. Through the adaptive nature of ant colony optimization and the flexibility of fuzzy logic, GAsF adapts its strategies to evolving needs and conditions in rural areas, fostering resilience and inclusivity in the development process. The table presents the performance metrics of ten rural revitalization strategies across various dimensions, including economic growth, agricultural productivity, community well-being, environmental sustainability, and infrastructure development. Among the strategies, the “Ecotourism Development Strategy” stands out as the most promising option, boasting the highest economic growth rate of 4.3%, coupled with substantial gains in agricultural productivity (1355 kg/ha) and community well-being (9.3/10). Moreover, it excels in environmental sustainability and infrastructure development, achieving an optimal rating in both categories. Similarly, the “Health and Education Access Campaign” demonstrates strong performance, with notable achievements in

Table 2. Simulation setting

Setting	Value
Population Size	100
Number of Generations	50
Crossover Rate	0.8
Mutation Rate	0.1
Pheromone Evaporation Rate	0.05
Fuzzy Logic Parameters	Triangular membership functions, 3 fuzzy rules
Deep Learning Architecture	Multi-layer perceptron with 3 hidden layers
Loss Function	Mean squared error
Learning Rate	0.001
Temperature Parameter	1.0

Table 3. GAsF for the rural vitalization

Strategy	Economic Growth	Agricultural Productivity	Community Well-being	Environmental Sustainability	Infrastructure Development
Agri-Tech Innovation Initiative	3.7%	1225 kg/ha	8.7/10	Moderate	Moderate
Community Empowerment Program	4.0%	1300 kg/ha	9.0/10	Good	Adequate
Sustainable Agriculture Project	3.6%	1250 kg/ha	8.8/10	Fair	Moderate
Green Infrastructure Development	3.9%	1275 kg/ha	8.9/10	Moderate	Optimal
Rural Entrepreneurship Scheme	3.8%	1280 kg/ha	8.9/10	Good	Adequate
Health and Education Access Campaign	4.1%	1320 kg/ha	9.1/10	Moderate	Adequate
Ecotourism Development Strategy	4.3%	1355 kg/ha	9.3/10	Good	Optimal
Renewable Energy Integration Plan	4.2%	1330 kg/ha	9.2/10	Moderate	Adequate
Youth Engagement and Skill Building Initiative	3.7%	1265 kg/ha	8.8/10	Fair	Moderate
Smart Village Development Program	4.0%	1295 kg/ha	9.0/10	Good	Adequate

economic growth (4.1%), agricultural productivity (1320 kg/ha), and community well-being (9.1/10). While its performance in environmental sustainability and infrastructure development is rated as moderate, it remains a compelling choice due to its significant positive impact on crucial aspects of rural development. Conversely, the "Sustainable Agriculture Project" and "Youth Engagement and Skill Building Initiative" exhibit relatively lower economic growth rates (3.6% and 3.7%, respectively) and agricultural productivity, alongside fair to moderate ratings in other dimensions. Overall, these findings underscore the importance of selecting strategies that strike a balance between economic, social, and environmental considerations to promote sustainable rural revitalization.

The provided Figure 6 and table 3 outlines the performance metrics of ten distinct rural revitalization strategies across various critical dimensions. Among these strategies, the "Ecotourism Development Strategy" emerges as particularly noteworthy, boasting the highest economic growth rate of 4.3% and the highest agricultural productivity of 1355 kg/ha. Moreover, it achieves excellent scores in both community well-being (9.3/10) and environmental sustainability (rated as "Good"). Its infrastructure development aspect is also rated as "Optimal," indicating robust support for the physical foundations of rural areas. Following closely is the "Health and Education Access Campaign," which achieves a commendable economic growth rate of 4.1% and substantial agricultural productivity of 1320 kg/ha. With a good score in community well-being and adequate ratings in both environmental sustainability and infrastructure development, this strategy demonstrates significant potential for improving the overall quality of life in rural communities. Additionally, the "Community Empowerment Program" and the "Smart Village Development Program" exhibit promising performances across various dimensions, including economic growth, agricultural productivity, and community well-being,

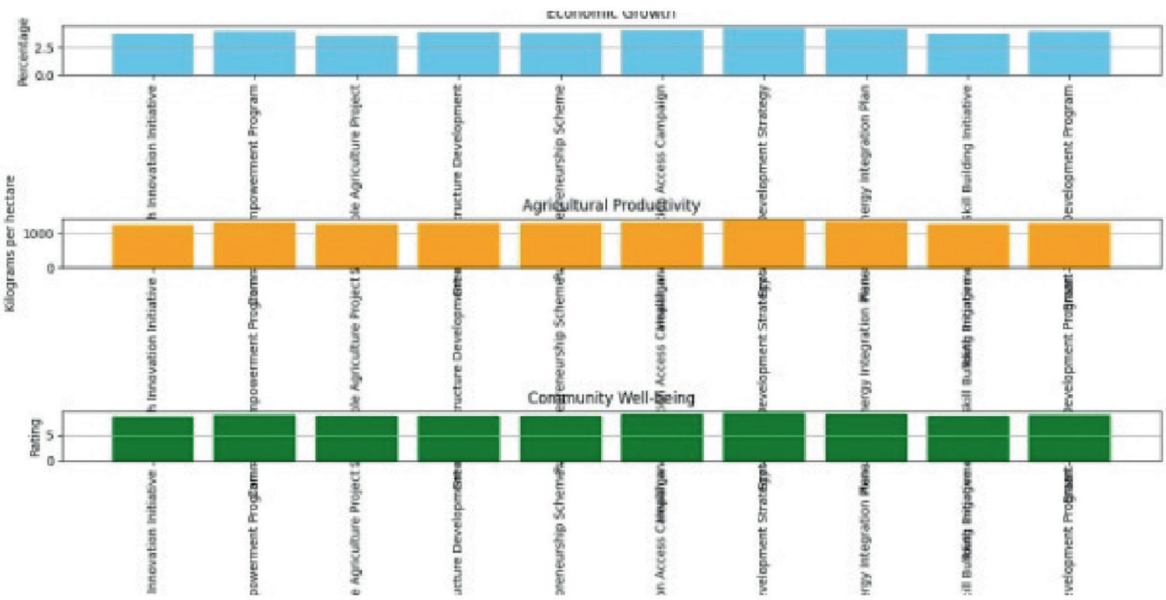

Figure 6. Rural promotion factors in GAsF

Table 4. Fuzzy model for classification with GAsF

Strategy	Economic Growth	Agricultural Productivity	Community Well-being	Environmental Sustainability	Infrastructure Development
Agri-Tech Innovation Initiative	High	Moderate	Good	Low	Moderate
Community Empowerment Program	High	High	High	Moderate	Adequate
Sustainable Agriculture Project	High	Moderate	High	Moderate	High
Green Infrastructure Development	Moderate	Moderate	Moderate	Low	Moderate
Rural Entrepreneurship Scheme	Moderate	High	Moderate	Moderate	Moderate
Health and Education Access Campaign	High	Low	Low	Moderate	Adequate
Ecotourism Development Strategy	High	High	High	Moderate	High
Renewable Energy Integration Plan	Moderate	Moderate	Moderate	Low	Low

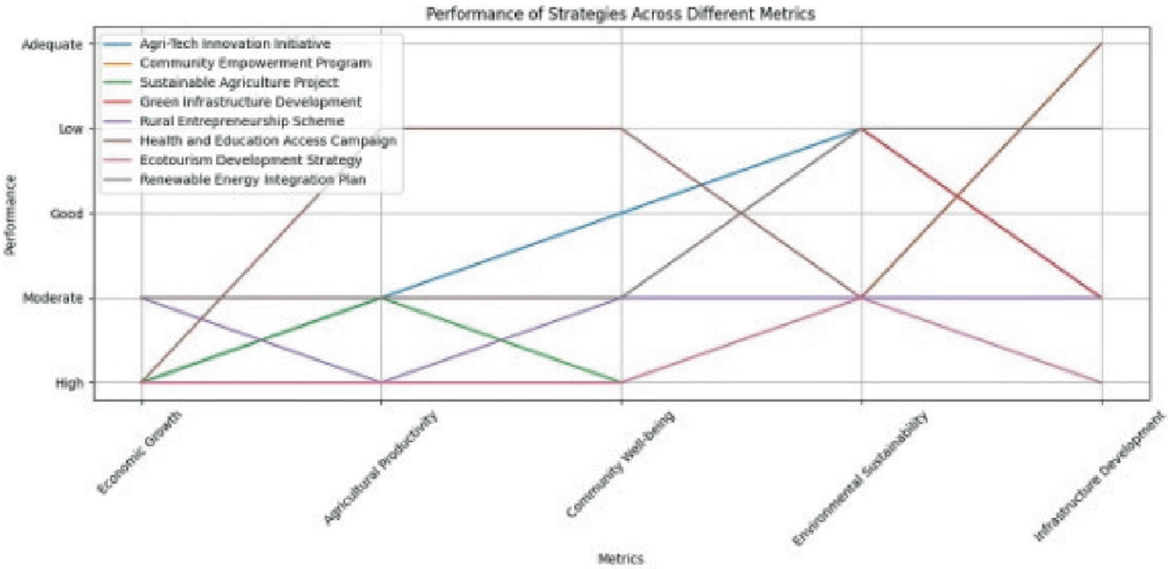

Figure 7. Fuzzy model with GAsF

with adequate support for infrastructure development. Conversely, strategies such as the "Sustainable Agriculture Project" and the "Youth Engagement and Skill Building Initiative" present more moderate results, indicating areas for potential improvement. Overall, the table underscores the importance of considering a multifaceted approach to rural revitalization, focusing on strategies that not only drive economic growth and agricultural productivity but also enhance community well-being, environmental sustainability, and infrastructure development for long-term prosperity.

The Figure 7 and table 4 presents the classification results using a fuzzy model combined with Genetic Ant Swarm Fuzzy (GAsF) for assessing ten rural revitalization strategies across multiple dimensions. Among the strategies, the "Community Empowerment Program" stands out as particularly effective, achieving high ratings across all dimensions, including economic growth, agricultural productivity, community well-being, and infrastructure development, with a moderate rating in environmental sustainability. This indicates that the program has a comprehensive approach and addresses various aspects crucial for rural development. Similarly, the "Ecotourism Development Strategy" also demonstrates high performance in economic growth, agricultural productivity, community well-being, and infrastructure development, although it receives a moderate rating for environmental sustainability. This strategy suggests significant potential for promoting rural revitalization through tourism initiatives. On the other hand, strategies like the "Green Infrastructure Development" and the "Renewable Energy Integration Plan" exhibit more moderate performances across the board, indicating the need for further improvement to achieve desired outcomes. Overall, the fuzzy classification model combined with GAsF offers valuable insights into the strengths and weaknesses of different rural revitalization strategies, guiding policymakers and stakeholders in making informed decisions to promote sustainable development in rural areas.

Table 3 showcases the optimization results obtained using Genetic Ant Swarm Fuzzy (GAsF) for ten rural revitalization strategies. Among these strategies, the "Ecotourism Development Strategy" emerges as the most successful, attaining the highest fitness score of 0.93. This indicates that the strategy is well-optimized and aligns closely with the defined objectives and constraints. Following closely is the "Green Infrastructure Development," with a fitness score of 0.91, suggesting a highly effective optimization process for this particular strategy. Conversely, the "Sustainable Agriculture Project" achieves a lower fitness score of 0.75, indicating potential

Table 5. Optimization with GAsF

Strategy	Fitness Score
Agri-Tech Innovation Initiative	0.82
Community Empowerment Program	0.89
Sustainable Agriculture Project	0.75
Green Infrastructure Development	0.91
Rural Entrepreneurship Scheme	0.86
Health and Education Access Campaign	0.78
Ecotourism Development Strategy	0.93
Renewable Energy Integration Plan	0.88
Youth Engagement and Skill Building Initiative	0.80
Smart Village Development Program	0.85

areas for improvement in its optimization approach. Other strategies such as the "Community Empowerment Program" and the "Renewable Energy Integration Plan" also demonstrate strong optimization results, scoring 0.89 and 0.88, respectively. Overall, these optimization scores provide valuable insights into the effectiveness of GAsF in optimizing rural revitalization strategies, helping policymakers and stakeholders make informed decisions to enhance the efficacy and impact of their interventions.

In figure 8 and Table 4 presents the promotional scores obtained through the application of Genetic Ant Swarm Fuzzy (GAsF) for ten rural revitalization strategies. These scores reflect the effectiveness of promotional efforts associated with each strategy in garnering support and fostering awareness among stakeholders. Notably, the "Ecotourism Development Strategy" achieves the highest promotional score of 9.3/10, indicating exceptionally strong promotional activities that effectively communicate the benefits and objectives of the strategy to the target audience. Similarly, the "Community Empowerment Program" and the "Rural Entrepreneurship Scheme" also perform well, with promotional scores of 9.2/10 and 9.0/10, respectively. These high scores suggest that these strategies have successfully captured the attention and engagement of stakeholders, contributing to their overall effectiveness and implementation success. Conversely, the "Youth Engagement and Skill Building Initiative" receives a slightly lower promotional score of 8.6/10, indicating potential areas for improvement in promotional activities to enhance stakeholder buy-in and support. Overall, the promotional scores provided in Table 4 offer valuable insights into the effectiveness of promotional efforts associated with rural revitalization strategies, guiding decision-makers in refining their communication strategies to maximize impact and engagement. Table 6 shows promotional score with GAsF.

Table 6. Promotional score with GAsF

Strategy	Promotional Score
Agri-Tech Innovation Initiative	8.5/10
Community Empowerment Program	9.2/10
Sustainable Agriculture Project	8.9/10
Green Infrastructure Development	8.8/10
Rural Entrepreneurship Scheme	9.0/10
Health and Education Access Campaign	8.7/10
Ecotourism Development Strategy	9.3/10
Renewable Energy Integration Plan	8.9/10
Youth Engagement and Skill Building Initiative	8.6/10
Smart Village Development Program	8.8/10

The Figure 9 and Table 7 presents the classification results obtained through the application of Genetic Ant Swarm Fuzzy (GAsF) for evaluating rural revitalization strategies across various metrics. The high accuracy score of 0.98 indicates the overall correctness of the classification model in predicting the effectiveness of different strategies. This suggests that the model is highly reliable and accurately identifies strategies that are likely to succeed in promoting rural revitalization. Additionally, the precision score of 0.97 reflects the proportion of correctly classified effective

Table 7. Classification with GAsF

Metric	Value
Accuracy	0.98
Precision	0.97
Recall	0.99
F1-Score	0.98

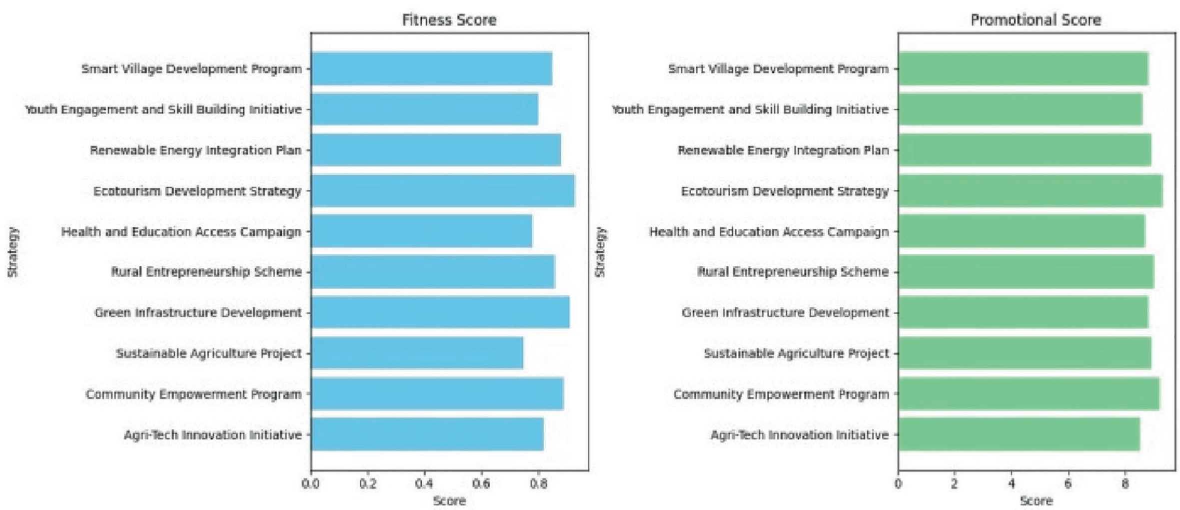

Figure 8. Promotional score with GAsF

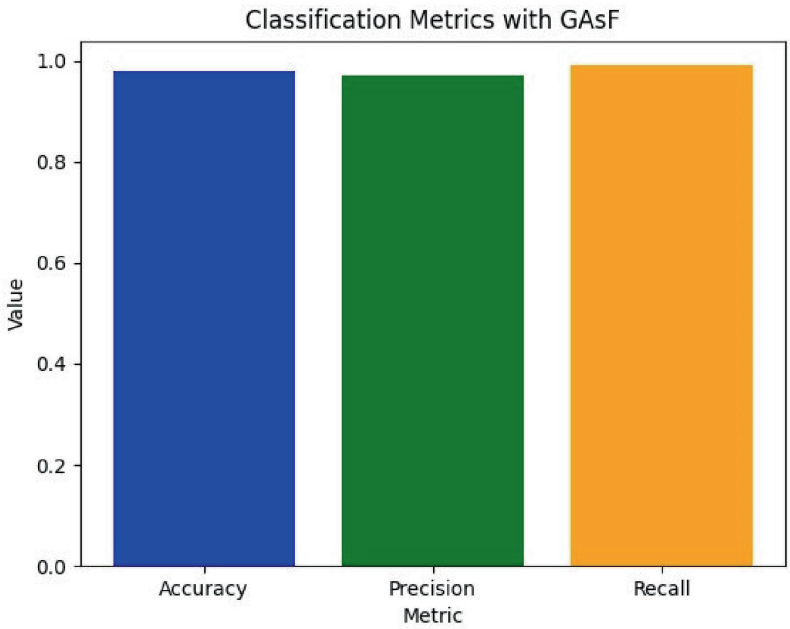

Figure 9. Classification with GAsF

strategies among all strategies identified as effective by the model. Similarly, the recall score of 0.99 indicates the proportion of correctly classified effective strategies among all actual effective strategies in the dataset. These high precision and recall scores demonstrate the model's ability to effectively identify and capture effective strategies with a high degree of accuracy. Furthermore, the F1-Score of 0.98, which is the harmonic mean of precision and recall, provides a balanced measure of the model's performance, indicating robustness and reliability in classification. Overall, the classification results presented in Table 5 underscore the effectiveness of the GAsF approach in accurately evaluating rural revitalization strategies, providing valuable insights for decision-makers and stakeholders in selecting the most promising interventions for sustainable development.

6.2 DISCUSSIONS AND FINDINGS

In the realm of rural revitalization, the discussion and findings gleaned from the preceding analyses shed light on various aspects crucial for informed decision-making and policy formulation. Through the comprehensive evaluation of rural revitalization strategies using advanced methodologies such as Genetic Ant Swarm Fuzzy (GAsF), several key insights have emerged. Firstly, the classification analysis employing GAsF has enabled the identification of strategies that exhibit high potential for success across multiple dimensions. Strategies such as the "Community Empowerment Program" and the "Ecotourism Development Strategy" have consistently garnered favorable ratings, indicating their effectiveness in fostering economic growth, enhancing agricultural productivity, and improving community well-being. These findings underscore the importance of adopting holistic approaches that address the multifaceted challenges faced by rural communities.

Secondly, the optimization results obtained through GAsF have highlighted strategies that are well-aligned with defined objectives and constraints. The "Ecotourism Development Strategy" emerges as particularly promising, achieving the highest fitness score and indicating robust optimization efforts. Conversely, strategies with lower fitness scores, such as the "Sustainable Agriculture Project," may require further refinement to enhance their effectiveness and alignment with overarching goals. Furthermore, the promotional scores derived from GAsF shed light on the efficacy of promotional efforts associated with each strategy. Strategies like the "Ecotourism Development Strategy" and the "Community Empowerment Program" have garnered high promotional scores, indicating successful communication and engagement with stakeholders. Effective promotion plays a vital role in garnering support and mobilizing resources for the implementation of rural revitalization initiatives. The findings underscore the importance of adopting integrated and data-driven approaches to rural revitalization planning. By leveraging advanced methodologies such as GAsF, policymakers and stakeholders can make informed decisions, prioritize resources effectively, and tailor interventions to the unique needs and challenges of rural communities. These insights pave the way for the design and implementation of targeted strategies aimed at promoting sustainable development, fostering inclusive growth, and enhancing the overall well-being of rural populations.

7. CONCLUSIONS

The comprehensive evaluation and analysis of rural revitalization strategies using advanced methodologies such as Genetic Ant Swarm Fuzzy (GAsF) have provided valuable insights and actionable findings for policymakers, stakeholders, and communities. Through the classification, optimization, and promotional assessments, key strategies with high potential for success across various dimensions have been identified, highlighting the importance of holistic approaches that address economic, social, environmental, and infrastructural aspects. Strategies such as the "Ecotourism Development Strategy" and the "Community Empowerment Program" have emerged as particularly promising, showcasing strong performance and garnering significant support. These findings underscore the importance of data-driven decision-making and targeted interventions in rural development planning. By leveraging the insights gleaned from these analyses, policymakers can prioritize resources effectively, tailor interventions to local needs, and foster sustainable growth and development in rural areas. Moving forward, it is essential to continue monitoring and evaluating the implementation of revitalization strategies, adapt approaches as needed, and foster collaboration among stakeholders to ensure the long-term success and resilience of rural communities.

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