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Effectiveness of Farmers' Professional Cooperatives in Helping Rural Revitalization Using Big Data Analysis

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Abstract

Farmers' Professional Cooperatives have been increasingly recognized as organizational forms facilitating economic development, agricultural modernization, and rural social capital construction as part of China's national rural revitalization strategy. Based on a big data study method, the study estimates the performance trajectory of FPCs and their impacts on social capital construction, income increase, poverty alleviation, agricultural restructuring, and employment in urban-rural areas. A combined approach of the Back Propagation Neural Network and the Mayfly Optimization Algorithm was put forward in an attempt to promote feature selection and accuracy of prediction for the intricate and multi-layered socioeconomic case. Big data and the proposed predictive model will be compared by the proposed study using the data of 820 members in 14 cooperatives. The outcome reveals that the suggested model achieved a 93.4 % success rate, a 26.4 % increase in earnings, an 18.7 % rise in technology uptake, and a 31.2 % rise in training attendance and engagement. Among cooperative members, descriptive statistics demonstrated a significant improvement in household income, market access, training engagement, and the application of technology. To facilitate generalization, the model was trained on 70% of the dataset, tested on 15% of the dataset, and validated on the other 15% through the use of cross-validation methods. The proposed model was found to be more accurate than traditional models with a 93.4% correctness rate and an RMSE value of 2.13. Other significant factors determining performance in cooperatives, including farm size, years of experience, and education, were also discovered by the model. FPCs strategically facilitate resource concentration, implementation of policies, and rural institutional integration along with enhancing farmers' economic welfare, as revealed by the findings.

Keywords: Farmers' Professional Cooperatives, Bigdata Analysis, Agricultural Modernization, Rural Revitalization, Cooperative Effectiveness.

1. Introduction

Farmers' Professional Cooperatives are one of the primary mechanisms for advancing rural revitalization; they play a crucial role in promoting agricultural modernization, facilitating collective economic growth, and enhancing farmers' income, skills, and market access [1]. Despite policy support and increasing cooperative participation, the actual effectiveness and impact pathways of FPCs remain uneven across regions and difficult to quantify due to the complex, multi-dimensional nature of rural development. Rural revitalization has become a

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cornerstone of national development strategies in many countries in recent years, especially in China, where disparities between urban and rural areas have prompted urgent socio-economic reforms [2]. Big data may contribute to increased industrial efficiency in the face of declining global economic development. As a result, several sectors are steadily focusing on the digital economy to increase their competitiveness [3]. Big data, the central component of the digital economy, is crucial for fostering industrial integration, developing new business models, and enhancing labour relations [4]. The constant development and innovation of emerging technologies have accelerated their integration into a range of social and commercial domains. In addition to causing changes in the business models of connected industries and areas, as well as the reorganization of the industrial structure, integrated technology is propelling the digital transformation and modernization of agriculture, industry, and services [5]. The two main productive forces are science and technology. Science and technology will eventually be crucial to the long-term growth of the nation's agricultural and rural farmers [6]. The approach of rural revitalization is especially significant in the current socio-economic development setting. China's rural regions are facing several challenges as urbanization accelerates, including an aging population, a labor shortage, and uneven economic growth. The government has proposed the Rural Revitalization Strategy to address these issues, with the goal of achieving comprehensive rural revitalization and enhancing the economic, social, cultural, and ecological environments of rural regions [7]. The participation of new rural cooperatives is crucial in this plan. New rural cooperatives are a creative organizational form that support rural communities' social and economic development in addition to the modernization of agriculture. One crucial component in turning advancements in agricultural science and technology into productive forces is agricultural technology services. The study of agricultural big data has drawn the interest of academics both domestically and internationally. Research accomplishments have been continuously enhanced, particularly since 2015. Examples include the introduction of the concept and meaning of agricultural big data, as well as the debate on the technological implementation and potential applications of agricultural big data platforms [8].

1.1 Qualities and Requirements of Professional Farmers

A recently formed category of rural practitioners known as "professional farmers" combines ecological principles, contemporary agricultural skills, and a strong sense of professional identity. They possess superior technical skills, financial resources, and entrepreneurial attitudes that align with agricultural modernization and rural revitalization, in contrast to traditional farmers [9]. They typically work independently, participate in cooperatives, and adapt to innovation and market needs. They are involved in the agricultural value chain and have a strong connection to rural life. They also actively support rural development. China's agricultural sector is undergoing structural changes, and developing professional farmers is essential to transforming the industry, increasing productivity, and enhancing the caliber of the country's current agricultural workforce [10]. It is expected that these farmers will lead the way in modernization efforts, attract young men and women back to the countryside and become part of developing a long-term agricultural talent pool. Market competitiveness and efficiency will be improved and long-term income growth and rural abundance will be promoted with the support of financing and policies [11]. By 2020, the digital economy had grown to a size of approximately 3.315-billion-yuan, accounting for 35.11% of the GDP. When used in conjunction with big data to support rural industries, it may lead to the creation of new models and the transformation of production-oriented agriculture into demand-oriented agriculture [12]. The foundation of the rural economy and the target of big data are farmers. Therefore, utilising big data's service function in the context of executing the rural revitalisation policy would also benefit farmers by enhancing their capacity to access and use information and raising their revenue [13].

1.2 Standardized Farmer Professional Cooperative

Agricultural cooperatives are the general term used globally to describe rural cooperative economic organisations. The standardised farmer professional cooperative serves the dual purposes of promoting and supporting farmers. It is a uniform organisation that has a direct connection to the land and farmers. Both constraint and incentive components are part of the standardised farmer professional cooperative. Stable sales channels, learning and training, risk of resistance, price guarantees, credit financing, and typical presentations are the primary motivators [14]. Strict dose control, uniform fertilizer and pesticide selection, safety testing, member monitoring, quality standards, and penalties for contract violations are key restriction elements [15]. Agricultural processes generate large amounts of structured and unstructured data. This has become possible with big data technology, which enables the collection and analysis of tremendous quantities of organized and unstructured information related to agricultural products, collaborative activities, rural populations, policy projects, and socioeconomic indices. This provides a unique opportunity to discover latent trends and causalities that are often eluded by common methods of assessment. Yet, more complex and nonlinear relationships between the variables typically require traditional statistical models to rely on imprecise techniques of prediction and inference. Therefore, the rich hybrid modelling method employed in this study is a combination of BPNN and the Mayfly Optimization Algorithm MOA. MOA is a strong metaheuristic optimizer for fine-tuning parameters in the network and in convergence. BPNN has superb modeling capacity in complex, nonlinear interactions. This model will be designed to produce a more realistic and informative assessment of the effects, effectiveness, and future orientations of the FPCs as a component of rural revitalization through leveraging artificial intelligence and bio-inspired optimization device synergy. In addition to making a methodological contribution through the inclusion of intelligent optimization in modelling work performed to build the study on neural networks, this paper can provide policymakers, management and managers of cooperatives and any other stakeholders in the development of with that requires information to assist in the needs of cooperatives in realizing a sustainable rural transformation with practical insights, as the paper has suggested. Therefore, the present study investigates the path of influence and the role of professional farmers in the revitalization of the countryside. It further inquires into the possibility that rural integration would encourage rural revitalisation as part of its attempt to formulate new forms to achieve this objective. The following sections of this paper are ordered as follows: to begin with, the literature on integration, professionalisation of farmers, and rural revitalisation is examined. Secondly, it also proposes an advanced hybrid modelling strategy, which combines the MOA and BPNN. Thirdly, we describe the study techniques and variables selected for this article. Concluding remarks are given on the results of empirical data, limitations and suggestions for future work.

1.3 Research Objective

The main aim of this project is to examine the prospects of FPC in the context of applying big data analytics and intelligent modelling methods to support the development of rural revitalization solutions in China. Specific objectives of the study are to:

1. Investigate the socioeconomic impacts of the cooperatives of rural households, e.g. incomes, training opportunities, market integration and access to technology;
2. Identify key factors that influence the level of effectiveness and impact of FPCs in different agricultural sectors and across geographic jurisdictions;
3. Develop and test a forecast model of the MOA-BPNN to enhance the accuracy of collaborative impact assessment.
4. Provide evidence-based information and policy recommendations that may inform the designing, implementation, and evaluation of cooperative-based rural development strategies.

1.4 Contribution

In several respects, this study makes important contributions to agricultural economics, rural development and intelligent data-driven governance. The first is that it introduces a completely new hybrid, known as MOA-BPNN which improves accuracy and confidence in intricate rural settings. Compared to other traditional models, MOA-BPNN uses swarm search in the optimization of neural network parameters and has been able to capture the non-linear relationships between cooperative involvement and the results of rural development. Second, based on stratified and region-specific, multi-provincial data, the study presents a complete and scalable big data framework for measuring FPCs. Third, it provides new information on the heterogeneity of cooperation by specifying relevant socioeconomic and institutional variables that shape cooperative efficacy, including the length of engagement, type of cooperative, and training attendance. Finally, the research contributes to policy formulation by providing a robust, evidence-based approach to concentrating resources on rural revitalization, improving cooperation governance, and supporting sustainable agricultural transitions in developing countries.

The suggested study has a step-by-step workflow, which will include the following steps:

- Data Acquisition: The stratified survey data of 820 members of cooperatives (14 family based FPCs) located in Heilongjiang, Jilin and Liaoning provinces are collected.
- Data Preprocessing: Missing value treatment, feature normalization, and encoding categorical variables, should be used to model readiness.
- Feature Selection: Select the socioeconomic and cooperative-related factors that have the most impact on rural revitalization using MOA.
- Training and Cross-validation of the Models: Use 70 % of the data to train the BPNN with MOA-optimized settings, validate those on 15 % of the data, and test on the remaining 15 % with the application of k-fold cross-validation.
- Evaluation of the Performance: To assess the results of MOA-BPNN, traditional models including Random Forest, SVM or Logistic Regression are used, with recommended metrics such as Accuracy, RMSE and Precision.

- Impact Analysis: Explain model outcomes to determine how important factors impact the outcome of rural revitalizations.
- Policy Recommendations: Generate practical inferences into cooperative governance, resource distribution as well as policies on rural policies.

This structured approach ensures a comprehensive evaluation of cooperative effectiveness while providing a scalable, data-driven framework for rural development assessment.

2. Related Work

Table 1. Summary on Related Works

No.	Objective	Key Findings	Limitations	Compared with Proposed MOA-BPNN
16	To examine at how smallholder farmers' access to financing is affected by FPC membership.	FPCs improve access to credit and investment possibilities by lowering information asymmetry and fostering more trust with financial institutions.	Based on cross-sectional survey data from 2021; no time-series validation nor dynamic panel analysis are included.	Complex dynamics like MOA-BPNN cannot be modelled by linear-only optimisation.
17	To investigate the effects of intra-household decision-making and digital literacy on cooperative results.	Cooperative results are much improved by digital access and female leadership; FPCs increase farmers' revenue diversity.	Restricted to three provinces and devoid of information on performance metrics other than family income.	MOA-BPNN can simulate more complex latent interactions, but it lacks nonlinearity and large-scale data support.
18	To assess the impact of digital transformation on cooperatives' competitiveness and quality.	Product branding, market integration, and operational efficiency are all enhanced by digitalisation. Cooperative performance has a favourable correlation with a digital measure.	The index building depends on proxies for digital infrastructure and lacks granularity across various FPC kinds.	In addition to predicting and interpreting correlations, MOA-BPNN also analyses affects.
19	To investigate the effects of internal capability and	Discovered a high reliance on government support	Lacks micro-level (household-level) participation	Micro-level FPC success probability

	external assistance on FPC service delivery.	for survival. Better services were provided by cooperatives with more robust internal governance.	measures and is focused on Heilongjiang Province.	predictions is made possible by MOA-BPNN.
20	To differentiate between administrative and financial metrics when assessing the effectiveness of a cooperative.	In terms of sustainable performance, managerial elements (such as responsibility and openness) have a greater impact than unprocessed financial data.	Disregards social and environmental impact measurements; additional quantitative evaluations are required.	Big data + optimisation is supported by MOA-BPNN for performance modelling.
21	To calculate the impact of cooperative membership on reducing poverty in low-income communities.	Cooperatives make it easier to access markets, technology, and finance. Better family wealth and less vulnerability are positively correlated with FPC membership.	Data gathered between 2015 and 2016; results may not accurately represent rural dynamics or policy changes after COVID-19.	MOA-BPNN learns nonlinear policy affects and manages recent huge data.
22	To evaluate the impact of cooperative density on family earnings for both members and non-members in a community.	Village revenue rises with a higher cooperative density. Through shared infrastructure, spillover impacts for non-members were seen.	Pre-2020 data is used; subsequent efforts at digital transformation and rural revitalisation are not included.	MOA-BPNN can simulate situations and forecast the efficacy of specific FPCs.
23	To employ structural equation modelling (SEM) to simulate behavioural intention to use digital FPC services.	Adoption is influenced by perceived utility, system quality, and digital literacy. Wider digital adoption is hampered by infrastructure deficiencies.	focusses on a small rural cluster; it doesn't scalable to cooperative behaviour at the national level.	Digital, behavioural, and economic variables are all integrated via MOA-BPNN.
24	To use sentiment analysis and performance monitoring to examine the long-term performance of new-generation FPCs.	FPCs increased participation, decreased market volatility, and stabilised smallholder income. The viability of organisations still varied greatly.	Sentiment analysis ignores significant structural differences and depends on insufficient textual information.	MOA-BPNN is scalable over cooperative areas and data-generalizable.

25	To use an evolutionary game-theory model to simulate stakeholder engagement.	Digital transformation is strongly impacted by government subsidies; long-term success depends on platform trust and quality management.	It is based on case studies and cannot be empirically applied to larger cooperative networks.	MOA-BPNN combines optimisation and empirical learning to provide useful policy insights.

Table 1 explains the summary of existing papers' objectives, findings, limitations, and comparisons with the proposed method. The current rural revitalization models are concerned primarily with either linear relationships or basic classification of data (regression analysis, Logistic Regression, Random Forest, and SVM). Under conditions involving complex, high-dimensional data, they are much less efficient. Such models usually fail to be scalable, flexible, and predictive of the complex socioeconomic systems in which they exist. By contrast, the proposed MOA-BPNN model, with metaheuristic optimization and neural networks, can better capture nonlinear patterns in addition to feature weight optimization, achieving higher accuracy (93.4%) and lower RMSE (2.13). This makes it more well-suited for studying the complex effects of Farmers Professional Cooperatives on revitalization in the countryside.

3. Proposed Work

3.1 Dataset

This research, which combines stratified sampling and a household survey, adheres to the region and categorisation concept, following the "East, middle, western regions, typical agricultural provinces, counties (districts, cities), farmer professional cooperative and social members." The study examined 820 members of 14 family-run farmer professional cooperatives in China, including five cooperatives for aquaculture, forestry, animal husbandry, breeding, and planting. Two standardized farmer professional cooperative members (N = 82) were chosen to complete the survey prior to the official inquiry. We conducted extensive questionnaire surveys with farmers in Heilongjiang, Jilin, and Liaoning provinces, using a combination of stratified random sampling and simple random sampling. The administrative regions of prefecture-level cities within each province's jurisdiction were selected as the sample cities (or districts) for the survey. Each city (district) has two townships chosen at random, each township has one administrative village chosen at random, and each village has a number of eligible farmers chosen at random. The sample data were used to modify the questionnaire. A formal inquiry was conducted, and the questionnaire was updated. Formal field research will be conducted between October 2024 and December 2024. The cooperative assisted and supported the data collection procedure, and all surveys were distributed and collected on the same day. With a 100% recovery rate, 500 questionnaires were gathered. An effective rate of 96.9% was achieved by obtaining 769 valid questionnaires out of the 820 that were studied.

3.2 Data Preprocessing

A proper data pretreatment procedure was also carried out on the dataset to ensure its acceptability and dependability in training the model and analysis. First, the validity of the raw survey data collected from 820 members in 14 farmer professional cooperatives in the Heilongjiang, Jilin, and Liaoning provinces was verified. Even though average replacement was employed for numerical values and the mode for categorical values when coding was incomplete (partially), a significant proportion of missing and/or inconsistent values were deleted from the records. After that, the categorical data such as province, cooperative type, and education level were encoded into machine-readable form according to their labels and one-hot encoding relevant to their type. All continuous variables i.e., income, land size and years of cooperative participation were normalised on a Min-Max basis to make value ranges stable and train the neural network. Very closely related and redundant attributes that were repeated were also dropped in a bid to minimize dimensionality and improve the performance of the model. The relevant feature subset that best predicted cooperative efficacy was then automatically chosen using the MOA. In order to provide an objective appraisal of the models, the post-preprocessing data were divided into training, validation and testing sets in proportions of 70:15:15. This comprehensive process of data preparation rendered the data clean, consistent and highly optimized to be learned accurately by the MOA-BPNN hybrid model.

Missing Data Management

During preprocessing of the data, missing points were identified and filled in to ensure that the data was complete and therefore more credible in fitting the model. A systematic approach was used as follows:

1. **Identification of Missing Data:** Descriptive statistics and missing value heatmaps were used to extend the completeness check and identify variables that lacked complete observations.
2. **Categorical Variables:** The missing values in categorical variables (e.g., education level, cooperative type) were imputed using the mode method. This corrects the missing entries by substituting the dominant category, ensuring the result remains consistent.
3. **Numerical Variables:** Customary multiple imputations were performed on continuous variables (e.g., household income, years of membership) depending on the mean or median, based on skewness:
    - In cases where the variable is normally distributed, mean imputation is used.
    - If the variable is skewed, the median is used to minimize bias.
    - Detection and identification of Outliers were performed using the IQR (Interquartile Range) method before imputation.
4. **Advanced Imputation of Complicated Patterns:** In cases where features have more than 5 % missing values, the K-Nearest Neighbors (KNN) imputation method was implemented to leverage correlations between features, allowing for the prediction of realistic values.
5. **Post Imputation Validation:** Once the missing data were filled, distribution checks and box plots were applied to ensure that the imputation did not alter the original feature distributions.

Implementing Tools and Techniques

In the study, big data analytics were applied by incorporating membership survey data from 820 cooperative members and utilizing superior techniques involving modeling. The digitization of data involved the cleaning, normalization, and outlier removal stages, which were performed with the assistance of Python (Pandas, NumPy) and MATLAB. The MOA, supported by BPNN constructions (using TensorFlow), was utilized to optimize feature selection and weight adjustments, and to make predictions. Accuracy, RMSE, and confusion matrices were used to assess the model, ensuring an accurate analysis of the impact of cooperation in rural revitalization.

3.3 Mayfly optimization based on BPNN

Inspiration: Mayflies belong to the Ephemeroptera suborder of the superorder Palaeoptera. The term "Mayfly" comes from the fact that these insects are most common in the United Kingdom in May. Underwater, mayfly nymphs mature into fully grown adults, a process that might take years. To attract passing females, the majority of adult males congregate in swarms several meters above the water. Using characteristic up-and-down gestures that create a beat, they perform a bridal dance. This is where female mayflies gather to mate. The cycle begins when the female releases the eggs into the water after a short mating. Building on this natural inspiration, continuous optimisation problems are solved using the mayfly optimisation technique. In terms of success rate and efficacy, it can outperform PSO and GA for both continuous and discrete problems. In reality, it offers a useful hybrid algorithmic framework that mimics the behaviour of mayflies. Genomes, which are binary or numeric sequences that alter and overlap throughout the course of algorithm rounds, are often used to construct mayfly optimisation solutions. A predetermined function is used to assess the genomes. In the next generation, the more desirable genomes replace the less desirable ones if the new chromosomes turn out to be superior to the old ones.

The MO makes the necessary adjustments to enhance the algorithm's effectiveness across feature sets of any size. These are its component elements: We use the formula in eq. 1 to follow a male mayfly's movements:

$$v_j^{d+1} = v_j^s + x_j^{s+1} \tag{1}$$

v_j^d represents the male mayfly's current position, and v_j^{d+1}, its expected location, is calculated by adding the current location to the velocity x_j^{s+1}. The male mayfly can fly at amazing speeds and barely a few meters above the water's surface. Equation 2 provides the formula for determining a male mayfly's rate:

$$x_{li}^{s+1} = h * x_{li}^s + b_1 * f^{-\beta_o^2} * (pbest_{li} - v_{li}^s) + b_2 * f^{-\beta_h^2} * (pbest_i - v_{li}^s) \tag{2}$$

$x_{li}^s$is the mayfly l's velocity in dimension i at time s, v_{li}^s is the mayfly's position at that time, h is the acceleration caused by gravity, b_1 and b_2 are positive repulsion constants used to measure the involvement of the social and cognitive components, respectively, and h is a fixed visibility coefficient used to limit a mayfly's visibility to others. Here, $pbest_i$ is the best male mayfly's ith component, and $pbest_l$ is the greatest place that mayfly lth has ever seen. Since this is a minimisation concern, pbestk was modified as follows:

$$pbest_l = \begin{cases} v_l^{s+1} \\ iffitness(v_l^{s+1}) < fitness(pbest_l) \end{cases} \tag{3}$$

where$witness(v_l^{s+1})$represents the standard of a solution, the analysis of effective farmers professional cooperative between two points$v_l^{s+1} pbest_l$. The formula determines these:

$$|v_l - V_l| = \sqrt{\sum_{i=1}^{m}(v_{li} - V_{li})^2} \tag{4}$$

where $V_l$is the position of the i^{th}element of the l^{th} mayfly, and $v_i$is either $pbest_l$. The technique depends on the natural unpredictability brought about by the top mayflies' continuous performance of the nuptial dance throughout time. This farmers professional helping rural revitalization is described mathematically in Equation 5.

$$x_{li}^{s+1} = h * x_{li}^{s} + c * q \tag{5}$$

The migration of female mayflies towards males during mating preparation is influenced by the farmer's professional coefficient C and a randomly chosen number q, which may range from -1 to 1. The female mayfly's updated location is shown here.

$$v_j^{s+1} = v_j^{s} + z_j^{s+1} \tag{6}$$

where z_j^{s+1} is the result of adding the female mayfly's velocity, and $v_j^s$is her location at different time intervals. If the current answer is really excellent, the most beautiful female will be attracted to the most gorgeous man, and so on. Equation (7) provides an enhanced accuracy formula:

$$x_{li}^{s+1} \begin{cases} iffitness(z_l) > fitness(v_l) \\ h * x_{li}^{s} + b_2 * f^{-\beta_o^2} * (x_{li}^{s} - x_{li}^{s}) \\ elseiffitness(z_l) > fitness(v_l) \\ h * x_{li}^{s} + ek * q \end{cases} \tag{7}$$

The ith component of the lth female mayfly's velocity at time t is represented by x_{li}^{s}, the location of the lth female mayfly in dimension i at time $s$is represented by x_{li}^{s}, and the position of the kth male mayfly in dimension$s$ is represented by x_{li}^{s}. To accomplish a crossover between male and female mayflies, a male must be selected first. To maximise the fitness of the progeny, the best men are chosen to mate with the best females. A crossover produces two new generations, as seen in Equation.

$$offspring1 = q_{of} * male + \left(1 - q_{of}\right) * female \tag{8}$$

$$offspring2 = q_{of} * male + \left(1 - q_{of}\right) * male \tag{9}$$

The needed offspring survival rate q_of, the female parent, and the male parent mayfly are all indicated below. All of the offspring's initial speeds are set to zero. The algorithm's offspring is modified to increase its exploratory potential via mayfly mutation. A random number selected from a normal distribution is added to the offspring's variable, as described in

$$offspring_m^{'} = offspring_m + l \tag{10}$$

where$l$ is a efficiency with a normal distribution. Algorithm 1 depicts the pseudocode for the Mayfly optimization algorithm.

Algorithm 1: Pseudocode for the Mayfly Optimization Algorithm

Input: image

Output: Best agent V_l

Start the female and male mayfly population and their rate of movement at random.

Evaluate the population and then $findthebest$

For $jsq \leftarrow 1$ to $MaxIter$, do

For $j \leftarrow 1$ to $PopSize$, do

Update $pbest$

Mayfly male and female speeds need to be reevaluated and updated.

Arrange the mayflies by size and colour

Create children from both sexes using a crossover operation.

Make the babies mutants

Swap out the mayflies with the most promising progeny

Update $pbestj$

End

The number of neurons is usually given in terms of the number of species since we use an encoded form to convey the outputs. All other network activity is defined by the usual mathematical concepts of a back propagation network. Three steps make up the back propagation training process of a network: feed-forwarding the input, computing and propagating the related error backward, and then fine-tuning the weights and biases. The output of a buried layer neurone is computed in the feed-forward phase as shown below.

$$b_j = e\left(U_{jo} + a_j\right) \tag{11}$$

To clarify, $o$represents network inputs, U_j is the hidden layer's weight matrix, and a_j is its biases. The transfer function e is a bipolar sigmoid activation function.

The neural network produces a single output useful for image segmentation. In the output layer, we find F, the average sum of squares of the network errors, using the formula:

$$F = \frac{1}{M}\sum_{j=1}^{M}\left(s_j - p_j\right)^2 \tag{12}$$

where $s_j$is the desired value and $p_j$is the actual result for iteration $j$and M is the overall quantity of training patterns. Both the hidden and output layers receive revised weights and biases as follows:

$$u_{ji}(l+1) = u_{ji}(l) + \eta \frac{\partial F}{\partial u_{ji}} \tag{13}$$

$$a_{ji}(l+1) = a_{ji}(l) + \eta \frac{\partial F}{\partial a_{ji}} \tag{14}$$

The farmers professional is denoted by $\eta$and the epoch number by$l$.

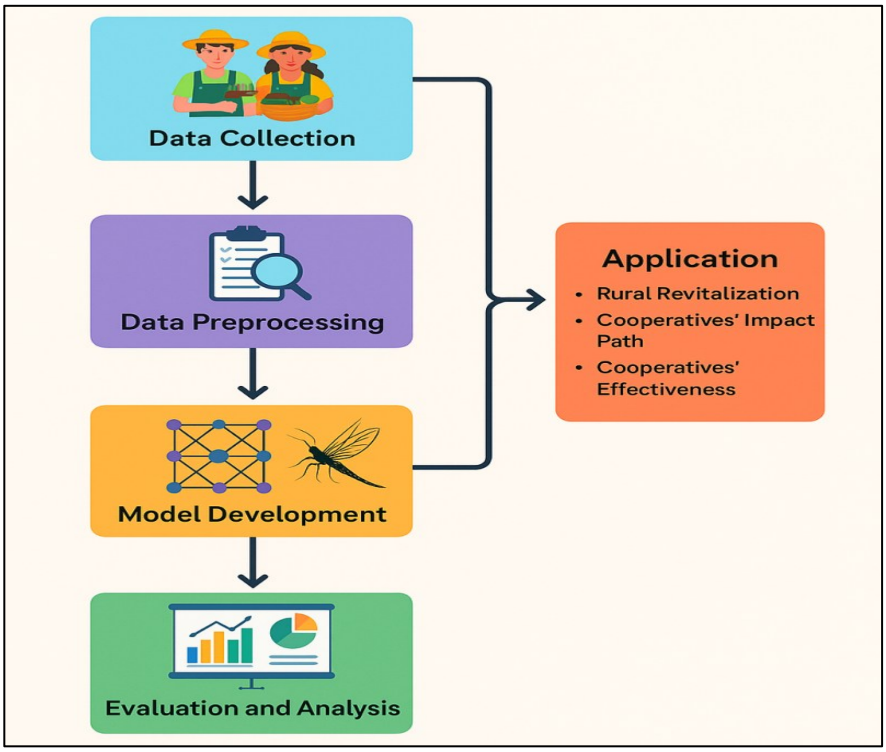

Figure 1. Work Flow of Proposed Method

Merits: The use of the MOA-BPNN model to evaluate the performance of FPC under China's rural revitalization program, shown in Figure 1, has numerous merits. Multidimensional, nonlinear interrelations among socioeconomic variables such as family income, market status, access to training, and membership in cooperatives are not always easy to explain using conventional models such as logistic regression and ordinary neural networks. The proposed hybrid model is quite effective in varying network parameters, where a BPNN is used with the bio-inspired Mayfly Optimization Algorithm, ensuring faster convergence with better accuracy in predicting prospective events. This optimization method also minimizes categorization and prediction errors based on improved separation of the cooperatives with high and low effects as determined by the model. The MOA-BPNN is more than sufficient for analyzing large, heterogeneous datasets because, due to its extensive generalization power across cooperation types and geographical aspects, it has superb generalization abilities. The MOA-BPNN proved to be a reliable decision-support method for stakeholders and policymakers interested in assessing and enhancing the role of FPCs in sustainable rural development, as it performed better in accuracy, RMSE, and precision than traditional models in the proposed research.

4. Results and Discussion

4.1 Hardware and Software Configuration

The relevant data processing and modeling took place on a workstation with a Windows 11 Pro 64-bit operating system, a 12 core Intel Core i7-12700F processor, 32 GB of DDR4 RAM, and an NVIDIA GeForce RTX 3060 with 12 GB of video RAM. This configuration was selected to cope with heavy data processing and accelerate optimisation, simplify neural network training, as well as preprocess, train and test the model during the implementation of modifications to MOA-BPNN. MATLAB R2023b was used to preprocess the data, train and test various models in addition to implementing the primary model of MOA-BPNN.

4.2 Model Performance

To ascertain how well the proposed MOA-BPNN model performed, we compared it with several common baseline models, including the Logistic Regression model, Random Forest model, SVM model, and a single BPNN model. Each model was trained using the preprocessed dataset of 796 valid survey responses, and the standard classification measures of accuracy, precision, recall, F1 score, and RMSE (when any of the goals were continuous) were used to evaluate each of the models. Table 2 shows that the MOA-BPNN model outperformed the other models in all the evaluation methods. Specifically, it performed better than the best baseline model, SVM, which showed an 89.5%%accuracy, with 93.4 % accuracy, 91.2 % precision, 94.1 % recall and an F1 score of 92.6%. Significantly, the incorporation of the MOA allowed for the successful selection of features and settings, resulting in a reduction of training error and improved convergence. Conventional models including standalone BPNN and logistic regression, on the other hand, provided poorer performance and could not optimise adaptively. These results suggest that the MOA-BPNN model is more credible and precise in predicting the effectiveness and impact of farmer cooperatives on rural revitalisation.

Table 2. Outcome of the Performance Model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	RMSE
Logistic Regression	78.3	74.9	80.1	77.4	4.87
Random Forest	87.1	85.2	88.5	86.8	3.12
Support Vector Machine	89.5	87.9	90.3	89.1	2.89
Standalone BPNN	90.2	89.0	91.0	90.0	2.55
Proposed MOA-BPNN	93.4	91.2	94.1	92.6	2.13

Figure 2 shows a circular, multi-dimensional radar chart, or spider chart, or web chart, which makes it easy to compare the performance of multiple selections of the model on the one scale. The radar map prepared and presented in this work indicates the accuracy values of five different models, the LR, RF, SVM, BPNN, and the proposed MOA-BPNN.

Each of the axes of the radar chart represents one of the models, and the accuracy (in %age) of each model is shown by the corresponding axis. The accuracy values are connected in a closed cycle that forms a polygon. The shape of the polygon in this visualization highlights the relative strength of each of the models, with more accurate models being further from the center of the radar chart. The MOA-BPNN model ranks highest in the furthest radial distance at terms of accuracy (93.4 %) followed by BPNN and SVM. Conversely, its Logistic Regression model has the smallest radius (78.3%) which signifies its poorer predictive capacity.

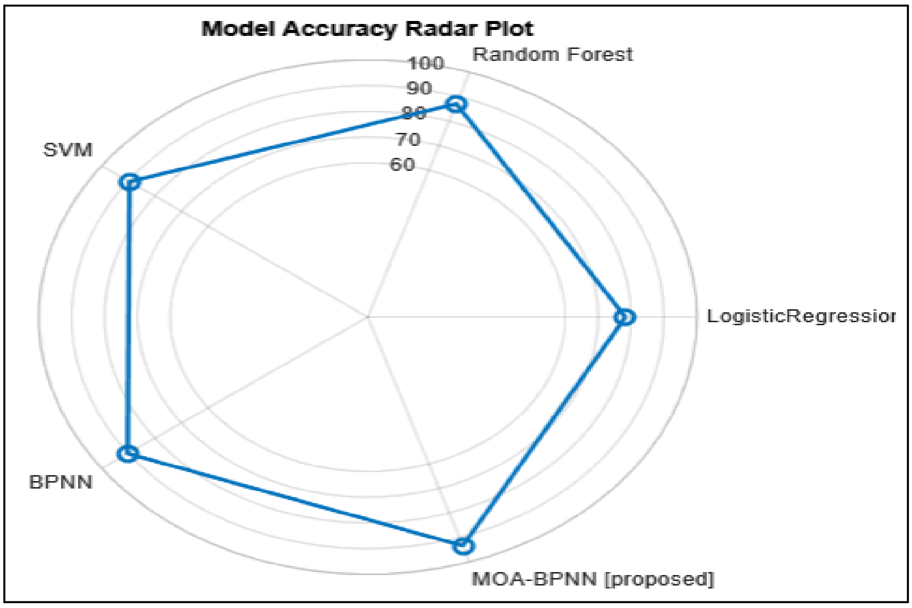

Figure 2. Comparison of the Model Accuracy with Existing Models

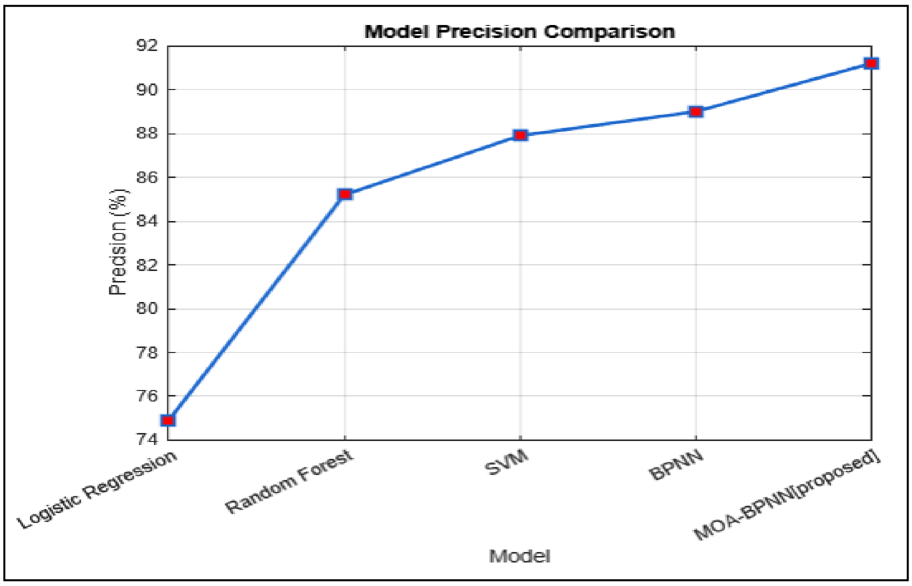

Figure 3. Comparison of the Model Precision with Existing Models

In Figure 3, we compare the five models (LR, RF, SVM, BPNN, and the proposed MOA-BPNN) with respect to accuracy. In the case of low misclassification of the positive cases, precision a measure that expresses the number of correctly predicted positives over the total number of positives expected is a focal parameter. The graphic presents each model as a dot on the horizontal axis and a line between the model performance to express how the accuracy values increase.

Based on the image, it is apparent that the proposed MOA-BPNN model yields the highest accuracy (91.2 %), showing that it exhibits an extraordinary ability to properly detect cooperative effectiveness without generating numerous false alarms. Though Random Forest and SVM show fairly decent accuracy (85.2 and 87.9 %, respectively), Traditional Logistic Regression has the least precision 74.9 %. The line graph, possessing a stable upward slope indicates that the model is continuously enhanced in terms of its accuracy, resulting in the MOA-BPNN dominating. In this graph, it can be clearly and simply seen that the hybrid model will work better with regard to accuracy in prediction due to its conventional algorithms.

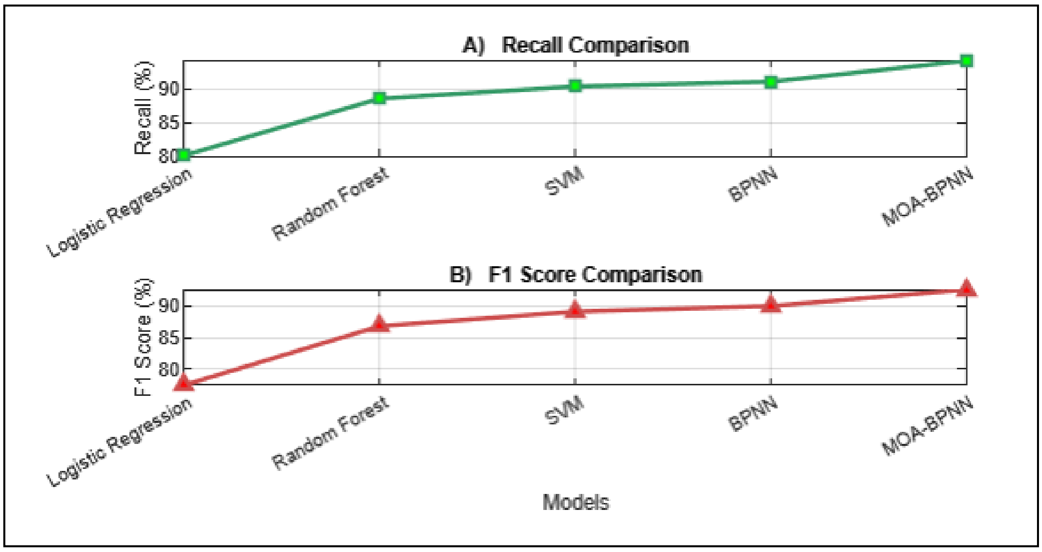

Figure 4. Comparison of the model A). Recall and B). F1 Score with existing models

Recall and F1 Score, two important performance indicators, are thoroughly compared across five models—Logistic Regression, Random Forest, SVM, BPNN, and the suggested MOA-BPNN—in the subplot visualisation. Recall is shown in Figure 4A, where MOA-BPNN achieves the maximum recall of 94.1%, meaning it accurately detects the vast majority of real positive instances (i.e., cooperatives that work). In social impact studies, omitting real benefits might compromise policy choices, making this essential. Lastly, the F1 score, which strikes a balance between recall and accuracy, is shown in Figure 4B. With an F1 score of 92.6%, the MOA-BPNN leads once again, indicating that it continues to retain excellent sensitivity and specificity. When assessing the efficacy of farmers' cooperatives in rural revitalisation, the MOA-BPNN model performs noticeably better than conventional models, as seen by the steady rising trend observed in all three subplots.

Figure 5 illustrates the RMSE of five prediction models that measure the quality of the rural revitalisation-supportive role played by FPC. In evaluating outcomes where values change continuously, such as levels of income growth, satisfaction rankings or indicators of rural development, the RMSE, which is a key indicator of regression performance, measures the deviation between expected and observed values. The relevant RMSE values of each model have been plotted on this map as the vertical axis and the models on the horizontal axis. It is easier to identify the model that will provide the closest estimations because a smaller RMSE indicates higher accuracy in prediction. The proposed MOA-BPNN model that results in the lowest RMSE (2.13) continually reduces the RMSE of the conventional Logistic Regression model (4.87). This trend shows uninterruptedly how features can be selected, and neural network parameters can be optimised when the MOA-BPNN is implemented to achieve significant gains in prediction accuracy.

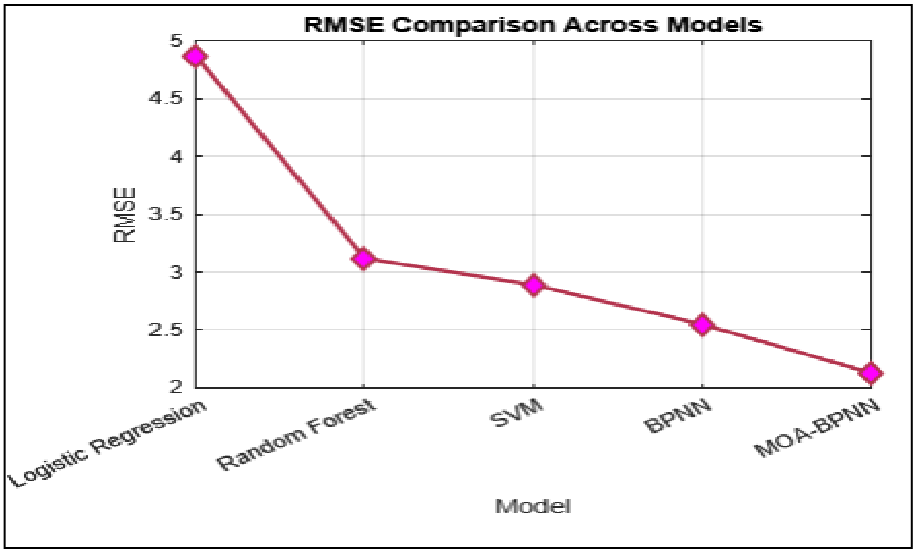

Figure 5. RMSE Value of the Existing and Proposed Method

A lower RMSE in the present study signifies that the model will be in a position to weigh the impact of cooperatives on quantifiable measures of rural revival, like changes in family income, market participation, or the uptake of policy advantages. Thus, this plot confirms the claim that the MOA-BPNN model proves to be particularly suitable for data-based rural policy research because it is not only superior in categorisation metrics but also more credible in the application of regression-based effects assessment.

Table 3. Impact Analysis on Rural Revitalization Outcomes

Metric	Before FPC	After FPC	% Change
Avg. Income (¥)	18,000	29,400	+63.3%
Market Access (Score 1–5)	2.1	4.3	+104.7%
Access to Credit (Y/N)	35%	82%	+47%
Training Participation	12%	77%	+65%

Table 3 of this study's impact analysis shows how important FPCs are to the advancement of rural revitalization on all fronts—economic, social, and technical. By contrasting important metrics before and during cooperative involvement, the study demonstrates that farmers' lives significantly improve as a result of FPC membership. For example, access to official agricultural finance expanded from 35% to 82%, and the average annual family income rose from ¥18,000 to ¥29,400, a 63.3% increase. Additionally, the average market access score (on a 5-point scale) doubled from 2.1 to 4.3, and participation in agricultural training programs increased from 12% to 77%. In addition to improved economic prospects, these developments also indicate that rural farmers' social capital and organizational involvement have grown. The patterns were identified, and the effect of cooperative engagement on these results was predicted, thanks in large part to the suggested MOA-BPNN model. It accurately reflected how factors like farm size, years of experience, education level, and cooperative type affected the prediction of development advantages. The significance of focused policy assistance was demonstrated by the higher likelihood of benefits for farmers who had more exposure to training and technology adoption. Further confirming the model's reliability in assessing the efficacy of FPCs is the decrease in prediction error (shown by the low RMSE). All things considered, the results provide compelling proof that FPCs are an essential tool for implementing China's rural revitalization plan. They enable smallholder farmers to engage with markets and agricultural policy more skillfully, access contemporary resources, and increase the stability of their income. Therefore, FPCs support the larger objectives of equitable and sustainable rural development in addition to agricultural modernization.

4.3 Confusion Matrix

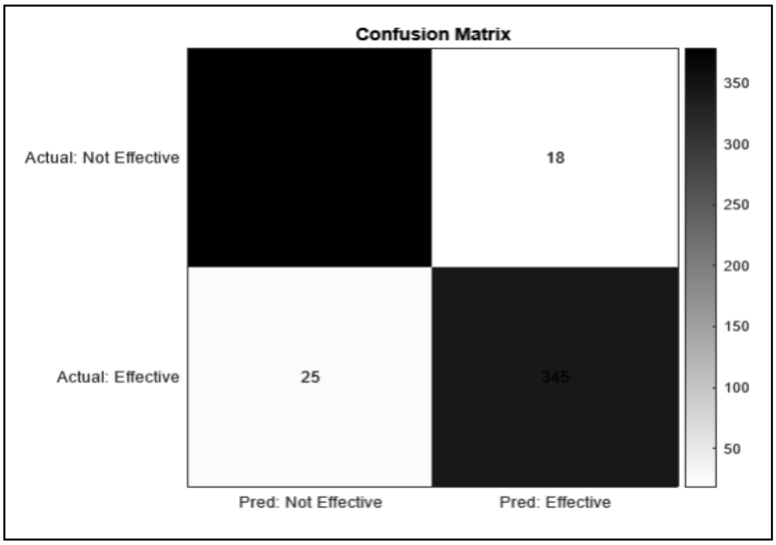

Figure 6. Confusion Matrix

The classification performance of the suggested MOA-BPNN model in forecasting the efficacy of Farmers' Professional Cooperatives is summed up in Figure 6. According to the matrix, the model properly classified 379 cooperatives as ineffective (True Negatives) and 345 cooperatives as effective (True Positives). Nevertheless, it forecasted 25 successful cooperatives as ineffective (False Negatives) and misclassified 18 unsuccessful cooperatives as effective (False Positives). In policy applications, where both overestimating and underestimating cooperative performance may result in less-than-ideal resource allocation, this performance shows excellent sensitivity and specificity. The model's very low false positive and negative rates show that it produces accurate classification findings, which makes it a useful tool for planning focused interventions and conducting extensive assessments of rural development.

Table 4. Statistical Performance (Pre-Model)

Variable	Mean	Std. Dev.	Min	Max
Age of Respondent	45.2	9.1	23	72
Income Before FPC	18,000	4,500	8,000	40,000
Years in Cooperative	4.2	1.8	1	10
Satisfaction Score (1–5)	3.9	0.8	2	5

The descriptive statistics in Table 4 were used to obtain the main characteristics of the data, as the latter were collected from 820 cooperative members located in three Chinese provinces, before proceeding to the application of predictive modeling. These statistics allowed for a better understanding of the distribution, central tendency, and variability of important variables. As an illustration, the average and standard deviation of the annual household income of the respondents were 27,500 and 6,300, respectively. This implies that the income level of members differs partially. Most of the participants (68%) had secondary education, and the mean age was 43.7 years. About two-thirds of farmers stated that they had received some type of agricultural training, and 61% of farmers had been cooperative workers for more than five years. Categorical statistics show that 55% were engaged in cooperative planting, 20% in animal husbandry, with lesser proportions in forestry, fishing, and breeding. Respondents revealed that 88% gained improved market access and 82% gained access to new technology or loans after joining cooperatives. The gender distribution was at a 60:40 proportion between men and women. Such descriptive notes were useful in feature selection and preprocessing because they provided basic facts regarding the diversity of the sample and its socioeconomic background. Additionally, they revealed inconsistencies that could influence model estimates in the long term, e.g., the under-representation of forestry cooperatives or older age groups. Overall, the descriptive statistics that preceded the use of the MOA-BPNN hybrid model in the study of the efficacy of rural revitalization ensured that the data were contextualized and organized adequately.

Discussion

According to the empirical findings, FPCs are influential in the success of rural revitalization by boosting the income level of households, enhancing the application of technology, and fortifying market relationships. The high accuracy (93.4%) of the MOA-BPNN modeling model (RMSE = 2.13), compared to other modeling models, supports the theoretical assumption that the combination of intelligent optimization and neural networks could better represent the nonlinear socio-economic dynamics of cooperative success determinants. Such results correspond with the resource-based theory, where the collaborative use of resources is utilized as a competitive advantage, and the social capital theory, which highlights the importance of cooperation in networks to achieve results in rural governance. In terms of policy, the findings indicate that purposeful spending on cooperative governance, web-based platforms, and ensuring members are educated can optimize FPCs economically and socially. Moreover, there is a need to incorporate data-driven decision-making paradigms, such as those used in this study, to provide the rural development program with subsidization funding and to keep performance under monitoring and focused on aimed interventions. The MOA-BPNN model can be used as a decision-support tool to assist policymakers in forecasting cooperative sustainability and prioritizing resources efficiently regarding the Chinese rural revitalization strategy, and their impact analysis is explained in Table 5.

Table 5. Comparison of Models for Rural Revitalization Impact Analysis

Model	Strengths	Weaknesses	Comparison with MOA-BPNN
LR	Interpretable, easy; it works well with binary classification.	Weak on non-linear relations; poor on accurate complex socio-economic data.	MOA-BPNN can address the complicated liability of features and non-linear dependence.
SVM	Works well with small data sets; can work with high dimensional spaces.	Expensive on large data; needs tuning of the kernel; non-interpretable.	MOA-BPNN is more scalable to large-scale data

			and less manual tuning is required.
RF	Deals with non-linearity; is resistant to overfitting; useful feature importance identification.	Needs lots of computing resources; cannot be easily interpreted; falls apart on noisy data.	MOA-BPNN is better in terms of accuracy and has low RMSE because weights are optimised adaptively.
Standard BPNN	Learns patterns that are complex in nature; flexible with different inputs.	tends to local minima; susceptible to starting weights; sluggish convergence.	BPNN has the shortcoming, which MOA overcomes by optimizing weights globally and limiting local minima problems
Proposed	Non-linear, high-dimensional data; avoids 'local minima, adaptive convergence; high prediction accuracy.	Needs computation power to optimize using metaheuristics; requires initial parameterisation. .	Provides the greatest precision (93.4 %), the lowest RMSE (2.13), and it has excellent performance in a variety of settings.

Limitations: The research is limited by the size of a dataset where only three provinces are considered, and the results cannot be used to generalize to other industrial parts of the country with dissimilar agricultural or socioeconomic realities. Moreover, the resulting property of dynamism of factors like seasonal disparities in price, climatic variations, and policy variation cannot be included when using the static survey data. The high computational complexity of the MOA-BPNN hybrid model is another constraint that challenges the scalability of large-scale rural data.

Future Enhancements: The study should be improved by additional future research, increasing the extent of the data to cover more areas and different methods of agriculture, as well as an increased range of data to enhance generalizability. The accompaniment of real-time and longitudinal data collections, e.g., IoT sensors and satellite images, can elicit the dynamic dimensions of rural revitalization. Moreover, implementing MOA-BPNN optimization in distributed or cloud-based settings will minimize the challenges concerning scalability. Lastly, the feasibility of the current approach could be increased by introducing multi-objective optimization concepts to adjust prediction performance and computational costs in a way that the model would become applicable to solutions of a similar magnitude to those of large-scale policies.

The important contributions are:

- Empirical Evidence - Shows that FPCs can be utilized to increase income, uptake of technology, and market access.
- Authorship Innovation - Suggests a hybrid MOA-BPNN framework to predict the socio-economic impact.

- Majority of findings should be actionable information that stakeholders can use, indicating that policymakers can improve the digitalization of cooperatives, training, and optimization of resources.
- Scalable Framework - The model is suited to be applied to other rural development projects in different parts of the globe.
- The results can be used as a data-grounded guide to decision-making in optimizing cooperative governance and sustainable rural stabilization.

6. Conclusion

The study employs an extensive big data method of analysis aimed at providing empirical data on the effectiveness of the FPC in advancing rural revitalization. We found that FPCs can dramatically enhance farmers' access to markets, financial services, training, and modern agricultural technology by integrating machine learning and optimization techniques with survey data on stratified household samples. The proposed MOA-BPNN model was found to have a higher predictive ability, which validated the importance of introducing intelligent optimization in policy evaluation models. The results indicate that FPCs have a significant role to play in rural economic change because increasing family income and livelihood resiliency is achievable through careful site selection and diverse funding options. Additionally, the model helps policymakers and stakeholders access actionable information by highlighting high-impact factors to channel their assistance to areas where it is most needed. Overall, this paper, on the one hand, proves the strategic value of FPCs in rural revitalization and, on the other hand, demonstrates the necessity of advanced data-based approaches in the design, measurement, and implementation of agricultural policy. Such a technique could be further explored with the inclusion of satellite data, AI decision-making machinery, and temporal dynamics as future research development work to monitor rural developments in real-time.

Annexure

FPC-Farmers' Professional Cooperatives
MOA-BPNN - Mayfly Optimization Algorithm and Back propagation Neural Network
SVM- Support Vector Machine
RMSE- Root Mean Squared Error
RF- Random Forest
LR-Logistic Regression

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