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Pathways for Rural Revitalization and the Development of New Quality Productivity from the Perspective of Smart Agriculture

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SUMMARY: *This paper proposes a computational framework for rural revitalization and new quality productivity development path driven by smart agriculture. The experimental data set was constructed from the aspects of Internet of things perception, remote sensing slices, agricultural machinery logs, circulation records and digital service information, covering 164 administrative villages, 4286 land units and multiple types of agricultural operation records. Firstly, a multi-source heterogeneous feature extraction module was designed to uniformly encode production intensity, facility activity, circulation smoothness and digital participation. Then, the graph correlation reasoning model was introduced to identify the development bottlenecks, and the path states of production, processing, distribution and service were described. Based on the intelligent decision-making algorithm, the development path under the constraints of resources, facilities and ecology is generated. Experimental results show that the accuracy of path generation is 91.5%, the macro-F1 value is 0.914, and the RMSE is 0.214. It maintains stable state expression and path ranking results in five types of regional samples, and the overall stability is also high. The framework provides a computable technical basis for rural development in smart agriculture scenarios, and has strong deployment interpretation ability.*

KEYWORDS: *Smart agriculture; Agricultural Internet of things; Graph association inference; New quality productivity Path modeling*

1 Introduction

Under the background of the continuous promotion of smart agriculture, the realization path of rural revitalization is shifting from empirical judgment to the computing mode driven by the collaboration of data perception, state recognition and intelligent decision-making. The continuous accumulation of farmland environmental monitoring, agricultural machinery operation records, remote sensing images, e-commerce circulation information and rural public service data has made the process of agricultural production, industrial organization and resource allocation have a technical foundation that can be modeled, calculated and tracked. Facing the development expression of new quality productivity, it is difficult for a single indicator to completely describe the technology input, facility linkage, circulation efficiency and digital participation degree in agricultural scenarios. The unified representation, correlation reasoning and path generation of multi-source heterogeneous data have gradually

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become important contents in the research of smart agriculture. Research on agricultural data computing and intelligent modeling can not only enhance the recognition accuracy of rural development status, but also provide more stable technical support for development path selection.

In recent years, the combination of intelligent perception, machine learning and agricultural iot has been deepened. Ojo MO and Zahid A studied the application progress of deep learning in controlled agricultural environment, and summarized the main technical paths of environmental perception, state recognition and intelligent regulation [1]. Altalak M et al. reviewed the application of deep learning in smart agriculture and proposed that intelligent computing in agricultural scenarios is shifting from single-point recognition to system-level collaborative analysis [2]. Murugamani C et al. studied the machine learning technology of precision agriculture in the 5G Internet of things environment, indicating that data-driven agricultural decision-making under real-time connection conditions has higher deployment adaptability [3]. Ihoume I et al. proposed a multi-label tinyML model for greenhouse microclimate control to realize lightweight reasoning on multivariate sensing data [4]. Picon A et al. studied the crop and weed segmentation method driven by deep learning, indicating that the visual perception model has formed a strong scene applicability in agricultural object recognition [5]. Žalik K R and Žalik M review the application of federated learning in agriculture, which provides a new organizational way for collaborative modeling of agricultural data across regions [6]. Akkem Y et al. studied the framework of smart agriculture supported by artificial intelligence and pointed out that perception, prediction and control in the agricultural production chain are forming an integrated intelligent process [7]. Yepez-Ponce D F et al. summarized the application trend of mobile robots in smart agriculture and expanded the technical boundary of agricultural intelligent equipment and automatic execution system [8]. Attri I et al. reviewed the deep learning technology in agricultural scenarios and further explained that multi-modal data fusion has become an important direction of agricultural intelligent analysis [9]. Muhammed D et al. proposed the architecture and technical scheme of AIoT for smart agriculture, which promoted the integrated development of agricultural sensing network, edge computing and intelligent services [10].

Based on the above research basis, this paper combines agricultural Internet of things and intelligent computing into the development path modeling scenario of rural revitalization and new quality productivity, and constructs a computing framework for development factor identification, bottleneck correlation reasoning and path generation. In this paper, multi-source heterogeneous agricultural data are used to represent the development state, and the structural relationship between different development links is depicted by graph association reasoning, and the development path with computable basis is generated under the joint action of resource constraints, facility foundation and ecological conditions. The research contents include the feature extraction of development factors from multi-source heterogeneous agricultural data, the identification of development bottlenecks and the modeling of path states based on graph correlation reasoning, and the generation of rural revitalization and new quality productivity development paths based on intelligent decision-making algorithms. On this basis, this paper further verifies the performance of the model in the consistency of path recognition, the stability of state description and the effectiveness of decision output through experimental analysis, and provides executable computational support for the digital expression of rural development process in smart agriculture scenarios.

2 Related Research

The research on the development path of rural revitalization and new quality productivity for smart agriculture shifts from experience induction to technical expression driven by perception data, supported by model reasoning and linked by calculation results feedback. With the continuous access of agricultural Internet of things, remote sensing platforms, edge devices and digital service systems, information such as field environment, operation process, storage circulation, facility operation and business collaboration form computable data objects. Around this change, related research has expanded from single perception or single identification to multiple directions such as multi-source fusion, digital twin, robot collaboration and supply chain intelligent decision-making, which provides a solid technical foundation for rural development state modeling and path generation.

Li et al. studied the application of basic models in smart agriculture and pointed out that big models are promoting the integrated development of agricultural knowledge representation, cross-task transfer and multi-scenario reasoning [11]. Soussi et al. proposed a collaborative framework of intelligent sensing and intelligent data for precision agriculture, which makes a closer computing connection between sensing terminals, data streams and analysis modules [12]. Ghazal et al. studied the application of computer vision in smart agriculture, indicating that visual recognition, target detection and crop state analysis have become important components of agricultural information processing [13]. Wang J et al. proposed an integrated method of remote sensing and machine learning, which provides a more stable data analysis path for plot monitoring, yield assessment and spatial state discrimination [14]. Zhang B and Qiao Y studied the application of artificial intelligence, sensor and robot collaboration in agriculture, so that perception, execution and feedback gradually form a closed-loop computing structure [15].

As shown in Table 1, the existing research has covered the basic model, intelligent sensing, visual analysis, remote sensing learning and robot collaboration, but the focus of different methods is not consistent with the computational focus.

Table 1: Summary of related research on smart agriculture

Author	Research Focus	Technical Emphasis	Relevance to This Study
Li et al. [11]	Application of foundation models in smart agriculture	Cross-task representation and knowledge transfer	Supports unified encoding of development factors
Soussi et al. [12]	Collaboration between intelligent sensing and smart data	Multi-source perception and data linkage	Supports the fusion of heterogeneous agricultural data
Ghazal et al. [13]	Computer vision applications in agriculture	Image recognition and state analysis	Supports feature extraction in agricultural scenarios
Wang J et al. [14]	Integration of remote sensing and machine learning	Spatial monitoring and predictive modeling	Supports regional state computation and representation
Zhang B et al. [15]	Collaboration of AI, sensors, and robots	Closed-loop computation of sensing and execution	Supports the linkage between path generation and execution

In higher level system modeling research, digital twin becomes an important extension of agricultural computing. Wang L studied the progress of agricultural digital twin, and believed that the twin could organize the sensing data, operation status and decision logic into the same computing space [16]. Escriba-Gelonch et al. proposed the arrangement and application framework of agricultural digital twin, which makes the multi-module collaborative operation have a clearer system structure [17]. Kim and Heo constructed an agricultural digital twin instance for citrus production, demonstrating the computational potential of individualized agricultural management [18]. Barbie et al. studied a digital twin prototype for integrated testing of intelligent agricultural applications, which makes automated verification and application tuning into a reproducible process [19]. Kalimuthu et al. proposed an intelligent decision-making framework for agricultural supply chain in emerging economies, further incorporating supply, circulation and collaborative configuration into a unified decision-making calculation process [20].

In summary, the existing research has formed a relatively complete technology spectrum in the aspects of agricultural perception, visual recognition, remote sensing learning, digital twin and supply chain decision-making. However, the computational modeling directly oriented to rural revitalization and new quality productivity development path still needs to further focus on the unified representation of multi-source heterogeneous data, graph association state reasoning and intelligent path generation. Based on this, this paper connects the feature extraction of development factors, bottleneck correlation identification and path state modeling in the environment of agricultural Internet of things and intelligent computing. On this basis, the generation of rural revitalization and new quality productivity development path is completed, which provides a unified computing framework for subsequent experimental analysis.

3 Rural revitalization and new quality productivity development path modeling based on agricultural Internet of Things and intelligent computing

3.1 Feature extraction of development factors based on multi-source heterogeneous agricultural data

This section constructs a unified feature space around the input of development factors in the agricultural iot environment. Field sensors continuously collect soil moisture, temperature and humidity, light, nutrients and irrigation status, remote sensing images provide plot texture, growth distribution and spatial heterogeneity information, agricultural machinery logs record seeding, fertilization, harvest and operation paths, and circulation systems retain storage, cold chain, distribution and trading rhythms. The public service platform presents technical training, financial support, digital participation and collaborative service intensity. Data from different sources have obvious differences in sampling frequency, spatial granularity, time scale and expression. If directly concatenated, it is easy to cause high-dimensional noise diffusion and dominant feature distortion. Therefore, this paper first establishes a multi-source heterogeneous agricultural data processing chain from four levels of access, cleaning, alignment and coding, and maps discrete records, continuous sequences, image features and event logs into a unified development element representation. The process not only emphasizes the computable relationship between the data, but also retains the production rhythm, facility activity and service accessibility differences in the agricultural scenario to provide a stable input for subsequent bottleneck identification.

As shown in Fig. 1, the system first reads sensing flow, remote sensing slice, device log, circulation ledger and service record in the access layer, and then completes abnormal truncation, missing test completion, noise smoothing and timestamp correction in the cleaning layer. Then, the alignment layer establishes a joint index according to the village number, land unit, subject identity and business period, so that multiple types of observations in the same development link can be located at the same time. The unified coding layer transforms the environment, job, circulation and service information into a shared vector, and then forms a trainable basic feature matrix.

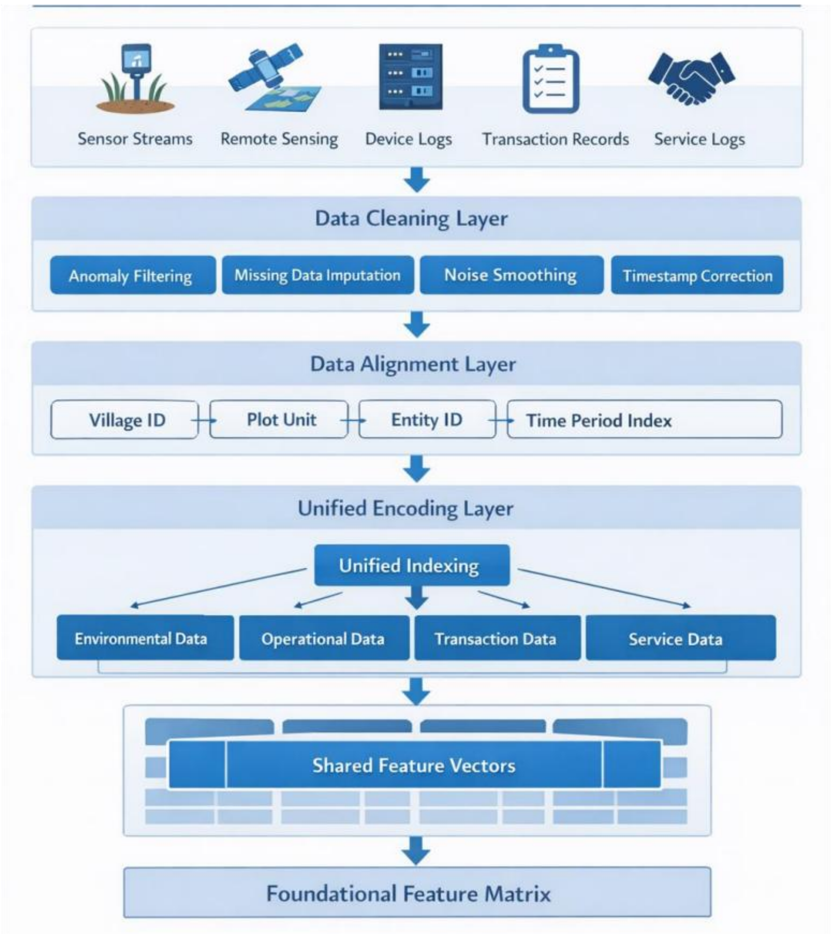

Figure 1: Flowchart of multi-source heterogeneous agricultural data access and unified coding

In order to make observations from different sources remain stable and comparable under a unified scale and enter into the coding calculation process:

$$Z_{a,b}=\frac{R_{a,b}\text{-med}(R_b)}{\text{iqr}(R_b)+\epsilon} \tag{1}$$

Here, $Z_{a,b}$ represents the normalized observations, $R_{a,b}$ represents the original data term, med represents the median, iqr represents the interquartile range, and ϵ represents the tiny constant. Equation (1) is used to weaken the pull effect of abnormally high and low values on the overall feature distribution, so that different modal inputs remain comparable in the same numerical interval.

In order to strengthen the effective response section and suppress the local redundant noise diffusion inside the multimodal input:

$$H_u=\sigma(W_uP_u+Q_u)\odot \tanh(V_uP_u) \tag{2}$$

Here, H_u represents the gated feature output, P_u represents the input vector of a certain modality, W_u and V_u represent the projection matrix, Q_u represents the bias term, σ represents the Sigmoid activation, and $\odot$ represents the element-wise multiplication. Equation (2) is used to retain the local information that is more sensitive to the development status, so that the environment, equipment and service data can complete a screening before coding.

As shown in Fig. 2, feature extraction is divided into basic perception layer, semantic aggregation layer and state expression layer. The basic perception layer deals with real-time observations and business records, the semantic aggregation layer compresses the relationships among parcels, subjects, nodes and service units into intermediate representations, and the state expression layer further outputs high-level variables such as production intensity, facility activity, circulation smoothness and digital participation. In this way, agricultural data from different sources are no longer isolated records, but are transformed into comprehensive features that can describe the foundation and coordination state of village development.

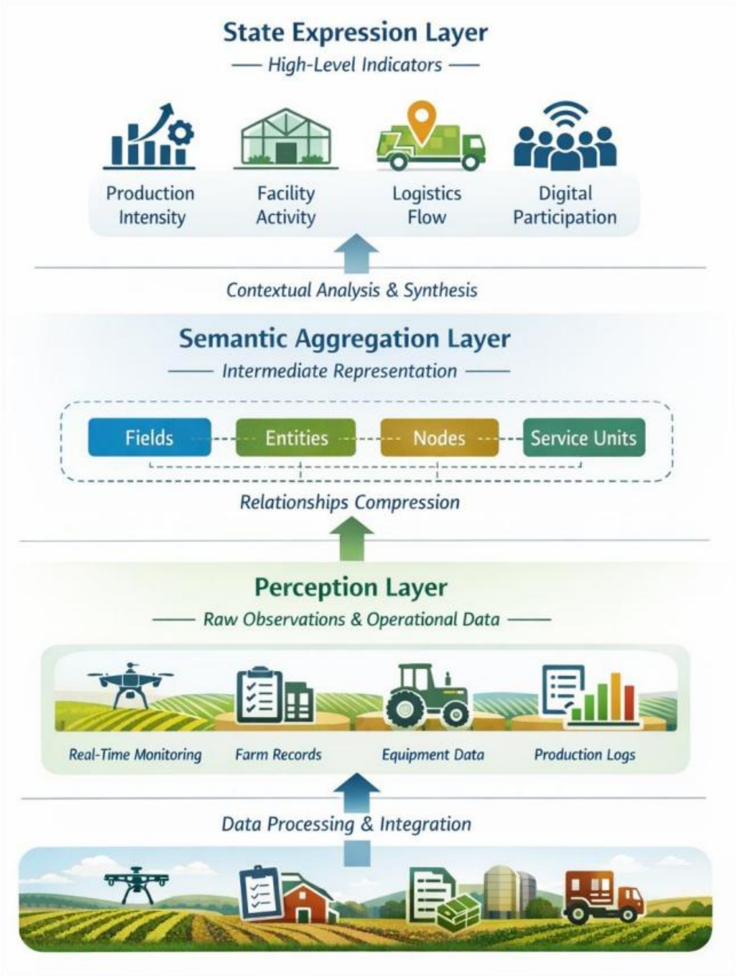

Figure 2: Hierarchical extraction and aggregation structure diagram of agricultural development factors

In order to compress agricultural information at different spatial levels into the same expression space and complete the joint representation process:

$$C_i=\sum_{m=1}^{M} \alpha_{i,m} E_{i,m} \tag{3}$$

Here, C_i represents the combined feature of the i object, $E_{i,m}$ represents the encoding result of the object at the m level, $\alpha_{i,m}$ represents the weight of the corresponding level, and M represents the number of levels. Equation (3) is used to complete the information aggregation among the village area, plot and link scales, so that the development elements can synchronously enter the subsequent reasoning module.

In order to ensure that the agricultural observation sequence under continuous sampling conditions has smooth evolution characteristics and retains trend information, the following process is carried out:

$$S_t=\lambda S_{t-1}+(1-\lambda)C_t \tag{4}$$

Here, S_t represents the smooth state at the current time, S_{t-1} represents the state at the previous time, C_t represents the current combined feature, and λ represents the smoothing coefficient. Equation (4) is used to reduce the interference of short-term fluctuations on path calculation and highlight the true change direction in long-term evolution.

In order to filter the core variables with stronger contribution to the expression of development status from high-dimensional input and form the ranking results:

$$G_d=\frac{\mu_d}{\sum_{j=1}^{J} \mu_j} \cdot \log(1+\nu_d) \tag{5}$$

Here, G_d represents the importance score of the d dimension feature, μ_d represents the average activation strength, ν_d represents the amplitude of cross-sample fluctuation, and J represents the total number of feature dimensions. Formula (5) is used to complete the screening of key development factors, so that the subsequent model will focus more computing resources on high-contribution dimensions such as farming, circulation, facilities and services.

After the above processing, the multi-source heterogeneous agricultural data is transformed into a development factor feature set with the ability of unified scale, hierarchical aggregation and temporal smoothing. The feature set not only preserves the basic state of the agricultural production end, but also presents the collaborative differences between the circulation end and the service end, which can fully express the technology input, facility linkage and digital participation in the rural revitalization scenario. More importantly, the unified coding result provides a clear input boundary for subsequent graph association reasoning, so that the bottleneck identification no longer depends on a single indicator judgment, but is based on the interaction of multi-dimensional states. At the same time, the coding result also retains the sample source label and regional context, so that the similar production conditions and similar service structures can be identified when modeling cross-village migration, reducing the accumulation of deviation caused by direct migration, and providing a clearer reference boundary for subsequent state comparison. The input set formed in this way has better interpretability and reusability, and is convenient for unified deployment in different agricultural types and different organizational modes.

3.2 Development bottleneck identification and path state modeling based on graph association reasoning

In this section, the agricultural development association graph is constructed based on the development element characteristics output in the previous section, which is used to identify the restricted links and path states in the rural revitalization process. The development bottleneck in the agricultural scenario is not reflected in the low single indicator, but often reflected in the insufficient synergy strength between production, processing, circulation, service and governance units, the decline of transmission efficiency and the imbalance of structural coupling. If only using static sorting method, it is easy to ignore the linkage effect between nodes. Therefore, this paper takes land parcel, cooperative organization, processing subject, logistics node and service agency as heterogeneous nodes, maps material flow, information flow, service flow and collaborative flow into multi-type edges, and introduces the combination feature generated in the previous section into the graph structure, so that bottleneck identification is based on the joint effect of local association and global conduction. The goal of graph association reasoning is not simply to find low-value samples, but to find the key positions that limit the development efficiency through structure propagation, and then compress these constraints into path state vectors for decision calls.

As shown in Fig. 3, the system firstly maps planting, storage, processing, distribution and service units into a unified graph space according to the village business chain, and then establishes heterogeneous edges according to transaction connection, spatial adjacency, service coverage and information interaction. The node attribute is composed of production intensity, facility activity, circulation level and service participation, while the edge attribute is jointly determined by linkage frequency, direction consistency and resource transmission intensity. The association network constructed in this way not only retains the hierarchical structure of agricultural links, but also can express the actual coupling relationship between different units.

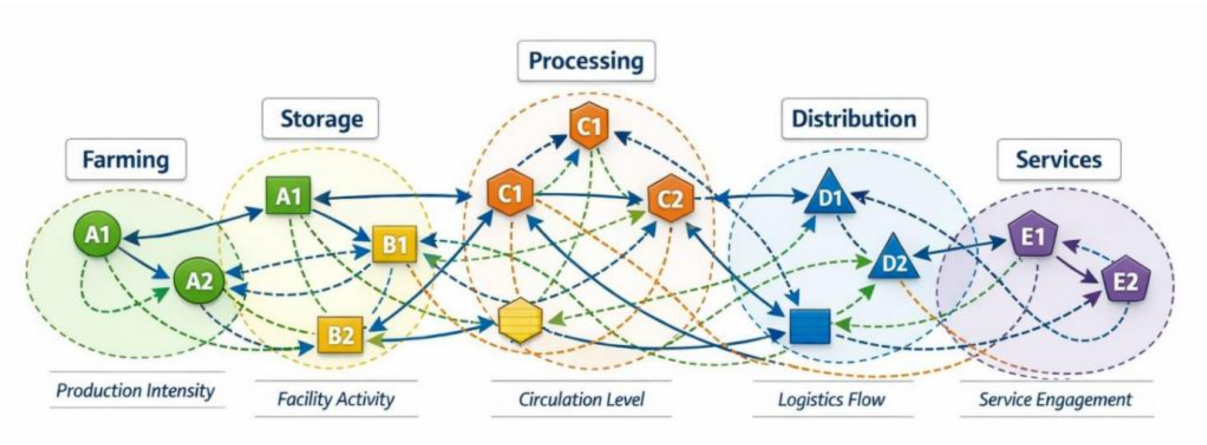

Figure 3: Schematic diagram of agricultural development association network construction and node mapping

In order to describe the real connection strength and direction characteristics between nodes in multi-agent multi-link agricultural network:

$$U_{r,s}=\exp\left(-\frac{\|D_r-D_s\|_2^2}{\eta}\right)\cdot 1(\kappa_{r,s}>\theta) \tag{6}$$

Here, $U_{r,s}$ represents the edge weight between node r and s, D_r And D_s represent the node attribute vector, η represents the distance attenuation coefficient, $\kappa_{r,s}$ represents the linkage strength, θ represents the effective edge threshold, and 1 represents the indicator function. Equation (6) is used to screen the edge connections with practical conduction significance, so that the subsequent reasoning focuses on the effective structure.

In order to identify the restricted positions with stronger influence on development conduction from within the association network and form the quantitative score process:

$$B_r=\frac{\sum_{s\in\Omega_r} U_{r,s}\,\delta_{r,s}}{\sum_{s\in\Omega_r} U_{r,s}+\zeta} \tag{7}$$

Here, B_r represents the bottleneck score of node r, Ω_r represents the set of its adjacent nodes, $\delta_{r,s}$ represents the development gap between adjacent nodes, and ζ represents the stability constant. Equation (7) is used to identify restricted locations in the structure by comprehensively considering node connection strength and local operation differences.

As shown in Fig. 4, node bottleneck scores propagate along high-weight edges in the local subgraph and gradually accumulate their impact on upstream and downstream links as they propagate. After the propagation, the model compresses the node-level results into link-level states, and combines the global statistical characteristics to form a unified path state vector. In this way, the development status of village no longer stays in the single-point description, but can present its restricted direction and coordination level in the form of structure.

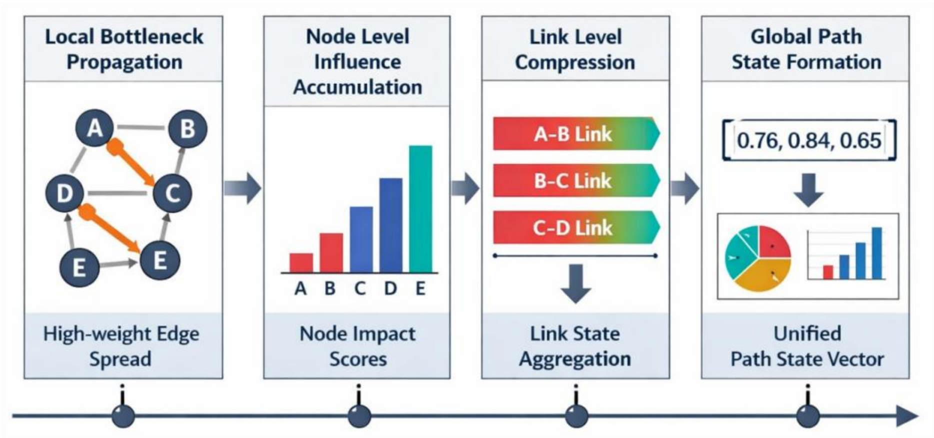

Figure 4: Bottleneck propagation and path state compression structure diagram

In order to make the node state continue to propagate between adjacent structures and reflect the change trend after constraint accumulation:

$$Y_r^{(q+1)}=\rho\left(\sum_{s\in\Omega_r} U_{r,s}\,\Gamma Y_s^{(q)}+\Phi B_r\right) \tag{8}$$

Here, $Y_r^{(q+1)}$ represents the state of node r after the q+1 round of propagation, ρ represents the activation function, Γ represents the adjacency mapping matrix, $Y_s^{(q)}$ represents the state of the adjacent node at the q round, and Φ represents the bottleneck injection coefficient. Equation (8) is used to introduce neighborhood states and restricted intensities synchronously in structure propagation.

In order to compress the local propagation results and global operation statistics together into a computable path state vector:

$$L_h=\omega_h M_h+(1-\omega_h)N_h \quad (9)$$

Here, L_h represents the state vector of the h developing link, h represents the structural representation obtained by local propagation, N_h represents the global statistical features, and ω_h represents the fusion weights. Formula (9) is used to compress the local bottleneck impact and the overall operation level into a unified state expression.

In order to measure the stability of different sample path states at the structure level and support the subsequent decision-making call process:

$$O=\frac{1}{|\Psi|}\sum_{(x,y)\in\Psi}\|L_x-L_y\|_2^2 \quad (10)$$

Here, O represents the structural consistency measure value, Ψrepresents the set of sample pairs, and L_x and L_y represent the state vectors of the two links. Formula (10) is used to compare the state proximity between different samples and provide a relatively stable state basis for candidate path generation.

In the process of graph association inference, we also set propagation boundaries for high-scoring bottleneck nodes to avoid local restrictions being magnified infinitely. At the same time, the model retains the difference of edge types, so that production coordination edges, circulation contact edges and service coverage edges play different roles in state propagation. After the above modeling, development bottleneck identification no longer relies on single point sorting, but system identification based on heterogeneous structure and propagation mechanism. The obtained path state vector not only contains the position of the constraint, but also reflects the direction, strength and influence range of the constraint, which provides more structural input for the subsequent intelligent decision-making algorithm to generate the development path. The state representation formed in this way can take into account both local diagnosis and global comparison, and enhance the migration stability of the model in different rural types. In addition, the state compression stage retains link time labels and regional context labels, so that the state changes of similar agricultural subjects at different time periods can be compared vertically, and the link performance between different village areas can be compared horizontally. This processing enhances the interpretability of the state vector and provides clearer computational boundaries for payoff evaluation, constraint filtering, and policy update in subsequent path ranking.

3.3 Rural revitalization and new quality productivity development path generation based on intelligent decision algorithm

The state modeling gives the constrained locations, collaboration levels, and structural stability of different links, but this information still needs to be transformed into executable paths before it can actually enter the deployment phase. Therefore, this paper divides the path generation process into five steps: candidate construction, utility calculation, feasible filtering, feedback update and ranking output. The candidate actions cover production enhancement, facility update, cold chain reinforcement, service access, digital governance and collaborative organization adjustment, etc., and form multiple groups of path schemes according to regional resource conditions, ecological boundaries and infrastructure carrying capacity. This process emphasizes computational traceability, that is, each path has a clear source of state, action combination and constraint basis, so that the output results are not only comparable, but also convenient for subsequent experimental verification.

As shown in Fig. 5, the system first reads the link state vector and regional context information, and then generates candidate paths according to the action template library. Each candidate path consists of action sequence, resource allocation, cycle arrangement and constraint label. The action template considers not only the transformation of the production side, but also the connection of the circulation side and the reinforcement of the server side, so as to ensure that the candidate set can cover multiple types of implementation scenarios in rural development. After the candidate set is generated, the model enters the utility evaluation stage to quantify the execution benefits and the structural coordination degree of different paths.

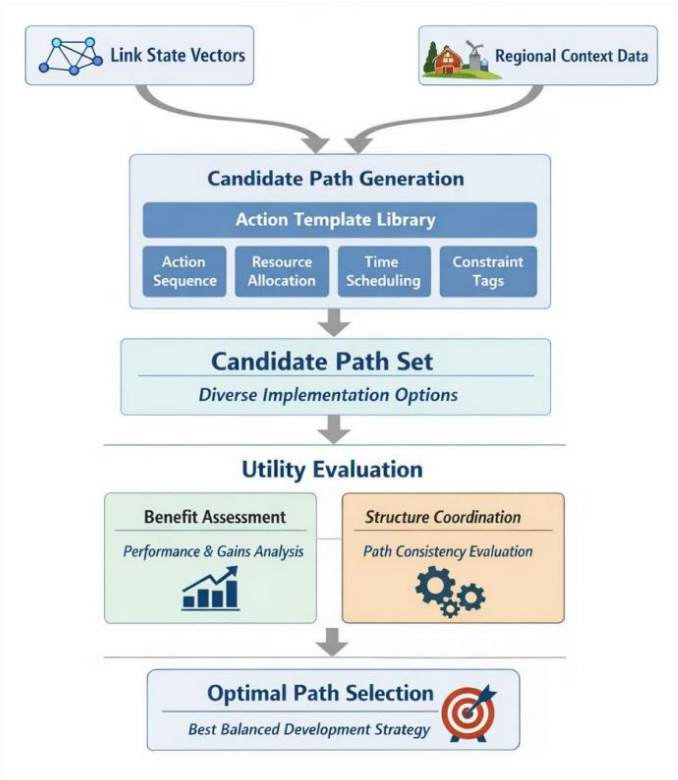

Figure 5: Flowchart of rural development path candidate construction

In order to transform the state modeling results into enumerable candidates and maintain consistency between different links:

$$\Pi_n=\mathrm{Cat}(\chi_n,\upsilon_n,\varrho_n) \tag{11}$$

Here, Π_n represents the encoding result of the n candidate path, χ_n represents the action sequence representation, υ_n represents the resource allocation vector, ϱ_n represents the constraint label vector, and Cat represents the splicing operator. Equation (11) is used to compress different forms of path information into a unified input space.

In order to comprehensively measure the joint effect of resource input, facility conditions, industrial coordination and ecological constraints on path selection:

$$\Lambda_n=m_n\chi_n^{'}+n_n\upsilon_n^{'}-o_n\varrho_n^{'} \tag{12}$$

Here, $\Lambda_n$represents the candidate path utility value, $\chi_n^{'}$ represents the benefit score, $\upsilon_n^{'}$ represents the synergy score, $\varrho_n^{'}$ represents the constraint cost, and m_n, n_n, and o_n represent the weight coefficients. Equation (12) is used to quantify the degree of balance between benefit and cost for different paths.

As shown in Fig. 6, after the utility calculation, the candidate paths first go through feasibility filtering, and then enter the policy update module according to the historical feedback. The update module will modify the action proportion, investment rhythm and service access order according to the execution performance of the past path, and the sorting module will output the final path set according to the corrected results. In this way, the path generated by the model is no longer a one-time static result, but a rolling decision scheme with continuous adjustment ability.

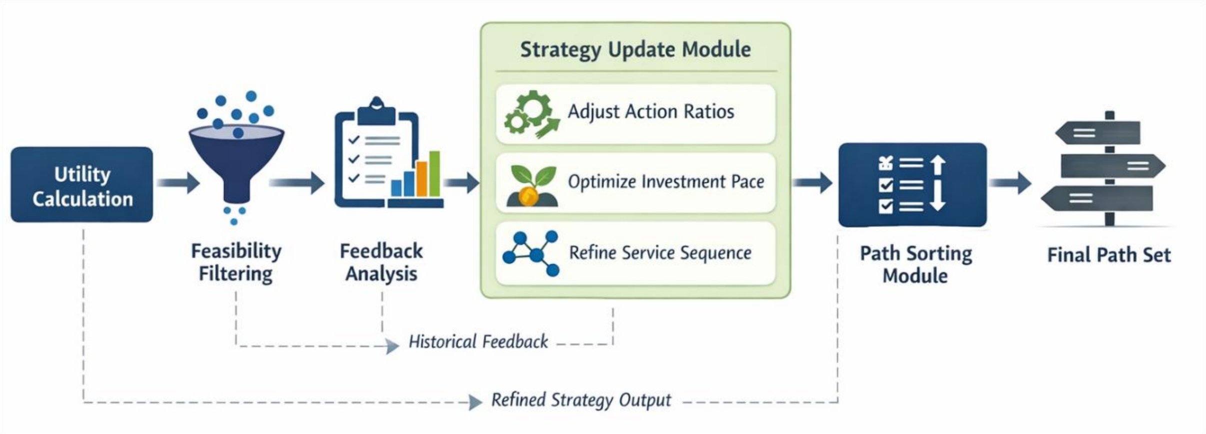

Figure 6: The rolling update and sorting output structure diagram of the intelligent decision algorithm

In the process of eliminating the set of low feasible solutions that do not meet the basic deployment conditions and boundary constraints before generation:

$$R_n=1(\Lambda_n>\tau)\cdot \exp(-\varsigma_n) \tag{13}$$

Here, R_n denotes the feasible index of the n candidate path, τ denotes the lowest utility threshold, ς_n denotes the degree of boundary violation, and 1 denotes the indicator function. Equation (13) is used to screen out schemes with insufficient benefits or too strong constraints before sorting to avoid invalid paths entering the update link.

In order to make the candidate path continue to modify the parameter configuration according to historical feedback in the rolling decision process:

$$\Theta_{k+1}=(1-\xi)\Theta_k+\xi R_n \tag{14}$$

Here, Θ_k denotes the decision parameters in round k, Θ_{k+1} denotes the updated parameters, and ξ denotes the feedback absorption coefficient. Equation (14) is used to modify the configuration of subsequent candidate paths using feedback information.

In order to output the final development path ranking probability result from the filtered and updated candidate set:

$$\Pr(g)=\frac{\exp(R_g/\omega)}{\sum_{h=1}^{K}\exp(R_h/\omega)} \tag{15}$$

Here, $\Pr(g)$ is the probability that the g path is selected, ω is the temperature coefficient, K is the total number of candidate paths, and R_h is the feasible index of each path. Equation (15) is used to complete the probabilistic ranking output of the candidate paths, so that high feasible, high collaborative and low constraint alternatives are given higher priority.

In the path generation stage, we also set an action diversity constraint to prevent the model from concentrating all calculations on a single high-yield action, resulting in the imbalance of production, circulation and service structure. At the same time, the model retains stage labels for candidate paths, so that short-term measures and medium and long-term deployments can be evaluated separately in the ranking. Through the above design, the discrete action description of rural revitalization and new quality productivity development path is transformed into comparable, updatable and orderable intelligent decision results. The output path not only reflects the constraint characteristics identified in the state modeling stage, but also reflects the comprehensive influence of regional resources, facility infrastructure and ecological boundaries, so as to form a computational path representation for smart agriculture scenarios. The results can be directly entered into the subsequent experimental analysis to verify the path consistency, deployment feasibility and revenue stability under different strategy combinations. In addition, the ranking output does not only give a single path, but retains several high-priority candidate sequences, so that managers can make secondary selection according to the funding pace, organizational capacity, and implementation window. The system also records the main revenue sources, the main constraint sources and the expected collaboration direction of each path synchronously, so as to facilitate the comparison of the execution differences under different strategy combinations in the subsequent experiment part.

4 Experimental analysis of rural revitalization and new quality productivity development path based on agricultural Internet of Things and intelligent computing

4.1 Selection of evaluation indicators

In this experiment, accuracy, recall rate, macro F1 value and root mean square error are selected as evaluation indicators to test the comprehensive performance of agricultural Internet of things and intelligent computing framework in rural revitalization and new quality productivity development path analysis. The accuracy represents the proportion of samples whose model output results are consistent with the real labels, which can reflect the overall correct degree of development path classification, node identification and state discrimination. The recall rate represents the proportion of real target samples that are effectively identified by the model, which is suitable to measure the coverage ability of the system for critical development links, limited links and high-value paths. Macro F1 value comprehensively considers precision and recall, and can more stably evaluate the recognition level of the model on different path types under the condition of agricultural samples with unbalanced class distribution. Root mean square error (RMSE) is used to measure the deviation between the continuous prediction value and the true observation value. It is suitable for testing the numerical fitting effect in the feature extraction stage, the offset amplitude in the state modeling stage, and the revenue estimation error in the path generation stage. In order to ensure the unity of the evaluation process, this paper maps the classification task and the continuous prediction task to the corresponding indicators respectively, and completes the comparative analysis under the same experimental framework. As shown in Table 2, different indicators correspond to different evaluation objects and functional focuses.

Table 2: Core evaluation metrics and their computational implications

Metric Name	Evaluation Target	Reflected Content
Accuracy	Path classification, state discrimination	Overall correctness of identification
Recall	Key nodes, key links	Effective coverage capability
Macro-F1 Score	Multi-class path samples	Overall recognition stability
Root Mean Square Error	Continuous prediction outputs	Level of numerical deviation

From the perspective of computational objectives, the extraction of development factors from multi-source heterogeneous agricultural data emphasizes the effective representation of environment, equipment, circulation and service variables, so it is necessary to observe the average deviation level between continuous output and real value by using root mean square error. The graph association inference stage assumes the tasks of bottleneck identification and path state description, and it is more necessary to jointly judge the recognition ability of the model for critical nodes and critical links through accuracy, recall rate and macro F1 value. The output of the intelligent decision algorithm is the sequence of development path candidates, and the result contains both category selection and intensity estimation, so the classification index and error index need to be used jointly. In this way, although different modules deal with different objects, they can all get comparable results under the unified evaluation logic. As shown in Table 3, there is a clear correspondence between each evaluation index and the experimental module.

Table 3: Correspondence between evaluation indicators and experimental modules

Experimental Module	Main Output Form	Corresponding Metrics
Development factor feature extraction	Continuous numerical vectors	Root Mean Square Error
Bottleneck identification and state modeling	Node and link categories	Accuracy, Recall, Macro-F1 Score
Path generation	Path categories and benefit estimation	Accuracy, Macro-F1 Score, Root Mean Square Error

In addition, this paper does not use a single indicator alone as the final judgment basis. The reason is that agricultural development path modeling involves simultaneously structure identification, state judgment and numerical estimation. If we only focus on the accuracy, it is easy to weaken the identification of a few critical paths. If we focus only on recall, we may amplify the interference caused by false positives. If we only rely on the root mean square error, it is difficult to express the effect of discrete path classification. Therefore, the accuracy, recall rate, macro F1 value and root mean square error are jointly selected as experimental evaluation indicators to reflect the recognition performance, stability performance and prediction performance of the model in the calculation of rural revitalization and new quality productivity development path.

4.2 Feature extraction and analysis of development factors based on multi-source heterogeneous agricultural data

This section focuses on the analysis of the effect of feature extraction of development factors from multi-source heterogeneous agricultural data. The experimental data comes from the self-built smart agriculture sample database, covering five typical scenarios: plain scale management area, hilly complex management area, coastal circulation coordination area, facility agriculture concentration area and ecological conservation transition area. It contains 164 administrative villages, 4,286 land units, 312 sets of iot sensing devices, 1,268 sets of agricultural machinery operation logs, 8,421 circulation records, 5,934 digital service records, and remote sensing slices updated quarterly. The experimental platform uses Python 3.10, PyTorch 2.2 and CUDA 12.1, and the server is configured with Intel Xeon Gold 6430 processor, NVIDIA RTX 4090 GPU and 128 GB memory. The number of model training rounds is set to 180, the batch size is set to 64, the initial learning rate is set to 0.0003, the optimizer uses AdamW, and the weight decay is set to 0.0001. The training set, validation set and test set were divided according to 7:1:2, and the five-fold cross validation method was used to group by village area to ensure that the boundary of regional samples was clear. The comparison methods include statistical concatenation method, single-modal convolutional coding method and ungated aggregation model, which are used to verify the effectiveness of the proposed method in unified coding, multi-modal fusion and developmental semantic preservation.

As shown in Fig. 7, before unified coding, the numerical span of different regional samples in the dimensions of facility activity, circulation efficiency and digital participation is large. The average response value of equipment activity in the facility agriculture concentration area reached 0.91, while that in the ecological conservation transition area was only 0.43. The average response value of circulation smoothness in coastal circulation coordination area is 0.88, and it is only 0.52 in hilly complex management area. After unified coding, the response interval of each dimension is concentrated between 0.61 and 0.84, and the bright and cold spots caused by extreme sampling points are significantly reduced. The results show that the robust normalization and gated screening can effectively compress the scale offset between modalities, make environmental monitoring, operation logs, remote sensing images and service records enter a more stable shared representation space, and provide input with clearer numerical boundaries for subsequent graph association reasoning.

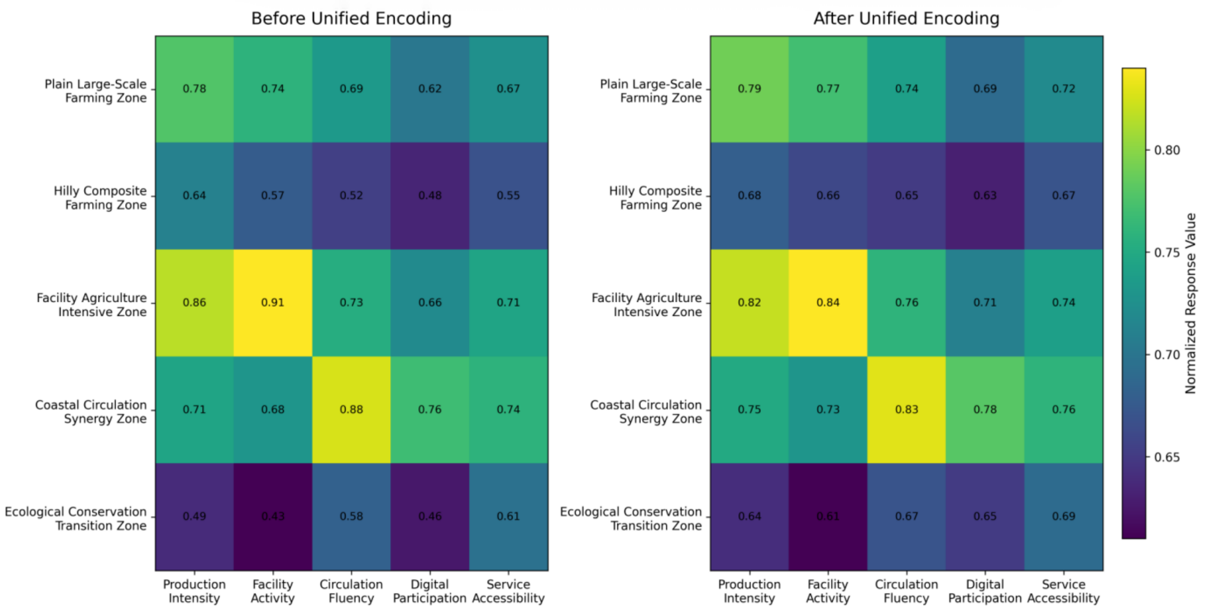

Figure 7: Heatmaps of distribution before and after unified coding for samples of five categories of regions

Fig. 8 shows the recognition confusion results of the three comparison methods and the proposed method on five types of region samples. The recognition accuracy of the statistical stitching method in the hilly complex management area is 81.3%, and 9.6% of the samples are misclassified as the ecological conservation transition area. The recognition accuracy of the single-mode convolutional coding method is improved to 86.7% in the coastal circulation collaboration area, but there is still a obvious intersection between the centralized area of facility agriculture and the coastal circulation collaboration area. The average accuracy of the ungated aggregation model on the five-class samples is 88.1%. In contrast, the proposed method achieves 92.4%, 90.8%, 93.1%, 94.2% and 89.7% in the main diagonal recognition rate of the five types of regions, respectively, and the misjudgment rate of the facility agriculture concentration area is only 3.8%. This result indicates that after hierarchical extraction and gated aggregation of multi-source heterogeneous agricultural data, the high-level semantic differences between regional development structures are more completely preserved, thus enhancing the separability of subsequent classification and modeling.

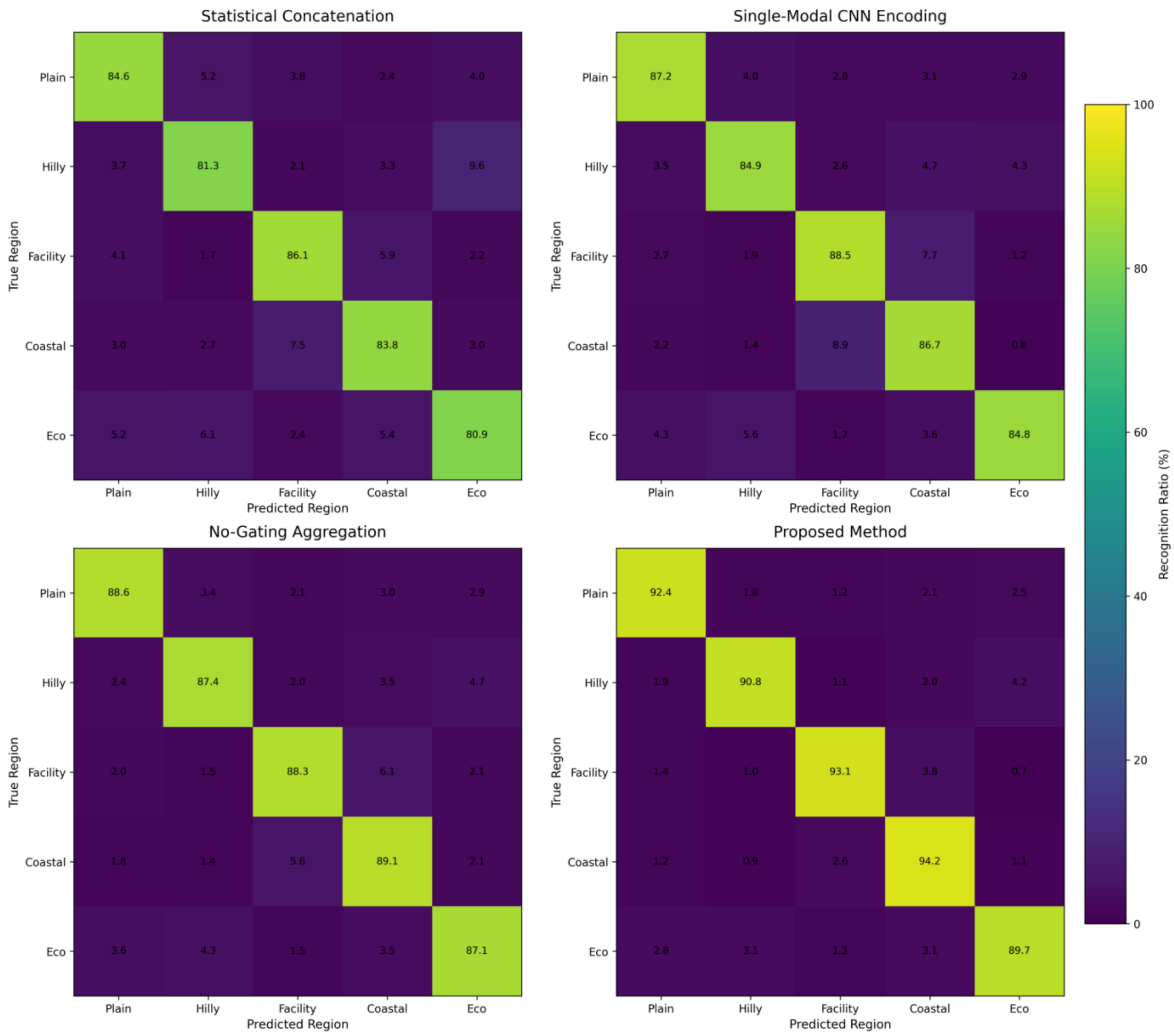

Figure 8: Confusion matrix plots of region identification for different feature extraction methods

Fig. 9 shows the clustering results of development elements under different feature extraction strategies using two-dimensional mapping. The boundary of the sample cluster formed by statistical stitching method is loose, and the contour coefficient is only 0.41. The single-mode convolutional coding method increased to 0.53; The ungated aggregation model achieves 0.61. The proposed method is further improved to 0.71. The inter-cluster distance between the plain scale management area and the coastal circulation coordination area increased from 1.84 to 2.67, and the overlap area between the hilly complex management area and the ecological conservation transition area decreased from 18.3% to 7.6%. It can be seen from the figure that the distribution of sample clusters obtained by the proposed method is more compact, and the transition region between classes is significantly reduced. This indicates that the hierarchical aggregation process does not weaken the fine-grained differences among parcels, subjects, and links, but rather enhances the structural discernibility of development elements by sharing the expression space.

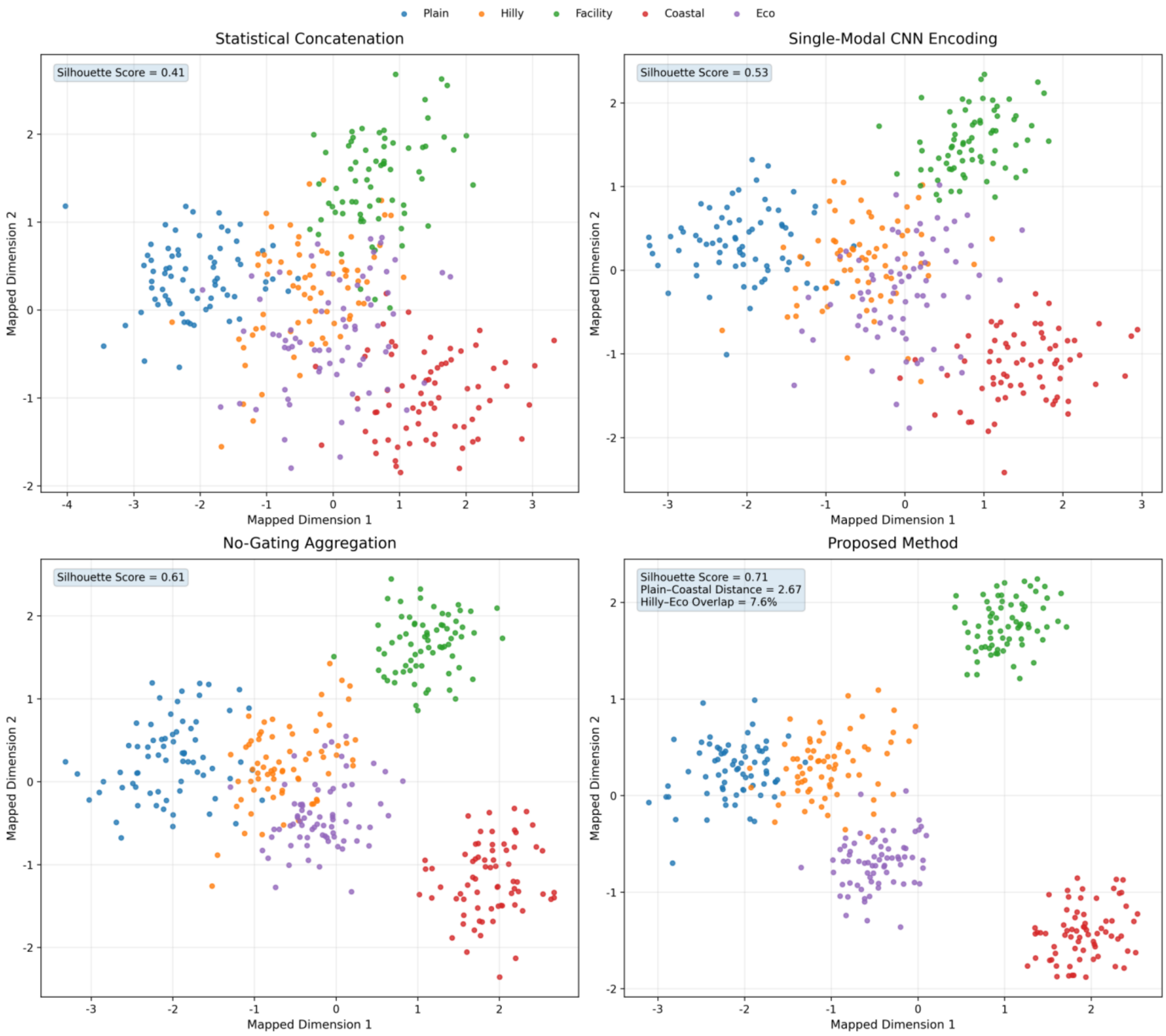

Figure 9: Scatter plot of two-dimensional mapping of feature space of development elements

Fig. 10 shows the response results of the five core development factors of production intensity, facility activity, circulation smoothness, digital engagement and service accessibility under different methods. The average response values of the statistical stitching method on the five indicators were 0.72, 0.75, 0.69, 0.63 and 0.66, respectively; the corresponding values of the single-modal convolutional coding method were 0.79, 0.82, 0.76, 0.71 and 0.73, respectively; the ungated aggregation model was 0.81, 0.84, 0.79, 0.74 and 0.76, respectively.

However, the proposed method achieves 0.86, 0.89, 0.84, 0.81 and 0.83. Especially in the two dimensions of digital participation and service reachability, the proposed method is 0.18 and 0.17 higher than the statistical stitching method respectively, indicating that the model can not only maintain the information of the production side, but also effectively encode the operation semantics of the circulation and service side.

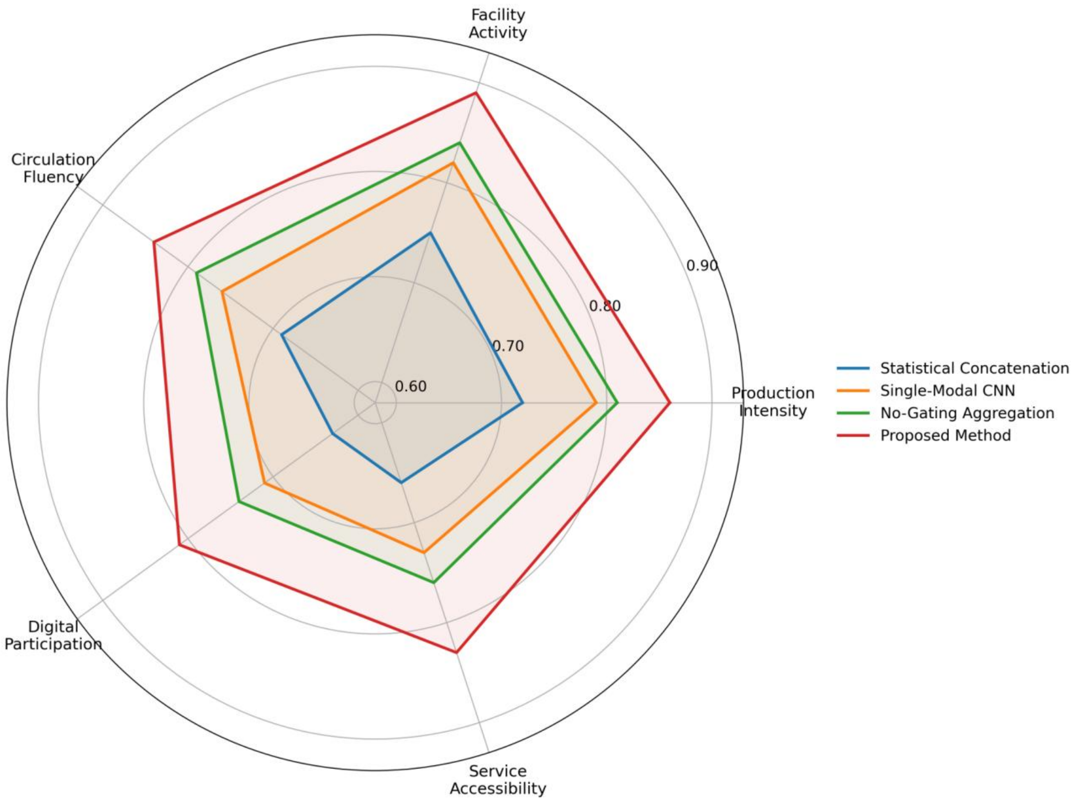

Figure 10: Radar chart of response intensity of core development elements

Combining the above results, it can be seen that the proposed feature extraction method of development elements is superior to the comparison methods in terms of unified coding ability, regional discrimination ability, and key semantic preservation ability. Additional tests on low-frequency service records and intermittent device logs also show that the basic method is prone to response collapse on these two types of data, while the proposed method can still maintain relatively stable feature amplitudes and class boundaries. This shows that the feature extraction mechanism of multi-source heterogeneous agricultural data constructed in this paper has strong robustness, and can provide reliable data basis for bottleneck identification and path state modeling of subsequent development.

4.3 Development bottleneck identification and path state modeling analysis based on graph association reasoning

After the feature extraction of development factors, this paper further analyzes the effects of development bottleneck identification and path state modeling of graph association reasoning. In the experiment, the unified features output in Section 4.2 are used as the node attribute input, and the land parcel units, cooperative organizations, processing enterprises, logistics nodes and service institutions are mapped into heterogeneous nodes, and the production coordination, warehousing connection, circulation and distribution, technical services and information interaction are mapped into multi-type edges. The final constructed agricultural development graph contained 18240 nodes and 56318 effective edges, of which production coordination edges accounted for 31.6%, circulation connection edges accounted for 24.8%, service coverage edges accounted for 21.3%, and information and capital linkage edges accounted for 22.3%. The experiment uses a three-layer graph propagation structure, the hidden dimension is set to 128, the propagation rounds are set to 4, and the node dropping rate is set to 0.15. The comparison methods include the basic graph convolution model, the edge-free type discrimination model, and the bottleneck-free injection model. In addition to the precision, recall and macro F1 value given in Section 4.1, the evaluation metrics include bottleneck localization bias and state consistency, which are used to investigate the stability of the model for the expression of development restricted locations and path states.

As shown in Fig. 11, the agricultural development association graph shows a more obvious community stratification under the heterogeneous structure. The model identified 7 stable communities, including 2 production-oriented communities, 2 circulation-oriented communities, 2 service-oriented communities, and 1 comprehensive transition community. The average clustering coefficient under this structure reaches 0.437, which is higher than 0.361 of the basic graph convolution model. The modularity of the model reaches 0.528, which is higher than 0.472 of the model without edge type discrimination. The service nodes and logistics nodes in the boundary area in the figure are connected across communities, which is consistent with the actual operation mode of the rural development link, indicating that the model can better distinguish the core conduction cluster and the cross-cluster transition cluster after adding the edge type and bottleneck propagation, so as to provide a clearer structural boundary for the subsequent restricted link identification.

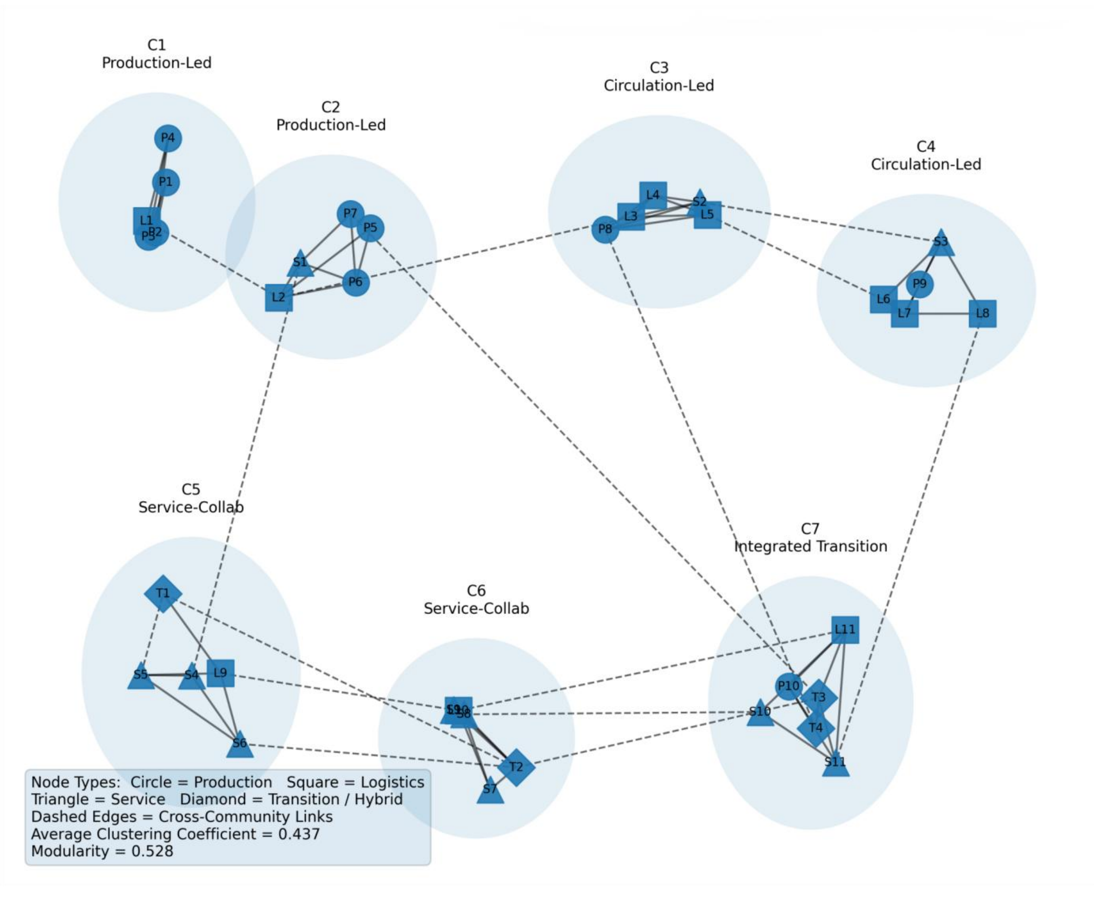

Figure 11: Community division graph of heterogeneous agricultural development network

Table 4 shows that the accuracy of the proposed method in node-level bottleneck identification reaches 91.8%, which is 3.9 percentage points higher than that of the basic graph convolution model. The recall rate reaches 90.6%, which is 3.8 percentage points higher than that of the edge-free type discrimination model. The macro F1 value was increased to 0.912. The bottleneck location deviation is reduced to 0.153. This result illustrates that although graph-structure convolution alone can capture adjacency information, it is difficult to precisely locate restricted locations that have a greater impact on developmental conduction. After introducing heterogeneous edge discrimination and bottleneck injection, the model's identification of key nodes and key links is more stable, and it is also closer to the constraint distribution in the real agricultural development link.

Table 4: Bottleneck identification results for different models

Model	Accuracy / %	Recall / %	Macro-F1	Bottleneck Localization Error
Basic graph convolution model	87.9	85.7	0.868	0.214
Model without edge-type distinction	88.6	86.8	0.874	0.201
Model without bottleneck injection	89.4	87.9	0.886	0.187
Proposed method	91.8	90.6	0.912	0.153

Fig. 12 uses box plots to show the distribution of bottleneck scores in the samples of five categories of regions. The median bottleneck score of the ecological conservation transition area was 0.68, and the interquartile range was 0.59 to 0.77, with the largest fluctuation range. The median value of facility agriculture concentration area was 0.54; Coastal circulation coordination area is 0.47; 0.44 in hilly complex management area; The lowest value was 0.39 in plain area. This result indicates that the ecological conservation transition area and the facility agriculture concentration area are more likely to form constraint accumulation, and the internal sample difference is larger. The recognition fluctuation of the comparison model is generally high in these two types of regions, while the proposed method still maintains a relatively concentrated distribution in high fluctuation regions, indicating that the constructed path state vector can stably express the local limitation degree under different development stages.

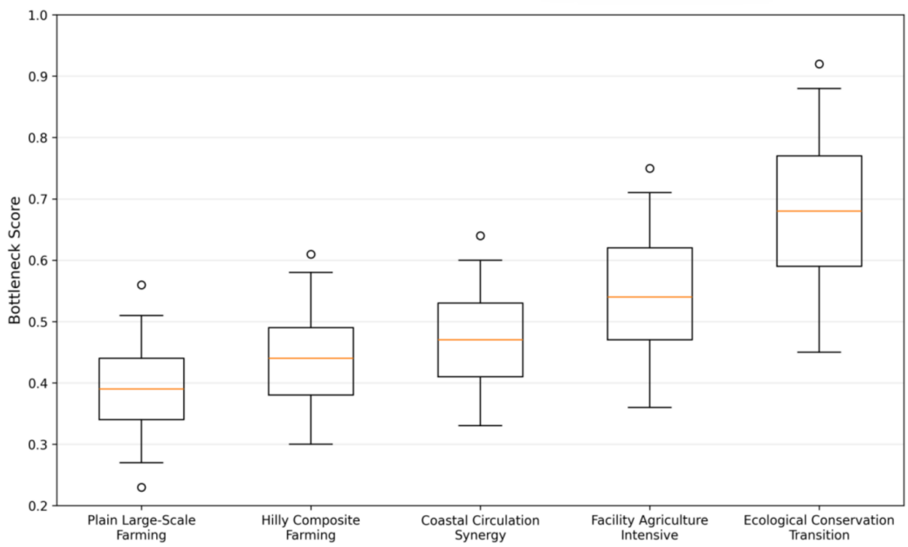

Figure 12: Box plots of bottleneck score distribution in different regions

From Table 5, we can see that the state consistency of the proposed method is higher than that of the control model on the five types of regions. Among them, the coastal circulation coordination area reached 0.851, the plain scale management area reached 0.842, and the ecological conservation transition area remained 0.824 although the structure was more complex. This shows that the path state vector is not only suitable for local bottleneck diagnosis, but also can support stable comparison between cross-region samples, and provide a unified state basis for subsequent path generation.

Table 5: State consistency results for different regional samples

Regional Type	Basic Graph Convolution	Without Edge-Type Distinction	Proposed Method
Plain-scale farming area	0.781	0.796	0.842
Hilly mixed-operation area	0.764	0.778	0.831
Coastal circulation-coordination area	0.789	0.804	0.851
Facility-agriculture concentration area	0.772	0.786	0.839
Ecological conservation transition area	0.751	0.769	0.824

Taking the above into account, it can be concluded that the graph correlation reasoning model constructed in this paper can compress the node relationship and link logic in multi-source agricultural features more completely, generate the path state representation more suitable for decision-making calls, and provide accurate and stable input for the intelligent decision-making algorithm in the next section.

4.4 Analysis of rural revitalization and development path of new quality productivity based on intelligent decision algorithm

After obtaining the path state vector, this paper further analyzes the effect of the intelligent decision-making algorithm in generating the development path of rural revitalization and new quality productivity. The experiment takes the link state results output in Section 4.3 as input to build a candidate action library and a rolling update mechanism. The candidate actions cover six types of operations: production enhancement, facility update, cold chain reinforcement, service access, digital governance and organizational collaboration, and are combined according to three implementation stages: short cycle, medium cycle and long cycle. A total of 3120 groups of candidate paths were formed in the experiment, covering a variety of development scenarios of 164 administrative villages under different resource bases, facility conditions and coordination levels. The comparison methods include rule ranking method, random forest decision method, and static decision method without feedback update. The evaluation indicators include accuracy, macro F1 value, root mean square error and path consistency. At the same time, the revenue estimation bias, resource matching bias and action sequence stability are recorded to observe the path generation ability of different algorithms in the real deployment environment.

Table 6 shows that the proposed method outperforms the control methods in the four indicators of path classification accuracy, macro F1 value, root mean square error and path consistency. Compared with the rule ranking method, the accuracy is improved by 6.8 percentage points. Compared with the static decision method, the RMSE was reduced from 0.247 to 0.214. The path consistency is improved by 4.2 percentage points. The results show that the candidate constraint filtering and feedback update mechanism can improve the path identification ability and the stability of revenue estimation at the same time, and make the path results generated by the model more suitable for the actual deployment stage.

Table 6: Performance comparison results of different path generation methods

Method	Accuracy / %	Macro-F1	RMSE	Path Consistency / %
Rule-based ranking method	84.7	0.836	0.298	85.4
Random forest decision method	87.9	0.871	0.263	88.2
Static decision method	88.6	0.882	0.247	87.1
Proposed method	91.5	0.914	0.214	91.3

Table 7 shows the ablation experiment results of the intelligent decision algorithm. After removing the candidate constraint filtering, the misjudgment of the model on the high-yield samples increased significantly, and the RMSE increased from 0.214 to 0.246. After removing the feedback update, the path consistency decreased from 91.3% to 87.1%, and the decrease was the largest. After removing the action diversity constraint, the model is more likely to repeatedly select the facility upgrade action, resulting in a significant decrease in the proportion of service access and circulation reinforcement. The complete model maintains the best results on the four indicators, indicating that candidate construction, constraint filtering, feedback update and action diversity control are not independent components, but key links that jointly support the quality of path generation.

Table 7: Results of ablation experiments for intelligent decision algorithms

Model Configuration	Accuracy / %	Macro-F1	RMSE	Path Consistency / %
Full model	91.5	0.914	0.214	91.3
Without candidate constraint filtering	89.2	0.889	0.246	88.6
Without feedback updating	88.7	0.881	0.252	87.1
Without action diversity constraint	89.5	0.892	0.239	88.4

Fig. 13 uses the stacked area diagram to show the action distribution changes under different stages. In the complete model, cold chain reinforcement, facility repair and service access were preferentially configured in the short cycle stage, and the total proportion of the three reached 58.6%. In the middle cycle stage, the proportion of production intensification and circulation coordination increased to 47.3%. In the long cycle stage, the proportion of digital governance and organizational collaboration rises to 33.8%. In contrast, the static decision method gives a higher proportion of long-term input actions in the short cycle stage, resulting in an obvious misalignment between resource scheduling and state change. The results show that the proposed method can dynamically adjust the action sequence according to the bottleneck source and link state, so that the output path is more in line with the implementation rhythm from basic completion to structural coordination in the process of rural development.

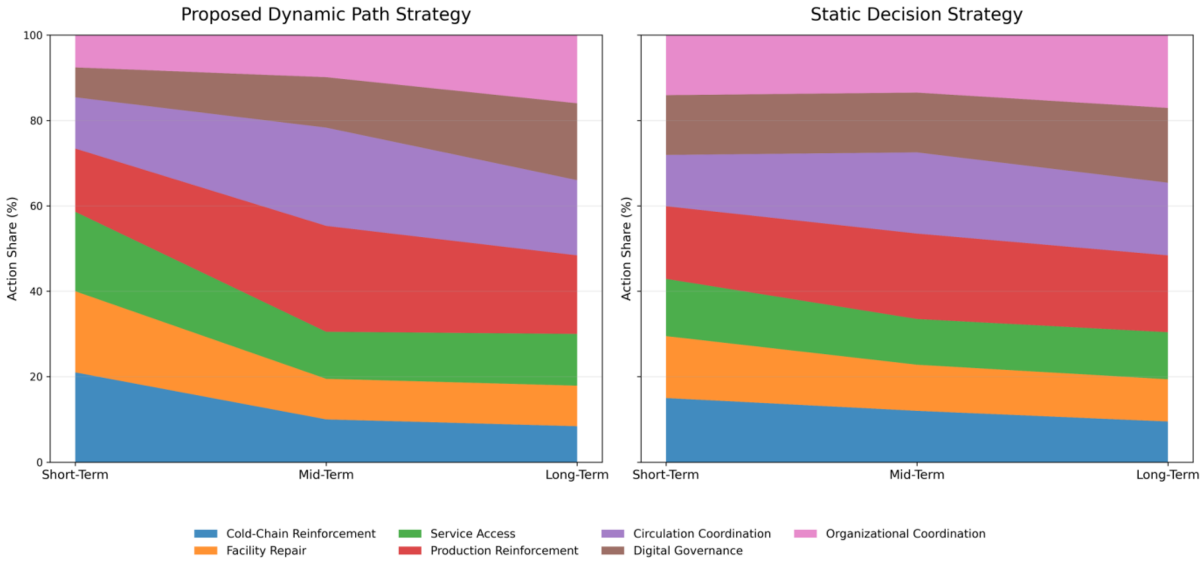

Figure 13: Stacked area plot of three-stage path action distribution

Combined with the above, it can be seen that the intelligent decision algorithm not only improves the classification accuracy of path generation, but also shows lower error and higher stability in revenue estimation, resource matching and action sequencing. The zoning test of plain scale management area, hill complex management area and coastal circulation coordination area also shows that the proposed method can maintain a relatively stable candidate path ranking results under different agricultural basic conditions. It can be seen that the constructed path generation mechanism can effectively transform the state results obtained by graph correlation reasoning into executable development paths, which provides strong support for the calculation of rural revitalization and new quality productivity development paths from the perspective of smart agriculture.

5 Conclusion

This paper focuses on rural revitalization and development path calculation of new quality productivity from the perspective of smart agriculture, and constructs a complete framework consisting of multi-source heterogeneous agricultural data feature extraction, graph correlation reasoning state modeling and intelligent decision path generation. At the data level, agricultural iot sensing streams, remote sensing slices, agricultural machinery logs, circulation records and digital service information are uniformly coded as development factor features. At the modeling level, the heterogeneous graph structure is used to identify bottleneck nodes, propagate constraint effects, and compress path states. At the decision level, candidate action generation, feasible filtering and feedback update jointly complete path ranking. Experimental results show that the proposed method has high stability in the three stages of feature extraction, bottleneck identification and path generation. The recognition accuracy of development elements extraction on five types of regional samples is more than 90%, the bottleneck identification accuracy is 91.8%, the path generation accuracy is 91.5%, the macro F1 value is 0.914, and the root mean square error is controlled at 0.214. The results show that the state of agricultural development can be clearly expressed through the computational model, and the rural revitalization path can be structurally generated through the intelligent decision-making mechanism. The method formed in this paper provides an accessible, comparable and scalable technical support for the county agricultural digital platform, and also provides a more engineering feature implementation way for the quantitative analysis of new quality productivity in rural scenes. At the same time, the scattered agricultural observations, link relationships and resource constraints are integrated into the same calculation process, so that the path output no longer stays at the level of empirical judgment, but has the ability of continuous update and deployment verification.

6 Discussion

The discussion of this paper mainly focuses on three aspects: method boundary, result interpretation and subsequent expansion. The existing framework has been able to complete multi-source agricultural data integration, bottleneck identification and path generation, but there is still room for further refinement. First, the samples mainly come from five types of typical regions, which cover a variety of agricultural operation forms, but extreme climate disturbances, multi-annual disaster shocks and sudden market fluctuations account for a limited proportion in the training set. Therefore, the adaptation ability of the model to strong non-stationary scenarios still needs to be further verified. Second, current graph association reasoning mainly relies on the types of nodes and edges that have been constructed, which can better express the connections between production, circulation and services, but the description of weak structural factors such as policy adjustment, financial constraints and organizational governance changes is still indirect. Third, the feedback update and action diversity constraints have been added to the intelligent decision-making algorithm, but the path revenue is still based on the periodic observation results, and the longer period closed-loop verification has not been formed. The follow-up research can be further promoted from three paths: expanding multi-regional samples across years to enhance the robustness of the model to dynamic disturbances; The digital twin and spatio-temporal large model were introduced to improve the state evolution simulation ability. Combined with online learning and edge deployment mechanism, the county platform can complete real-time update and adaptive optimization after continuous access to new data, so as to further enhance the interpretability and engineering applicability of path calculation in smart agriculture scenarios.

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