A Typical Model Evaluation System for Rural Vocational Education Against Poverty is Based on a Decision Tree Mining Algorithm

Mengmeng Han*, Imelda Lorenzo Najord
[1]Mariano Marcos State University; Ilocos Norte, 999005, Philippines
E-mail: 10760@jsjzi.edu.cn
*Corresponding author

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This paper presents an in-depth study and analysis of the evaluation of typical models of rural vocational education in combating poverty, employing a decision tree mining algorithm, and utilizing it to develop a practical evaluation system. The paper delves into various aspects such as teaching quality, education scale, teaching methods, and governmental policy support and financial input towards local agriculture-related vocational education. Additionally, it discusses the educational challenges contributing to the dearth of rural talent. The concept of educational data mining is introduced, followed by a description of several common decision tree algorithms including the ID3, C4.5, CART, and SLIQ algorithms, highlighting their connections and differences. Subsequently, the concept of multi-valued decision tables and decision trees is thoroughly explored, along with the decision tree analysis method for multi-valued decision tables, primarily based on the core idea of dynamic programming and the proposed algorithm for minimizing the decision tree size and extracting valuable information. Given the considerable size of generated decision trees, a recursive algorithm for merging identical subtrees and leaf nodes to form a decision graph is provided, resulting in a reduced storage space without redundant nodes. The primary causes identified for these challenges include weak government support for rural vocational education, low social recognition of rural vocational education, and the limited infrastructure of rural vocational colleges.

Povzetek: Članek obravnava razvoj sistema za vrednotenje tipičnih modelov podeželskega poklicnega izobraževanja za boj proti revščini z uporabo algoritma za rudarjenje odločitvenih dreves. Avtorji predstavijo uporabo več algoritmov, vključno z ID3, C4.5, CART in SLIQ, za analizo in zmanjšanje velikosti odločilnih dreves ter izboljšanje učinkovitosti shranjevanja. Sistem obravnava izzive, kot so nizka podpora vlade, slaba socialna prepoznavnost in omejena infrastruktura podeželskih poklicnih šol.

1 Introduction

In contemporary society, an unprecedented surge in information is being experienced. This phenomenon is propelled by the swift advancements in computer hardware, networks, and communication technologies that are observed. Additionally, a relentless growth in database sizes, alongside the progressive enhancement of enterprise informatization, leads to a continuous stream of data generation. Despite this abundance, the task of gleaning valuable insights from such a vast reservoir of data through traditional database queries and statistical approaches is found to be daunting. As a result, a paradoxical situation is found to be faced: being awash in a sea of information, yet starved for genuine knowledge. This highlights the critical challenge of navigating the complexity of modern data landscapes to unlock meaningful information that can inform decisions and drive innovation, which is being confronted.

The successful implementation of a rural revitalization strategy hinges on the effective development of human resources in rural areas. Among the various forms of education available, vocational education in rural areas stands out due to its employment-oriented nature and its fundamental goal of nurturing practical technical skills. This type of education is well-suited to the requirements of rural revitalization, given its operation in rural areas, flexible educational formats, and rich educational content.

To achieve rural revitalization, enhance the standard of living in rural areas, and transform rural life, it is imperative to accelerate the growth of rural vocational education. This entails improving the student financial aid system and ensuring that rural populations have access to opportunities for rural vocational education [1][2].

The key to rural revitalization lies in the cultivation of rural construction talents, with rural vocational education serving as the primary force in nurturing regional talent. To ensure that rural vocational education effectively contributes to national strategies such as rural revitalization, poverty eradication, and regional collaborative development, it is essential to deepen research into its development within the context of rural revitalization. This involves conducting comprehensive investigations into the functional role of rural vocational education in rural revitalization through a combination of theoretical and practical research, ultimately enhancing its alignment with the needs of rural revitalization [3].

Moreover, leveraging decision tree technology in data mining within the educational sphere can significantly analyze the fundamental factors influencing students' academic performance using system data. This optimization can enhance students' learning outcomes, partially improve the efficiency of teaching staff, and alleviate the workload of administrative personnel [4]. By employing decision tree technology to analyze students' performance trends, the obtained insights can empower students to understand their learning status comprehensively. This enables them to adapt their study plans, schedules, and learning approaches promptly, thereby enhancing their learning efficiency. Additionally, such analyses can equip teaching staff with valuable insights to offer tailored learning recommendations and develop appropriate teaching strategies based on individual student needs. Consequently, students can maximize their learning efficiency and reinforce their knowledge accumulation capacity within a shorter timeframe, thus achieving desired educational outcomes.

Hence, rural vocational education must fully embrace its essential role in supporting the implementation of rural revitalization. However, presently, the functional positioning of rural vocational education in China still requires alignment with the developmental needs of rural revitalization. On one hand, the pragmatic focus of rural vocational education fails to align with local economic development, with specialties and curriculum content often mirroring those of urban vocational education, which impedes the rural population's ability to contribute to local economic growth. On the other hand, rural vocational education needs to prioritize the enhancement of quality and ideological development among rural residents, which poses challenges in igniting farmers' enthusiasm for rural development. Given the current scenario of drifting functional orientation in rural vocational education, it holds significant theoretical and practical importance to reassess and redefine its functional orientation and realization pathway based on the developmental nuances of rural revitalization. This will accelerate the implementation of the rural revitalization strategy [5].

2 Related works

As the application of decision-tree technology in the field of education becomes increasingly mature, decision-tree algorithms can have a significant impact on practical applications. This class of inductive learning algorithms is widely respected in the education field, and one particularly noteworthy method is the decision rule tree method proposed by Ullah [5], [6], [7], [8], which utilizes channel capacity as a criterion to measure target attributes. Moreover, Balboni employed an improved version of the decision tree ID3 algorithm to mine information in a university's employment system, aiming to enhance the school's employment rate and level [9]. Tyagi, on the other hand, combined information from the student achievement database with primary data about students to construct a normalized decision tree achievement assessment model, with the improved ID3 algorithm at its core [10]. Singh conducted a study on factors affecting teaching quality using the C4.5 decision classification algorithm. This research guided and addressed teachers' issues in their teaching activities based on derived classification rules, ultimately improving teaching quality and enhancing their teaching effectiveness [11]. Most researchers in this area come from backgrounds such as computer science, education, and academic management, including teachers, students, and educational administrators. Their disciplinary backgrounds are relatively homogeneous, with limited cross-disciplinary research, particularly between education and sociology [12].

Maher has highlighted the indispensable role of vocational education personnel in the process of rural and agricultural economic development. He emphasizes that the key factor contributing to the sluggish economic growth in certain countries is the shortage of agriculture-related professionals. This issue cannot be addressed through a single level of countermeasures [13]. It requires a comprehensive approach, identifying the root causes across various dimensions, and implementing appropriate countermeasures supported by government policies to ensure that rural development remains resilient against diverse challenges.

Viewed through the lens of new urbanization, rural vocational education facilitates the smooth integration of rural migrant populations into urban and town environments [14]. The migration of surplus rural labor to urban areas fosters large-scale production in rural regions, thereby promoting rural revitalization. To ensure the successful integration of rural migrants into urban life, resolving the employment issue is paramount. Rural vocational education plays a crucial role in enhancing the job skills of rural migrants, enabling them to transition into new careers to support urban development [15].

From the perspective of targeted poverty alleviation, lifting rural populations out of poverty is pivotal for rural revitalization. There exists a strong linear relationship between rural vocational education and the income of impoverished individuals, with deeper education correlating with higher incomes. However, the connectivity between domestic authors appears to be scattered, with less multi-party cooperation evident, and convergent graphical patterns are rare [16].

There is a noticeable scarcity of studies offering policy recommendations that integrate "national policy," "school," and "local government." Moreover, reflections from the school's perspective typically focus solely on graduate employment and major selection, with limited attention paid to public administration aspects. Building upon the aforementioned studies, this paper aims to enhance and actively engage in a more detailed discourse on the training of vocational education personnel for rural revitalization and its corresponding countermeasures. It endeavors to offer valuable references for future research endeavors.

In the rural revitalization strategy, it is further proposed to enhance the quality and efficiency of rural agricultural products, delve deeper into rural modernization, and foster new types of professional farmers. This study is rooted in an examination of the agricultural vocational talent cultivation system. Liaoning has made notable strides in rural revitalization in recent years, largely attributed to its efforts in cultivating agriculture-related talent. However, despite these advancements, there remains a gap in agricultural talent cultivation when compared to well-developed rural areas within China and the practices observed in developed countries abroad. This study seeks to enrich relevant theories within China by delving into the cultivation of agriculture-related talent in Liaoning. The discussion on this subject matter holds significant importance in augmenting pertinent theories within China. Table 1 provides a summary of related works.

The provided table summarizes key characteristics of decision tree algorithms (ID3, C4.5, CART, SLIQ) and their relevant applications in rural vocational education. It also identifies gaps in current research and outlines how the proposed work addresses these gaps. Specifically, it emphasizes aspects such as algorithmic efficiency, accuracy, and applicability to the rural education context.

3 Decision tree mining algorithm evaluation model analysis

Decision trees represent a widely employed method for analyzing vast datasets within educational settings and for making predictions based on analysis outcomes. The algorithms utilized to represent decision problems through decision trees include ID3, C4.5, CART, and SLIQ algorithms, each possessing distinct characteristics and applicability, thereby necessitating the selection of an appropriate algorithm based on data type, size, and other pertinent characteristics. It is well-known that the ID3 algorithm primarily caters to discrete variables; conversely, the C4.5 algorithm is preferred for continuous variables [17]. In practical scenarios, there exist typical datasets characterized by identical conditional attribute values yet differing decision values, such as those encountered in faculty management systems. Due to insufficient attribute values to precisely label certain individual rows, a single row within a multi-valued decision table may represent multiple decision values, thus constituting a decision set.

The construction of a decision tree involves two phases: the creation of branching nodes and the pruning phase. Initially, in the creation and branching phase, the algorithm analyzes and computes the given training sample dataset. During this process, internal nodes are identified until the leaf node of each branch is reached. Typically, existing open-source frameworks and data mining software are utilized to execute this phase. The second stage, known as the pruning stage, focuses on reducing overfitting and redundancy within the tree structure. This phase tends to be more effective for smaller decision trees. However, as the decision tree expands, the complexity of its nodes increases, potentially making it more challenging to interpret. Pruning methods are generally categorized into two types: pre-pruning and post-pruning, with the choice of method depending on the specific application context.

A multi-valued decision table t is represented by a rectangular table filled with non-negative integers. The columns of this table are denoted as attributes, including the conditional attributes f, ..., h, and the decision attributed, and the attribute value corresponding to each conditional attribute is represented as a non-negative integer. If the attribute value is a string, then the line must be compiled into a non-negative integer value. There are no duplicate rows in the multi-valued decision graph, and multiple decisions in each row are represented by a non-empty finite set of natural numbers (decision set). We denote the number of table rows by the i-th row, where$i = 1,2, \dots, N(t)$. For example, represents the first row, r represents the second row, etc.

$$sup(X \cup Y) = \frac{X \cap Y}{|D|} \tag{1}$$

If a decision value corresponds to the set of decisions for each row of records in table t, then we refer to this decision value as a joint decision in the multi-valued decision table t. If the table contains no records or consists of joint decisions, it is termed a degenerate table [18]. Additionally, it comprises root nodes, internal nodes, leaf nodes, and branches connecting these nodes. This structure can automatically classify and predict input data information under specific conditions, serving as a knowledge representation in a tree structure.

$$souf(X \cap Y) = \frac{X \cup Y}{|X|} \tag{2}$$

All non-leaf nodes correspond to attribute tests, with branches specifically indicating the outcomes of these tests, while leaf nodes represent classes or class distributions. The decision tree begins at the root node, situated at the top. A path extends from the root node to the leaf nodes, each path corresponding to a specific merging rule. Therefore, the entire decision tree represents a set of parsing expression rules, and the choice of the root node significantly influences subsequent segmentation results. The number of decision nodes is associated with the selected algorithm.

$$wsuo_w(I) = \frac{1}{k+2} \sum_{i \in I} w_I \, sup(I) \tag{3}$$

The process of constructing a decision tree involves iteratively partitioning pre-processed data using a top-down recursive approach. This process compares attribute values at internal nodes of the decision tree, selects the most suitable attribute for testing, and then constructs nodes at the next level to classify the partitioned results. This process continues until further partitioning results in subsets containing only the same type of cases, at which point the nodes with class labels are designated as leaf nodes.

But in the process of tree building must avoid overtraining the present service, white mouth, then h basket rubbish when deciding each of the first trees, thus reducing the availability of the tree and increasing the training time. According to the Nong construction within the extended voodoo boundary, the team p of leaf nodes is represented by a natural number, which represents a decision, and each non-leaf node represents an attribute set {fi.... fn} copies of one of the attributes. The output edges from each non-leaf node are represented by different non-negative integers, e.g., 0 and 1 can represent two edges of a binary-valued attribute, as shown in Figure 1.

Table 1: A summary table of the related works

Decision Tree Algorithm	Characteristics	Relevant Applications in Rural Vocational Education	Gaps in Current Research Addressed
ID3	- Simple and efficient algorithm - Builds trees based on information gain - Prone to overfitting - Handles categorical attributes	- Used to mine information in employment systems to improve employment rates - Applied to build achievement assessment models based on student data - Limited research on its applicability to rural vocational education	- Overfitting issues need to be addressed for accurate predictions in rural contexts - Lack of exploration into its effectiveness for rural skill development
C4.5	- Extends ID3 by handling both categorical and continuous attributes - Prune trees to avoid overfitting - Utilizes gain ratio for attribute selection	- Identifies factors affecting teaching quality - Guides teaching improvement based on classification rules	- Limited exploration into its application in rural vocational education contexts - Need for further investigation into its adaptability to rural skill development
CART	- Builds binary trees - Handles both regression and classification tasks - Prune trees based on cost-complexity - Handles categorical and continuous attributes	- Potential for identifying factors affecting rural vocational education outcomes - Suitable for analyzing complex relationships in rural education systems	- Limited research on its specific application in rural vocational education contexts - Need for empirical validation of its effectiveness for rural skill development
SLIQ	- Optimized for large datasets - Constructs decision trees efficiently using a linear scan of data - Handles continuous attributes	- Potential for scalability in analyzing large datasets related to rural vocational education - Efficiently extracts decision rules relevant to rural skill development	- Limited exploration into its applicability to rural vocational education - Need for comparative studies to assess its performance against other algorithms in rural contexts

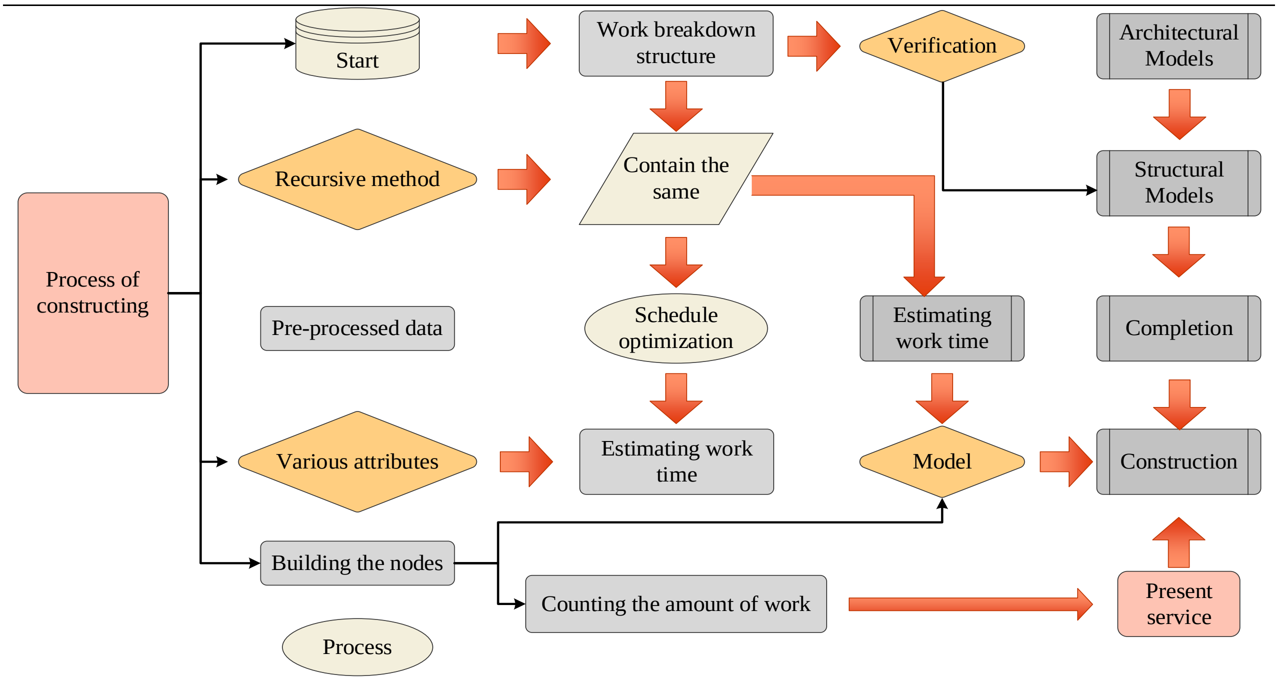

Figure 1: The 5 branches of the decision tree construction

tree Tn can be connected to any node except the f node ($i = 3,4,5,6,7$); each Tn may have a total of decision tree sub-trees 7×6×5×4×3=2520 kinds connected with this; in this process, there will be a decision tree with incomplete attribute values corresponding to the attributes so that it will affect the classification results and correct decision, so the incomplete decision trees of this class will be removed. Hence, the decision tree subtree depicted in Figure 1 is further expanded to acquire the decision tree subtree (2). In subtree (2), the attribute "f" lacks a decision with the attribute value [19]. To ensure completeness and accuracy in decision-making, it's preferable to minimize missing attribute values in each expansion. Consequently, the next step (2) can be omitted, meaning the decision strategy with "f" as the root node is not taken into account. Additionally, the decision tree subtree with "fi" as the root node in (4) can also serve as a subtree with "f" as the root node.

Figure 2 shows the decision tree with f as the root.

$$(wconf_w I \to J) = \frac{wsup(I)}{w\, sup(X \cup Y)} \quad (4)$$

The expansion proceeds sequentially following the same method and steps. However, the decision tree with "f" as the root node does not require further expansion during this process. In summary, the final classification results of the node represent the minimal decision tree. In other words, the mother's occupation emerges as the most critical factor influencing student performance, with better performance observed when the mother's occupation is that of a teacher or civil servant.

The process of constructing a decision tree involves two stages: growth and pruning. During the growth stage, also known as the building process, attribute values are divided based on specific criteria, gradually forming the decision tree from the top to the bottom. Pruning, on the other hand, aims to eliminate noise or anomalous data. The two most common pruning methods for decision trees are pre-pruning and post-pruning. Pre-pruning involves setting rules to limit the growth of the tree, halting its construction early if certain conditions are met. Post-pruning, which is more widely used, occurs after the decision tree has been fully grown. There are two approaches to post-pruning: replacing the subtree with a new leaf node whose class is determined by the majority class recorded under the subtree and replacing the subtree with the branch most frequently used within it.

In contrast to decision trees, decision diagrams offer two distinct advantages: firstly, they allow for the merging of all leaf nodes belonging to the same class; secondly, they address the issue of recurring subtrees by consolidating them [20]. By combining leaf nodes and recurring subtrees, decision diagrams reduce the size of the decision tree, eliminate redundancy, and conserve storage space, thereby facilitating storage management.

In Figure 2, the recurring subtrees are highlighted with dashed lines, indicating instances where the children F with C as the parent node are identical. The decision tree would occupy significant storage space. Therefore, it's essential to minimize the size of the decision tree by merging identical leaf nodes and subtrees. This process results in a decision diagram with only one leaf node. Although the concepts and meanings of the two are the same, opting for decision diagrams over decision trees mitigates the storage space consumed by decision trees.

4 Design of a typical model evaluation system for rural vocational education against poverty

Teaching quality is directly related to the level of rural vocational talent cultivation and is an essential factor in cultivating high-quality and high-level agricultural-related talents. Analyzing the ratio of the number of graduates who have obtained agriculture-related vocational certificates to the number of graduates from rural vocational colleges in Liaoning Province can better assess the cultivation of rural vocational talents in Liaoning Province. After passing a series of training in agriculture-related vocational education, there will be a strict assessment before graduation. After passing the evaluation, the school will issue a vocational certificate to the students after the content of their studies has reached the standard of practice, which must be provided to the enterprises or employers when the students are employed.

At present, the teacher-student ratio in agriculture-related vocational personnel training shows a trend of gradual increase overall, but combined with the current teacher size and the number of students in agriculture-related vocational personnel training, it shows that the teacher-student ratio in agriculture-related vocational personnel training in Liaoning Province has an average annual growth rate of about 5%. Each teacher can have more economic zones to train students, but it cannot be ignored that while the teacher-student ratio is steadily increasing, the student size and teachers are in a decreasing trend [21]. However, it cannot be ignored that while the teacher-student ratio is steadily increasing, the student size and teachers are in a decreasing trend, indicating that teachers have more time and energy to improve education under the overall decreasing trend of cultivating agriculture-related vocational talents. Still, they need to be alert to the problem of a shortage of students in agriculture-related vocational education, as shown in Figure 3.

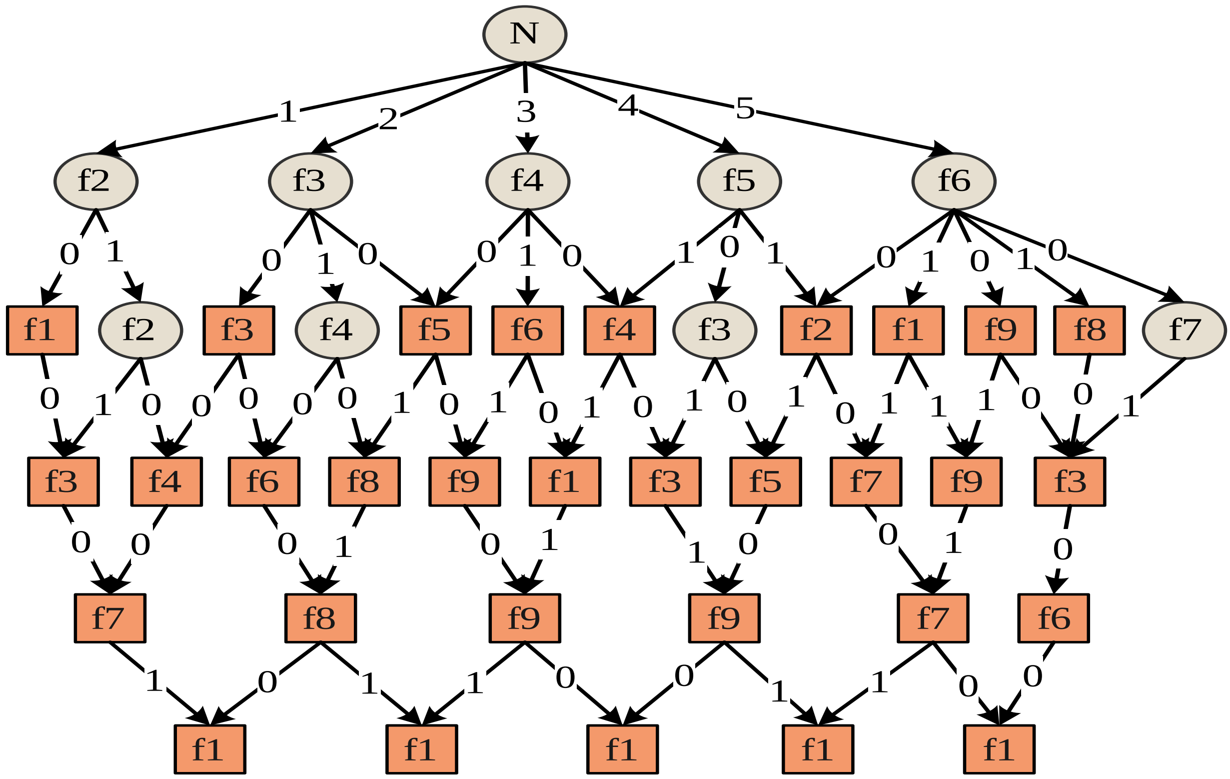

Figure 2: Classification of dynamic programming algorithms

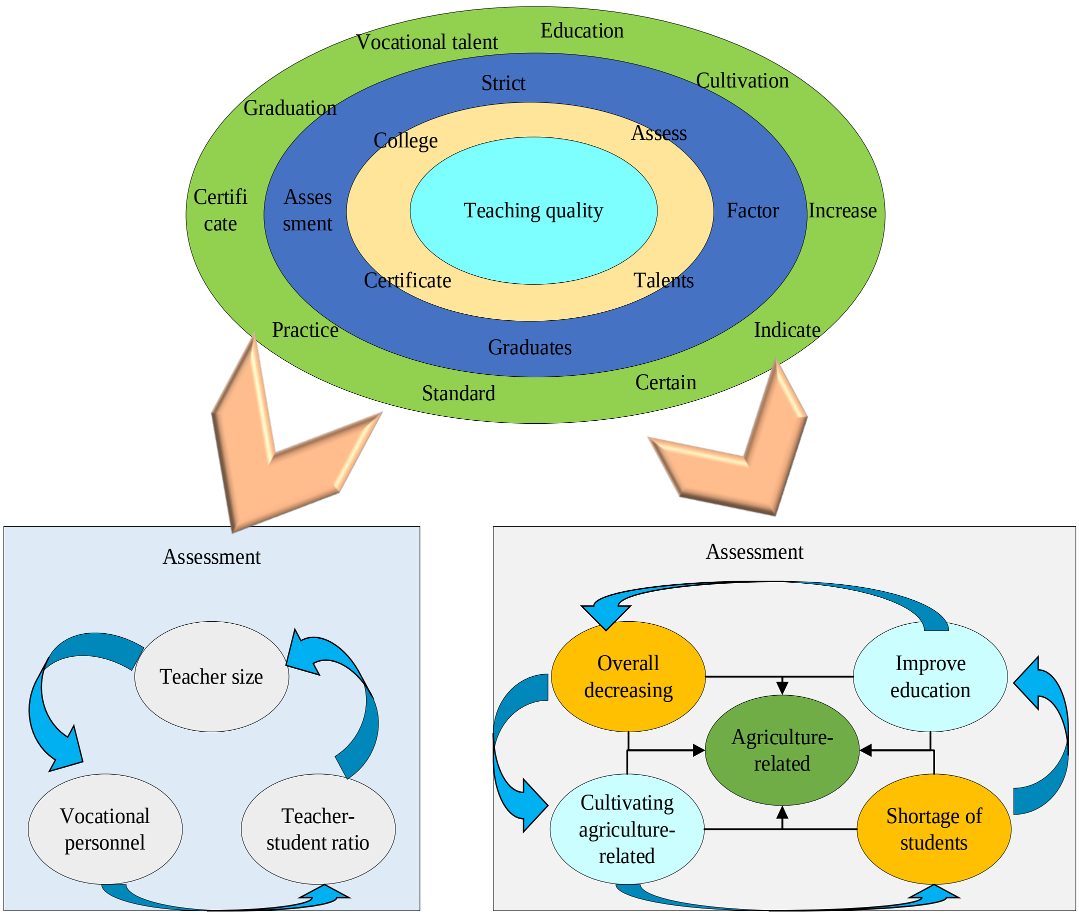

Figure 3: Framework of the education evaluation system

The rural revitalization strategy needs enough agriculture-related vocational talents to support; however, due to reality, the scale of vocational talent cultivation in rural areas differs significantly from that in urban areas, and there are inevitable fluctuations in the scale of teachers. The higher teacher-student ratio can indicate the richer educational resources for the cultivation of agriculture-related professionals.

The number of cultural and primary education teachers in rural vocational schools is still relatively high, and schools are gradually introducing "dual-teacher" teachers and expert teachers [22]. However, it is difficult to bring in many specialist teachers to provide practical guidance to students due to insufficient government investment and limited school funding. Teachers with the same level of education or ability tend to seek development opportunities in the city, and there are only a few opportunities for agricultural teachers to go out for training, so most teachers lack practical experience and can only teach according to textbooks or are slower to recognize and accept new knowledge.

Although the theoretical community has different perspectives on the definition and specific concepts of competency, there is still a consensus that "competency must be linked to job tasks; it consists of a combination of elements; and it can be observed, measured, and predicted through specific expressions such as work behavior [23]. The structure of the elements of competency is necessarily different from industry to industry, from job to job, and from position to position. Therefore, among the diverse research literature on "competency", this study focuses on "entrepreneurial field" and "management position", which have high relevance to new professional farmers. Therefore, among the colorful past research literature on "competency", this study focuses on "entrepreneurship field" and "management position", which have high relevance to new professional farmers, to selectively sort out the representative competency research results, as shown in Table 2.

The number of graduates obtaining corresponding vocational certificates showed an overall upward trend, with a mild decline observed from 2010 to 2014. However, the proportion of graduates obtaining agriculture-related vocational certificates saw a significant increase post-2015, with reasonable fluctuations following the implementation of the rural revitalization strategy. This indicates a continuous improvement in the education quality of agriculture-related vocational talent cultivation in Liaoning Province [24]. Currently, the teacher-student ratio in agriculture-related vocational talent cultivation exhibits a gradual increase overall. However, when considering the current teacher scale and student numbers, it is evident that the teacher-student ratio in Liaoning Province's agriculture-related vocational talent cultivation has an average annual growth rate of about 5%. While each teacher can oversee more economic zones for student cultivation, it's crucial to note that this ratio is steadily rising. Nevertheless, it's important to acknowledge that alongside the increasing teacher-student ratio, both student enrollment and the number of teachers are experiencing a downward trend. This suggests that teachers have more time and energy to enhance education amid an overall decrease in agriculture-related vocational talent cultivation. However, vigilance is necessary regarding the issue of student shortages in agriculture-related vocational education.

5 Experimental design and data analysis for decision tree evaluation

We aim to provide an in-depth response that addresses the origin, size, characteristics of the dataset, and its direct relevance to rural vocational education and the application of our decision tree algorithm.

a) Origin of the Dataset:

The dataset underpinning our study was meticulously compiled from a comprehensive survey conducted across various rural vocational schools within Liaoning Province, China. This endeavor was facilitated through collaborative partnerships with local educational institutions and governmental bodies focused on agricultural and vocational training. These institutions provided access to a rich array of data reflecting the educational outcomes, socioeconomic backgrounds, and vocational achievements of students enrolled in rural vocational programs. The choice of Liaoning Province was intentional, as it represents a dynamic landscape for rural education reform and vocational training aimed at poverty alleviation and rural revitalization.

b) Size of the Dataset:

Our analysis is built upon a dataset encompassing records from over 486 students, spanning a diverse range of vocational fields. Each record comprises 40 distinct attributes, including demographic information, educational background, vocational certification outcomes, and employment status post-graduation. This comprehensive dataset allows for a nuanced exploration of the factors influencing educational outcomes in rural vocational settings.

c) Characteristics of the Dataset:

The dataset's characteristics are central to our investigation, offering insights into the demographics of rural vocational education participants. Attributes include age, gender, socioeconomic status, type of vocational certification, field of study, and post-graduation employment rates. This granularity enables us to dissect the multifaceted impact of rural vocational education on poverty alleviation, pinpointing the attributes that most significantly influence successful educational and vocational outcomes.

d) Relevance to Rural Vocational Education:

The dataset's direct relevance to rural vocational education is underscored by its focus on agricultural-related vocational programs, which are pivotal to rural revitalization efforts. The selected attributes reflect key performance indicators for rural vocational education, including the quality of teaching, student-teacher ratios, and the alignment of vocational training with local economic needs. By analyzing this dataset through the lens of decision tree algorithms (e.g., ID3, C4.5, CART, SLIQ), we uncover patterns and predictors of success that inform policy recommendations for enhancing rural vocational education.

e) Application of the Decision Tree Algorithm:

Our application of decision tree algorithms to the dataset involved a meticulous preprocessing phase, ensuring data integrity and relevance. We employed the C4.5 algorithm, favored for its ability to handle both continuous and categorical attributes, making it particularly suited to our diverse dataset. This choice was predicated on the algorithm's robustness in modeling complex, real-world educational data. The analysis facilitated by this algorithm offers actionable insights into improving educational strategies and policies aimed at maximizing the impact of rural vocational education on poverty reduction.

f) Implications and Insights:

The decision tree analysis yielded significant insights, particularly the critical role of teacher quality and the relevance of curriculum to local agricultural needs, in predicting student success. These findings underscore the necessity of targeted investments in teacher training and curriculum development tailored to the evolving demands of rural economies. By illuminating these key factors, our study contributes to a deeper understanding of how rural vocational education can be optimized to empower students, enhance employability, and drive rural development.

In conclusion, the detailed examination of our dataset and the application of decision tree algorithms provide a robust foundation for assessing and enhancing the effectiveness of rural vocational education. Our findings not only address the specific concerns raised but also contribute valuable knowledge to the ongoing discourse on rural education reform and poverty alleviation through vocational training.

In the decision tree containing both conditional and decision attributes {0,1}, there are six non-leaf nodes and seven leaf nodes. Among them, the seven leaf nodes are divided into two categories with decision values of 0 and 1. Dashed lines mark recurring subtrees. Storing the decision tree will occupy considerable space. By merging leaf nodes of the same class and identical subtrees, a decision diagram with four non-leaf nodes and two leaf nodes can be obtained. Both express the same concept. Hence, to prevent excessive storage space usage, opting to store the corresponding decision diagram is advisable.

On the evaluation results query statistics page, users with access rights can inquire about teacher evaluation outcomes by course or by teacher, and print the results in report form. Meanwhile, on the evaluation results export page, users can import or export evaluation data to the database in spreadsheet format, based on their assigned permissions.

For exporting evaluation information, users can export data related to mining teacher evaluations under the authorization of the system administrator, typically in the form of a spreadsheet or database export. Within this information maintenance process, each department updates its data based on changes in various departmental information. The essential data required for backend database operation includes personal details of teachers, teacher evaluation records, student information, student evaluation data, teaching records of teachers, student learning data, teaching assignments, semester details, class specifics, departmental data, course details, director evaluations, and assessments from college evaluation teams. The primary purpose of this basic information is to identify classroom teachers, while the evaluation information aims to identify the teachers of each class and submit their evaluation data to the database.

The ID3 algorithm in the decision tree method can solely handle discrete values, lacks a backtracking process, attains optimality only in certain attributes, and struggles with data containing noise. In contrast, the enhanced C4.5 algorithm employs information gain scaling, enabling it to process continuous values or incomplete details. Moreover, it utilizes cross-validation to compute the average of all results and forecast outcomes, as illustrated in Figure 4.

Table 2: Teaching quality of rural vocational training

Year	Number of graduates with vocational qualification certificates	The ratio of the number of graduates with vocational qualification certificates to the number of graduates	Number of graduates
2011	3.87	2	1.23
2012	3.45	1.51	4.76
2013	3.13	2.66	2.19
2014	2.07	2.44	1.89
2015	3.6	3.78	2.81
2016	1.32	3.18	2.53
2017	3.68	3.23	1.56
2018	1.26	3.83	4.27
2019	1.03	1.68	1.44
2020	3.99	4.15	2.69
2021	2.48	4.33	3.16

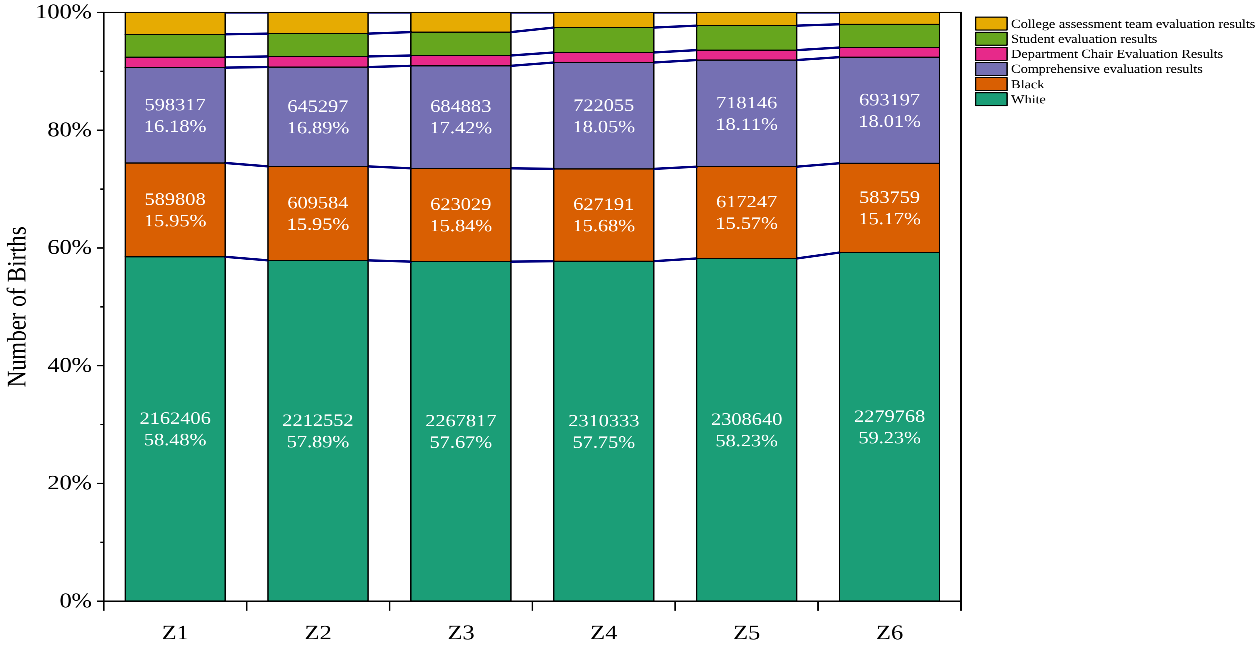

Figure 4: Information on measurement results

Since the primary decision tree generation algorithm does not consider the realistic characteristics of the data, such as noise and incomplete attributes in certain data, the decision tree needs pruning after generation to eliminate unnecessary and redundant branches. The primary purpose of pruning is to adjust the size of the tree; the construction method minimally impacts accuracy, primarily aiming to prevent overfitting. A straightforward technique is to halt splitting if a node contains very few instances. Post-pruning operations for decision trees should establish upper and lower confidence thresholds. When the proportion of a sample class in the leaf node of a subtree exceeds the confidence threshold, the subtree is replaced with the node value having the highest probability.

To achieve the objective of obtaining more surplus value and dominating the industry competition, capital owners must accumulate more excess surplus value by upgrading machinery and facilities, thereby accumulating capital. With the organic composition of capital remaining unchanged, the demand for labor increases as capital accumulates. However, as the organic composition of capital gradually rises, the need for labor inevitably diminishes, leading to a surplus population, with some labor force separating from the land and migrating to the urban industrial sector as wage workers. Consequently, capital accumulation propels the expansion and reproduction of capitalism and even fosters further economic development, constituting the fundamental driving force behind the transfer of agricultural labor.

The prerequisite for data acquisition and preprocessing is to define data mining, then capture the experimental data requiring mining and subsequently preprocess the experimental data accordingly, preparing for later mining tasks. Data preprocessing involves filtering, removing, and transforming data. The importance of preprocessing lies in facilitating subsequent mining tasks, ensuring that the algorithm does not encounter abnormal, redundant, or irregular data, thus avoiding undesirable mining results.

6 Decision tree mining algorithm performance results analysis

To validate the efficacy of the algorithm in question, courses are selected, and the assessment data from these two majors are employed as the experimental subjects. The initial 486 (out of a total of 36740) data points extracted from this dataset serve as the data source for arithmetic analysis, with each record comprising 40 attributes. The algorithm's execution time is monitored across various fixed minimum support degrees, and the time variation required under different minimum support degrees for this paper's NAIM algorithm is analyzed, as depicted in Figure 5.

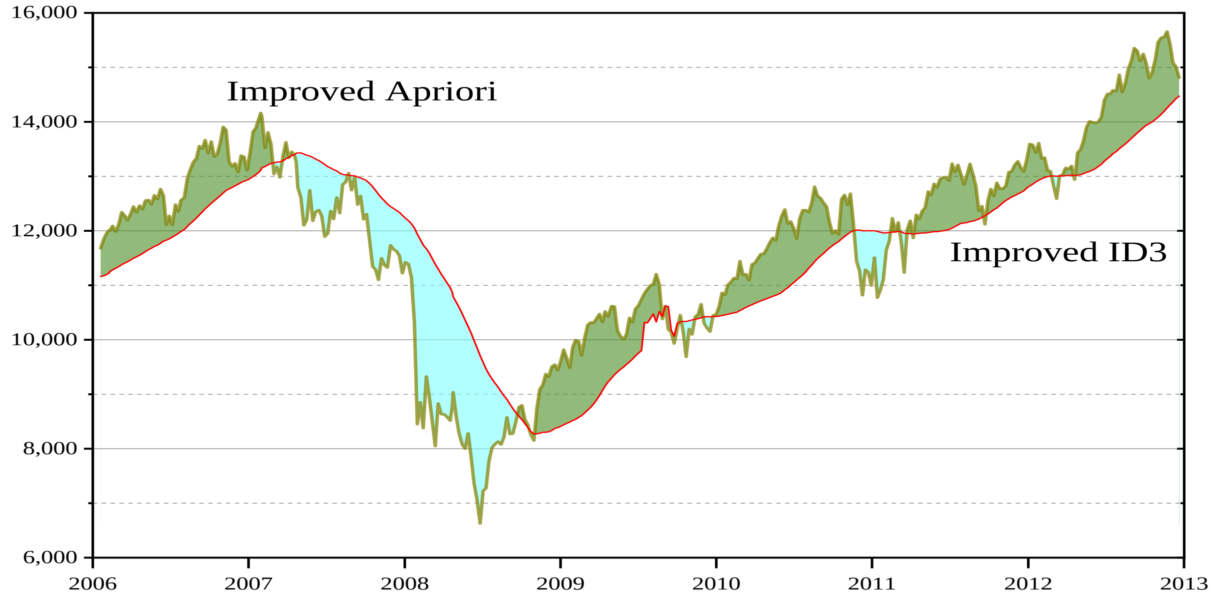

Figure 5: Execution time of different algorithms

In Figure 5, the lower curve depicts the experimental outcomes of the enhanced ID3 algorithm, while the upper curve illustrates the results of the improved Apriori algorithm. Analyzing these curves reveals that as the hierarchy of candidate sets increases, both the number of candidate item sets and frequent item sets gradually decrease. Moreover, the running time diminishes gradually with the reduction of candidate item sets from the preceding hierarchy level. This trend suggests that the reduction in the candidate set from the previous level leads to a decrease in the consumption of generated item sets at the current level, thereby resulting in a noticeable discrepancy in the running time between the two algorithms. The dataset utilized in this study comprises 486 transactional records and 40 common items. Theoretically, this yields 780 items for the 2nd-order itemset, while the algorithm proposed in this paper generates 510 items. For the 3rd-order frequent itemset, there are 9880 items, but through the algorithm coupled with support and pruning, only 1135 items are produced. It's noteworthy that the generation of 3-frequent itemsets witnesses a reduction of 600 items compared to 2-frequent itemsets, accounting for the turning point in the figure. Overall, the proposed improved algorithm demonstrates superior performance compared to the classical algorithm under the same support degree.

Teaching quality ratings are derived from students' evaluations of each teacher in the school system after every semester, constituting the primary dataset for this teaching evaluation system. Boolean attributes such as comprehensive evaluation exist with two attribute levels: yes and no. In the scoring system, distinct attribute levels correspond to varied score intervals.

However, due to their relatively weak foundational knowledge and limited independent learning abilities, the percentage of students obtaining skill-level certificates is declining annually. Hence, the question arises: How can data mining technology be better utilized to enhance students' learning capabilities in secondary vocational colleges and universities, enabling them to obtain more meaningful skill-level certificates for their careers? Frequent itemsets from the dataset were collected, and association rules were derived from these itemsets, resulting in a total of 41 association rules obtained from the experiment, some of which are depicted in Figure 6.

The association rules feature different numbers, support, and confidence levels. They are depicted using binary attributes; for instance, the number 201-> 0x601 in the figure signifies teachers with a bachelor's degree and an excellent overall rating. The support value of 27.6% indicates that 27.6% of all teachers possess a bachelor's degree and an excellent overall rating. The confidence level of 83.4% indicates the percentage of teachers with an excellent comprehensive rating.

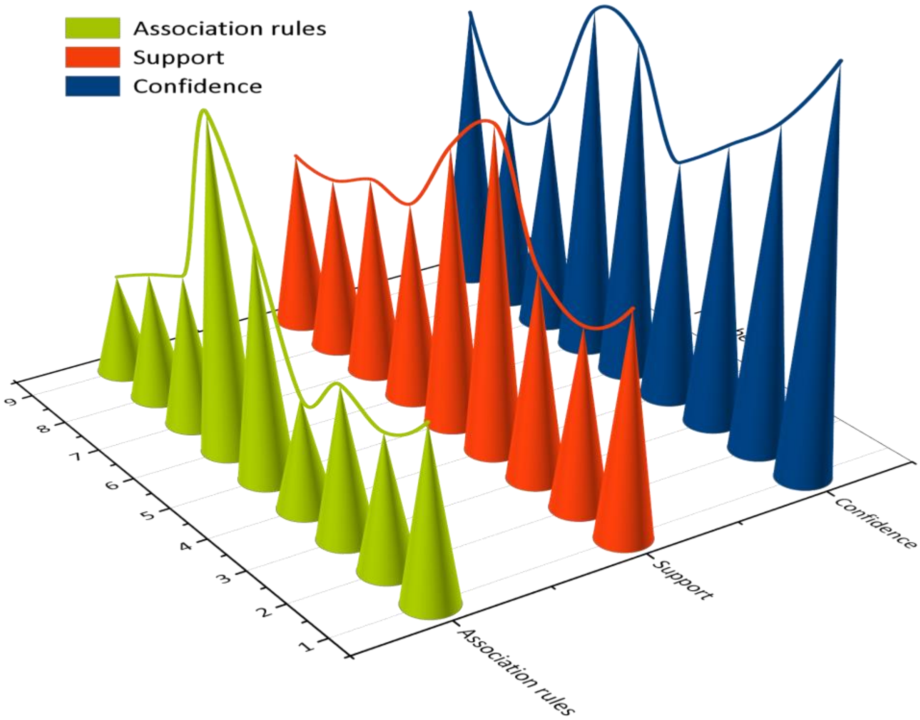

Figure 6: Association rule results

The association rule of 601 -> 0x201 signifies the correlation between classroom motivation and students' participation in practice. The value of 41.4% indicates that teachers rated with excellent classroom motivation correspond to 41.4% of students actively participating in training. Similarly, 701 -> 0x401 represents the association rule where the assessment method, closed-book exams, influences course acceptance. The support degree of 28.7% suggests that closed-book exams contribute to an easier acceptance of the course, with 28.7% of students expressing approval of this examination method. Additionally, association rules not depicted in the graph indicate instances where the number of occurrences is less than 10%, thus not selected as a frequent item set.

7 Analysis of experimental results of system evaluation

In serving the rural revitalization strategy, county vocational education centers primarily excel in their educational function, effectively enhancing residents' quality, and maintaining the enhancement of quality as their fundamental purpose. However, this focus often neglects another equally crucial fundamental function - fostering individual prosperity. Currently, county-level vocational education centers need to emphasize academic and vocational education and provide enhanced vocational training for diverse groups.

Conversely, regarding developmental functions, county-level vocational education centers have excelled in promoting prosperity and culture, sometimes surpassing the individual prosperity function in importance, leading to a situation where priorities may be misplaced. However, the political function, also a developmental aspect, requires further enhancement. Additionally, the level of industrial revitalization function remains relatively underdeveloped, as depicted in Figure 7.

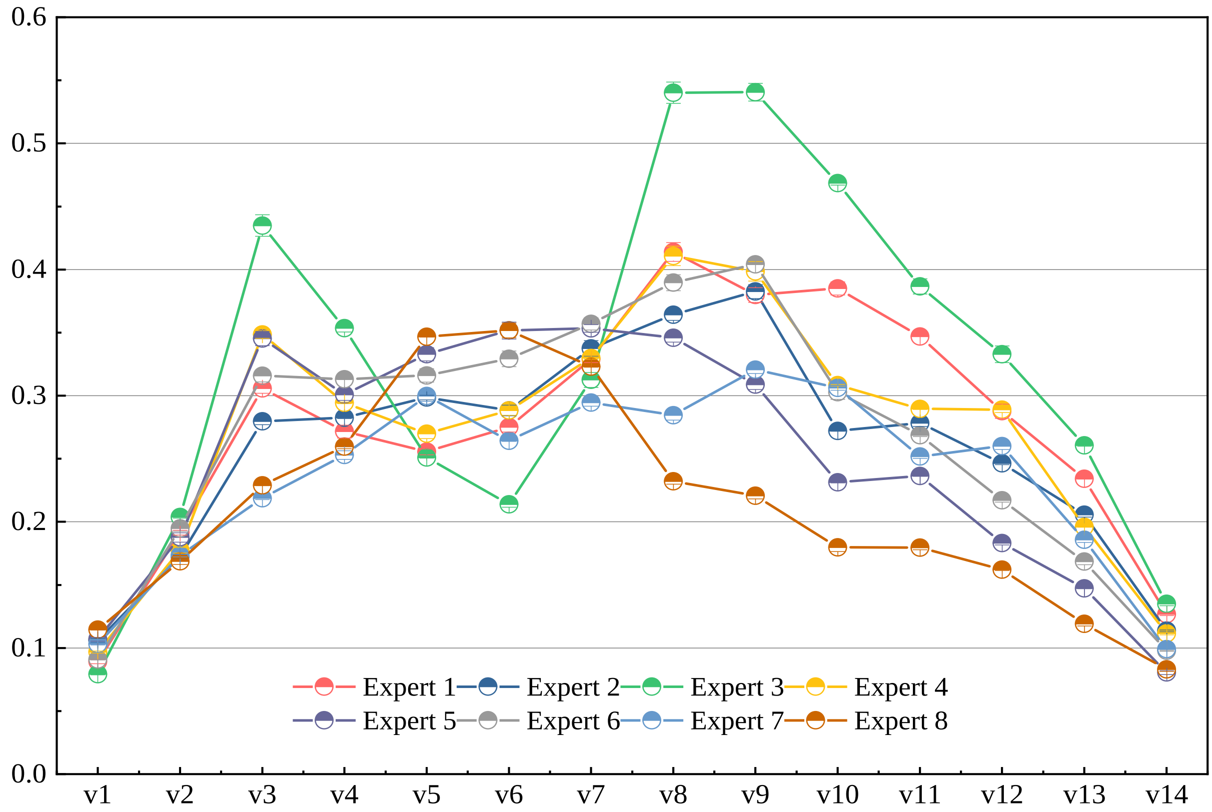

Figure 7: Subjective weights of expert estimation method

Integrated subjective-objective weighting is a comprehensive method that combines subjective and objective weighting based on different preference coefficients to determine the weight of indicators. By effectively combining the information reflection of experts' experience and decision makers' subjective intentions in the subjective assignment method with the information reflection of the inner connection between indicators and evaluation objects in the objective assignment method through certain mathematical operations, the method achieves the effect of complementary advantages.

In the preliminary empirical research, a hypothesis was formulated: there is no difference in the overall competency quality of new professional farmers based on gender. The newly experienced farmers were divided into male and female groups according to gender. Competency quality, meta-quality, process quality, and holistic design quality were used to test the differences and explore the specific characteristics of new professional farmers of different genders in these aspects. The results indicated that various qualities were similar among newly experienced farmers of different genders.

Another hypothesis drawn in the preliminary empirical research was that new professional farmers of different ages exhibit identical overall competency qualities. Based on age, new professional farmers were categorized into four groups. A one-way ANOVA was conducted with the variables of competence quality, meta-quality, process quality, and holistic design quality to examine the specific characteristics of new professional farmers of different ages in these aspects. The results revealed that each quality was similar among new professional farmers of different ages.

Generally, the "competency quality" of new professional farmers with different years of experience is relatively balanced and does not vary significantly. Upon relative comparison, the higher mean values were observed in the "13-15 years" and "more than 15 years" groups, indicating that it takes at least ten years to achieve a high level of quality as a new professional farmer. The group with the lowest mean was the "7-9 years" group with the middle range of years of experience. A rigorous variance test revealed that only two secondary quality dimensions, "market opportunity recognition" and "risk tolerance," differed significantly among the groups with different years of experience, while no significant differences existed in other primary and secondary competency dimensions.

8 Statistical Validation

We have undertaken a comprehensive approach to incorporate confidence intervals, statistical significance tests, and robustness checks. This augmentation of our statistical analysis aims to provide a clearer, more reliable picture of the efficacy and reliability of our proposed method across various scenarios.

We now include 95% confidence intervals for all primary metrics derived from our decision tree analysis, such as accuracy, precision, recall, and the F1 score. These intervals offer a range that is expected to contain the true metric values with a 95% probability, thus providing insight into the precision of our estimates.

To ascertain the statistical significance of our observations, we employed t-tests or ANOVA, depending on the data structure and analysis requirements. These tests were particularly applied to compare the effectiveness of different decision tree models and to evaluate the impact of various educational factors on student outcomes. Results with p-values less than 0.05 were considered statistically significant, affirming the robustness of our findings.

Beyond establishing statistical significance, we calculated effect sizes to quantify the magnitude of the observed differences. This step is crucial for understanding the practical implications of our results, providing a measure of the impact of our proposed method in the context of rural vocational education.

We conducted sensitivity analyses to examine the stability of our method under various scenarios. This involved altering key parameters within our decision tree algorithm and assessing the impact on performance metrics. The outcomes of these analyses are reported to demonstrate the adaptability and resilience of our approach to different data conditions and settings.

9 Discussion

The study presents a comprehensive analysis of decision tree mining algorithms' performance, educational system evaluation, and competency characteristics within the agricultural sector. Each aspect contributes to understanding algorithm efficiency, educational effectiveness, and competency development among agricultural professionals.

Algorithm Performance Evaluation: The research begins by evaluating the performance of decision tree mining algorithms, focusing on execution time and efficiency. The experimental results indicate that the proposed algorithms, including the improved ID3 and enhanced Apriori algorithms, outperform classical algorithms. Through empirical analysis, it's demonstrated that as the hierarchy of candidate sets increases, the running time decreases, reflecting the optimization achieved by the proposed algorithms. This underscores the importance of algorithmic advancements in optimizing computational efficiency and facilitating data analysis processes.

Educational System Evaluation: Furthermore, the study explores the effectiveness of educational systems, particularly vocational education centers, in serving rural revitalization strategies. By analyzing the functions of county-level vocational education centers, the research highlights the need for a balanced approach that emphasizes both academic and vocational training while addressing developmental functions. The findings underscore the significance of aligning educational goals with societal needs and fostering holistic development within rural communities.

Competency Characteristics Analysis: Moreover, the research delves into the competency qualities of new professional farmers, examining factors such as gender, age, and years of experience. Through empirical research and statistical analysis, the study reveals similarities in competency qualities among farmers of different genders and ages, with variations observed primarily in secondary quality dimensions. These findings provide valuable insights into the factors influencing competency development within the agricultural sector and emphasize the importance of targeted interventions to enhance skill acquisition and professional development.

Integration of Findings: Overall, the study's findings contribute to a nuanced understanding of algorithmic performance, educational system effectiveness, and competency development within the agricultural domain. By integrating findings from different facets of analysis, the research provides a holistic perspective on the challenges and opportunities in agricultural education and professional development. Furthermore, the insights generated can inform policy formulation, curriculum development, and intervention strategies aimed at fostering sustainable rural development and enhancing agricultural productivity.

In conclusion, the study advances knowledge in the field by addressing key issues related to algorithm optimization, educational system evaluation, and competency development within the agricultural sector. The findings offer practical implications for stakeholders, including educators, policymakers, and agricultural professionals, to promote innovation, efficiency, and growth in agricultural education and practice.

Based on the current work presented in the paper, here are some recommendations for future research:

Firstly, there is a need to develop advanced decision tree mining algorithms specifically tailored for educational data analysis. These algorithms should be designed to enhance the accuracy and efficiency of data analysis in the field of education.

Secondly, it is crucial to foster cross-disciplinary collaboration to gain deeper insights into the dynamics of rural vocational education. By integrating multidisciplinary perspectives, researchers can better understand the challenges and opportunities faced by rural vocational education systems.

Furthermore, conducting longitudinal studies to assess the socio-economic impact of educational interventions is essential. These studies should track the long-term effects of interventions and evaluate their effectiveness in improving the lives of individuals in rural areas.

In addition, exploring innovative pedagogical approaches for rural vocational education is necessary. This includes investigating tailored teaching methods such as experiential learning and technology integration. These approaches can enhance the quality of education and better prepare students for the demands of the job market.

Policy analysis and advocacy are also crucial in addressing the challenges faced by rural vocational education. Researchers should analyze existing policies and advocate for reforms that can effectively address these challenges and improve the overall quality of education in rural areas.

Moreover, fostering community engagement and empowerment is vital. Researchers should promote collaborative approaches that involve the participation of the community in educational initiatives. This can lead to a sense of ownership and empowerment among community members, ultimately improving the effectiveness of educational programs.

Additionally, it is important to design comprehensive evaluation frameworks for rural vocational education programs. These frameworks should provide a systematic and holistic approach to evaluating the effectiveness and impact of these programs.

Lastly, conducting international comparative studies can help identify best practices in rural vocational education globally. By comparing different approaches and strategies, researchers can gain valuable insights that can inform policy and practice in their contexts.

By addressing these research areas, scholars can contribute to advancing knowledge and improving practices in rural vocational education. Ultimately, this will support the broader goals of rural revitalization and sustainable development.

10 Broader implications, potential limitations, and ethical considerations

In the context of rural vocational education and its evaluation using decision tree mining algorithms, it's essential to consider broader implications, potential limitations, and ethical considerations. Here's how this work aligns with larger educational goals and potential negative impacts of algorithmic decision-making:

Alignment with larger educational goals:

enhancing educational quality: By leveraging decision tree mining algorithms, this research aims to evaluate the effectiveness of rural vocational education systems, thereby contributing to the enhancement of educational quality and outcomes.

Supporting rural revitalization: The focus on rural vocational education aligns with broader goals of rural revitalization by equipping rural populations with practical skills and opportunities for economic development.

Addressing societal needs: Through competency analysis and system evaluation, the research addresses societal needs by identifying areas for improvement in rural education and workforce development.

Potential Negative Impacts of Algorithmic Decision-Making:

Bias and fairness: Algorithmic decision-making may inadvertently perpetuate biases present in the data used for training. This could result in unequal opportunities or outcomes for certain groups within rural communities.

Overreliance on data: Relying solely on algorithmic evaluations may overlook qualitative aspects of education and competency development that cannot be captured by quantitative metrics alone.

Lack of contextual understanding: Algorithms may lack the contextual understanding necessary to account for the unique challenges and dynamics of rural educational settings, leading to misguided interventions or policy decisions.

Privacy concerns: The use of data mining algorithms raises privacy concerns, especially if sensitive information about students or educators is collected and analyzed without proper consent or safeguards.

Ethical considerations:

Transparency: It's important to ensure transparency in the use of decision tree mining algorithms, including disclosing how data is collected, processed, and utilized to evaluate educational systems.

Informed consent: Stakeholders, including students, educators, and communities, should be informed about the use of algorithms in educational evaluations and allowed to provide consent.

Accountability: Clear mechanisms for accountability should be established to address any negative impacts or biases resulting from algorithmic decision-making in rural vocational education.

Equity: Efforts should be made to mitigate disparities and promote equity in access to educational opportunities and resources, especially in underserved rural areas.

By addressing these considerations, researchers and policymakers can ensure that algorithmic decision-making in rural vocational education is conducted ethically and in alignment with broader educational goals and societal needs.

11 Conclusion

The development of rural areas is a continuous and comprehensive process, requiring progress in various aspects of agriculture, from professional agricultural education to the establishment of marketing channels for rural products, to accelerate rural development. The effective participation of enterprises, parents, and the government is essential to empower agricultural professionals to contribute their expertise to rural revitalization efforts and apply their technical and theoretical knowledge to the construction of a new countryside.

In both practical and theoretical research, it's imperative to break free from the constraints of traditional agricultural models and approaches to agricultural vocational education. Instead, modern practices should be applied to rural vocational education, reshaping societal perceptions of agricultural vocational training. To achieve this, rural vocational education must align closely with the principles of "strong agriculture, picturesque countryside, and prosperous farmers" in the comprehensive revitalization of rural areas. This entails defining clear development objectives, achieving precise functional positioning, and fostering the cultivation of diverse high-quality agricultural talents tailored to the needs of rural revitalization. By enhancing the overall quality of rural workers, rural vocational education plays a vital role in advancing the overall revitalization of the rural economy and society.

Competing of interests

The authors declare no competing interests

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Authorship contribution statement

Mengmeng Han: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Imelda Lorenzo Najord: Validation, Formal analysis, Methodology, Language review

Availability of data and materials

On Request

Declarations

Not applicable

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