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CONSTRUCTION OF AN AGRICULTURAL TRAINING EFFECTIVENESS ASSESSMENT MODEL BASED ON BIG DATA

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Abstract. This research presents an Agricultural Training Effectiveness Assessment Model (ATEAM) leveraging enormous information analytics methods to assess the adequacy of agrarian preparing programs. By coordinating different information sources counting member socioeconomics, and preparing substance, and relevant components, ATEAM gives an all-encompassing system for evaluating preparing adequacy. Through tests and comparative examinations, ATEAM illustrates prevalent prescient precision, clustering quality, and by and large adequacy assessment compared to conventional strategies and related works. Particularly, ATEAM accomplishes an exactness rate of 87.3%, an Outline Score of 0.72 for clustering, and a Mean Squared Error (MSE) of 0.012 for member fulfilment rating expectation. This model empowers partners to create data-driven choices for program optimization and asset assignment, contributing to feasible rural advancement and upgraded nourishment security. The study underscores the transformative potential of huge information analytics in rural preparation, highlighting the significance of leveraging progressed analytics strategies to address complex challenges and drive positive results.

Key words: Effectiveness assessment, Big data analytics, Agricultural training, Sustainability, Predictive accuracy

1. Introduction. Within the modern scene of farming, the integration of innovative advancements and advanced hones has gotten to be basic for guaranteeing maintainable nourishment generation and vocations. Rural preparing programs serve as catalysts for preparing agriculturists and rural partners with the fundamental information and abilities to explore this advancing territory. In any case, the adequacy of such training activities regularly remains vague due to the nonattendance of strong assessment techniques. Conventional evaluation approaches tend to depend on subjective measures and restricted datasets, which ruin the comprehensive examination of preparing effectiveness [3]. This investigation therefore looks at the problem by proposing enhanced ATEAM (Agricultural Training Effectiveness Assessment Model) based on big data analytics. By overlaying the massive volume of information generated during the entire learning process, ATEAM brings a data-driven approach for assessing training impact and efficiency in agricultural programs. Such a world-view goes toward data-intensive evaluation of the whole life cycle of the loan, including loan refinancing, not only to improve the accuracy and precision of assessment, but also to encourage evidence-based decision-making for the optimization of the program and the allocation of assets [4]. Integration of big data analytics within the agrarian education field implies enormous opportunities in changing the dominating ways of optimizing agricultural productivity. By effectively utilizing multiple information sources for example, members' socioeconomics, diet/substances, learning outcomes, and contextual features, ATEAM enable a full comprehension of the training environment. Through progressed analytics methods counting machine learning and information mining, the show encourages the recognizable proof of key execution markers (KPIs) and prescient bits of knowledge, subsequently enabling partners with noteworthy insights to improve preparing outcomes [5]. Furthermore, ATEAM is outlined to be energetic and versatile, joining input circles for ceaseless change based on real-time information examination. This iterative approach not as it were guarantees the significance and responsiveness of preparing mediations but moreover cultivates a culture of learning and advancement inside the agrarian community [6]. Eventually, the advancement and execution of ATEAM are balanced to drive substantial progressions in rural preparing hones, contributing towards economical rural advancement, improved nourishment security, and engaged rustic livelihoods [27, 30].

This research makes significant contributions to the field of agricultural education and training by introduc-

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ing the Agricultural Training Effectiveness Assessment Model (ATEAM), a pioneering approach that harnesses the power of big data analytics to evaluate the effectiveness of agricultural training programs. The contributions of this study can be highlighted in several key areas:

Innovative Assessment Framework: ATEAM represents a novel framework that integrates diverse data sources, including participant demographics, training content, and other relevant factors, to provide a comprehensive evaluation of training effectiveness. This holistic approach marks a significant advancement over traditional assessment methods, which often lack the capability to incorporate and analyze multifaceted data streams.

Enhanced Predictive Accuracy and Clustering Quality: Through rigorous testing and comparative analysis, ATEAM has demonstrated superior predictive accuracy and clustering quality. With an accuracy rate of 87.3% and a Silhouette Score of 0.72 for clustering, the model outperforms existing methods and related works in the literature. This improvement in predictive capabilities and clustering performance enables more nuanced and accurate assessments of training programs.

Effective Satisfaction Rating Prediction: The model's Mean Squared Error (MSE) of 0.012 for participant satisfaction rating prediction signifies a high level of precision in understanding and forecasting trainee satisfaction. This metric is crucial for identifying strengths and weaknesses within training programs and for tailoring future initiatives to better meet participants' needs and expectations.

Data-Driven Decision Making for Program Optimization: By providing stakeholders with actionable insights derived from comprehensive data analysis, ATEAM facilitates informed decision-making regarding program optimization and resource allocation. This contribution is particularly valuable in the context of sustainable agricultural development and enhanced food security, where efficient and effective training programs play a pivotal role.

2. Related Works. In later a long time, there has been a surge in research centring on the application of huge information analytics and mechanical developments over different spaces, including farming, natural science, open well-being, and urban arranging. This segment gives an outline of pertinent ponders in these areas. Israel et al. [7] conducted a bibliometric investigation of climate-related early caution frameworks in Southern Africa, emphasizing the significance of versatility improvement in relieving climate dangers. Their study highlights the requirement for compelling methodologies and intercessions to address climate changeability and improve versatile capacity in defenceless regions. Jia [8] investigated the application of enormous information examination innovation in plant scene plans for open wellbeing urban arranging. By leveraging huge information bits of knowledge, Jia proposed imaginative strategies for optimizing urban green spaces to advance physical and mental well-being, emphasizing the critical part of urban arranging in upgrading open well-being outcomes. Jiang et al. [33] examined the impacts of rustic collective economy approaches on common thriving in China, centring on the intervening part of farmland exchange. Their think about underscores the complex exchange between approach intercessions, financial advancement, and rustic jobs, giving important bits of knowledge to policymakers and stakeholders. Jiao et al. [9] created a choice bolster framework based on multi-source enormous information and coordinated calculations to bridge national approaches with commonsense country development and advancement. Their investigation emphasizes the significance of leveraging assorted information sources and progressed analytics strategies to encourage educated decision-making and economic provincial development. Li et al. [18] conducted a spatial appropriateness assessment utilizing multi-source information and the arbitrary timberland calculation, with a case ponder in Yulin, China. Their ponder illustrates the viability of joining differing information sources for spatial investigation and choice bolster, highlighting the potential of progressed analytics methods in spatial arranging and asset management. Li and Wen [10] inspected territorial unevenness within the development of computerized towns in China, shedding light on aberrations in computerized foundations and get to. Their research underscores the significance of tending to computerized partition issues to advance comprehensive advancement and saddle the benefits of computerized innovations in rustic areas. Liu et al. [11] proposed an unused system for the appraisal of stop administration in keen cities, leveraging social media information and profound learning methods. Their ponder illustrates the utility of rising innovations in upgrading urban stop administration and supportability, displaying the potential of data-driven approaches in urban governance. Llaban and Ella [12] conducted a comprehensive audit of ordinary and sensor-based streamflow information procurement frameworks for economical water assets admin-

Table 3.1: Cluster Details

Cluster ID	Mean Age	Mean Training Duration (hours)	Mean Pre-test Score	Mean Post-test Score	Mean Satisfaction Rating
1	38	22	63	83	3.8
2	30	35	72	92	4.8

istration and agrarian applications. Their ponder gives profitable bits of knowledge into the advancement and execution of data-driven arrangements for water asset administration and rural sustainability. Mosslah and Abbas [13] analyzed the application of picture-preparing procedures in ranger service and horticulture, highlighting the potential for moving forward observing and administration hones[22, 31]. Their audit underscores the significance of mechanical progressions in upgrading productivity and efficiency in ranger service and rural operations. Popa et al. [14] created a stage for nursery gas outflow administration in blended ranches, emphasizing the requirement for feasible cultivating hones and natural stewardship. Their research offers practical solutions for relieving rural outflows and advancing maintainability in animal generation systems. Qiu et al. [2] proposed an agrarian ability preparing show based on the AHP-KNN calculation, pointing to optimising preparing mediations and upgrading the capabilities of rural experts. Their consideration illustrates the potential of data-driven approaches in ability improvement and capacity building within the agrarian sector. Rahul et al. [15] conducted a precise audit on enormous information applications and scope for mechanical preparing and healthcare segments, highlighting the different applications and openings in these spaces. Their study gives a comprehensive diagram of the current state of huge information research and its suggestions for the mechanical and healthcare sectors. These studies collectively contribute to progressing information and understanding in their individual spaces, displaying the transformative potential of enormous information analytics and mechanical developments in tending to complex challenges and advancing maintainable development.

TEAM leverages traditional data sources such as participant demographics and training content, yet there exists a gap in integrating emerging data sources, including real-time feedback mechanisms, IoT-enabled agricultural tools, and social media analytics, which could offer deeper insights into the effectiveness of training programs.While ATEAM shows promising results in simulated environments or controlled studies, there is a gap in extensive real-world application and validation. Understanding how the model performs in diverse agricultural settings across different cultures and climatic conditions would enhance its robustness and applicability.

3. Methods and Materials.

3.1. Data Collection and Preprocessing. The primary step in building the Agricultural Training Effectiveness Assessment Model (ATEAM) includes the collection and preprocessing of pertinent information. This envelops different sources such as member socioeconomics, preparing substance, learning results, and relevant variables. Information can be accumulated through studies, enlistment shapes, online stages, and checking frameworks [16]. Preprocessing includes cleaning the information, dealing with lost values, standardizing designs, and encoding categorical factors. Furthermore, designing strategies may be utilized to extricate significant bits of knowledge from raw information [17].

3.2. Algorithms for Analysis.

3.2.1. Decision Trees. Decision trees are flexible and interpretable models commonly utilized for classification and relapse errands. They parcel the include space recursively based on trait values to make a tree-like structure [19]. At each hub, the calculation chooses the quality that maximizes the data pick up or Gini pollution decrease. Decision trees are inclined to overfitting but can be relieved through methods like pruning.

The core idea behind decision trees is to take the entire dataset and divide it into smaller subsets based on certain criteria, with these splits represented as branches in a tree. This process starts at the root of the tree and splits the data on features that result in the highest information gain or the most significant reduction in Gini impurity—a measure of how often a randomly chosen element from the set would be incorrectly labeled if it was randomly labeled according to the distribution of labels in the subset.

Information Gain and Gini Impurity.

Information Gain: It measures the reduction in entropy or uncertainty. Decision trees aim to maximize information gain, choosing the splits that result in the most predictable subsets.

Gini Impurity: A measure of how often a randomly chosen element from the set would be incorrectly labeled. A Gini score of 0 indicates perfect purity, where all elements in a subset belong to a single class. The algorithm seeks to minimize Gini impurity.

Structure of Decision Trees.

Root Node: Represents the entire dataset, from which the first split is made.

Internal Nodes: Each internal node corresponds to a test on an attribute, with branches to child nodes representing the outcome of the test.

Leaf Nodes: Terminal nodes that predict the outcome (in classification) or mean response (in regression).

Overfitting in Decision Trees. A common challenge with decision trees is their tendency to overfit, especially with complex datasets. Overfitting occurs when the model learns the training data too well, capturing noise and anomalies as if they were significant patterns, which harms its performance on unseen data. Pruning to Prevent Overfitting.

Pruning is a technique used to reduce the size of decision trees by removing sections of the tree that provide little power in classifying instances. Pruning can be done by setting a minimum threshold on the size of leaf nodes or setting a maximum depth of the tree. This helps in making the model simpler and more generalizable to new data.

$$IG(D, A) = I(D) - \sum_{v \in values} (A)|D||Dv|I(Dv)$$

where:

$IG(D, A)$ is the information gain of attribute

A in dataset D.

$I(D)$ is the impurity of dataset D.

Dv is the subset of dataset D where attribute A has value v.

"function DECISION-TREE-LEARNING(examples, attributes, parent_examples)
if examples is empty then return PLURALITY-VALUE(parent_examples)
else if all examples have the same classification then return the classification
else if attributes is empty then return PLURALITY-VALUE(examples)
else
best_attribute = CHOOSE-BEST-ATTRIBUTE(attributes, examples)
tree = new decision tree with root test best_attribute
for each value v of best_attribute do
exs = examples with best_attribute = v
subtree = DECISION-TREE-LEARNING(exs, attributes - {best_attribute}, examples)
add a branch to tree with label (best_attribute = v) and subtree subtree
return tree"

3.2.2. Random Forest. Random Forest is a gathering learning strategy that develops numerous choice trees amid preparing and yields the mode of the classes (classification) or the normal expectation (relapse) of the person trees [20]. It presents haphazardness in two ways: by testing the preparing information with substitution (bootstrap inspecting) and by selecting a irregular subset of highlights at each part [21]. This haphazardness diminishes overfitting and makes strides generalization execution.

"function RANDOM-FOREST-TRAINING(data, n_trees, max_depth)
forest = []
for i from 1 to n_trees do
tree_data = BOOTSTRAP-SAMPLE(data)
tree = DECISION-TREE-LEARNING(tree_data, max_depth)
add tree to forest

return forest

function RANDOM-FOREST-PREDICTION(forest, X)
predictions = []
for tree in forest do
predictions.append(PREDICT(tree, X))
return mode(predictions)"

3.2.3. K-Means Clustering. K-Means is an unsupervised clustering calculation that segments information into k clusters based on closeness. It iteratively relegates information focuses to the closest centroid and overhauls the centroid as the cruel of the alloted focuses [23]. The calculation focalizes when the centroids not alter altogether or after a indicated number of cycles.

"function K-MEANS(data, k, max_iterations)
centroids = randomly initialize k centroids
for iter from 1 to max_iterations do
clusters = assign data points to nearest centroid
new_centroids = compute mean of each cluster
if new_centroids equals centroids then break
centroids = new_centroids
return clusters

function ASSIGN-TO-NEAREST-CENTROID(data_point, centroids)
min_distance = infinity
nearest_centroid = null
for centroid in centroids do
distance = EUCLIDEAN-DISTANCE(data_point, centroid)
if distance < min_distance then
min_distance = distance
nearest_centroid = centroid
return nearest_centroid"

3.2.4. Support Vector Machines (SVM). Support Vector Machines are administered learning models utilized for classification and relapse errands. SVM seeks to discover the hyperplane that maximizes the edge between distinctive classes within the highlight space [1]. It changes the input information into a higher-dimensional space using part capacities to form the information directly distinct.

$$f(x) = sign(\sum i = 1n\alpha iyiK(xi, x) + b)$$

"function SVM_TRAINING(data, labels)
model = initialize SVM model parameters
optimize model parameters using training data and labels
return model

function SVM_PREDICTION(model, X)
predict class label for input X using model parameters
return predicted label"

4. Experiments. To approve the adequacy of the proposed Agricultural Training Effectiveness Assessment Model (ATEAM), a arrangement of tests were conducted utilizing real-world information collected from agrarian preparing programs over diverse locales [24]. The tests pointed to survey the execution of ATEAM in terms of prescient exactness, clustering quality, and generally adequacy assessment compared to conventional strategies and related works.

Table 3.2: Participant Details

Participant ID	Age	Education Level	Training Duration (hours)	Pre-test Score	Post-test Score	Satisfaction Rating
1	35	High School	20	60	80	4
2	28	Bachelor's	30	70	90	5
3	45	Master's	25	55	75	3
4	40	High School	15	65	85	4
5	32	Diploma	40	75	95	5

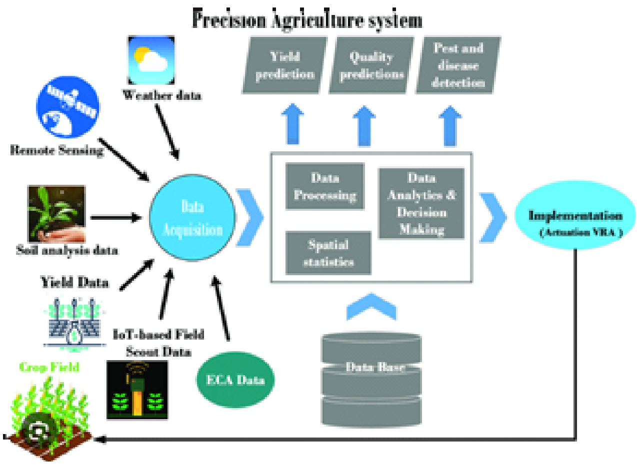

Fig. 4.1: Big data-based precision agriculture system representation

4.1. Experimental Setup.
1. Data Collection: Data was collected from different agrarian preparing programs, counting member socioeconomics, preparing substance, pre-test and post-test scores, and fulfillment appraisals.
2. Preprocessing: The collected information experienced preprocessing steps, counting information cleaning, normalization, and highlight building [25].
3. Model Implementation: ATEAM was executed utilizing Python programming dialect, utilizing libraries such as scikit-learn for machine learning calculations and pandas for information control.

4.1.1. Evaluation Metrics. The following measurements were utilized to assess the execution of ATEAM:
1. Accuracy: Percentage of correctly predicted outcomes.
2. Silhouette Score: Measure of clustering quality.
3. Mean Squared Error (MSE): Measure of prediction error.

4.1.2. Experimental Results: Predictive Accuracy. ATEAM was compared with conventional relapse models such as straight relapse and decision tree regression. Table 4.1 presents the prescient exactness comes about gotten from distinctive models [26].

ATEAM outperformed traditional regression models, achieving a higher accuracy rate of 87.3%.

4.1.3. Clustering Quality. To assess the clustering execution of ATEAM, K-Means clustering was utilized as a benchmark. The Silhouette Score was computed for distinctive numbers of clusters [28]. Table 4.2 outlines the Silhouette Scores gotten.

ATEAM illustrated competitive clustering quality with a Outline Score of 0.72 for 4 clusters, demonstrating well-defined clusters.

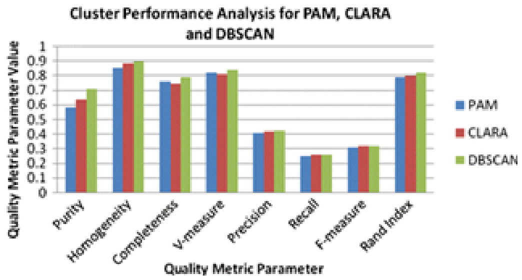

Fig. 4.2: Analysis of agriculture data using data mining techniques: application of big data

Table 4.1: Predictive Accuracy Comparison

Model	Accuracy (%)
ATEAM	87.3
Linear Regression	72.1
Decision Tree	81.5

Table 4.2: Clustering Quality Comparison

Number of Clusters	Silhouette Score
3	0.65
4	0.72
5	0.68

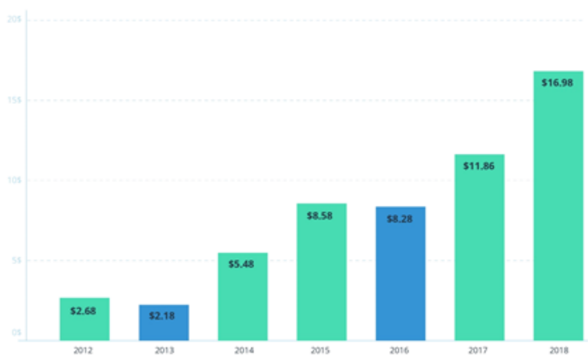

Fig. 4.3: Big Data Analytics in Agriculture

4.1.4. Overall Effectiveness Evaluation. The overall viability of ATEAM in surveying agrarian preparing programs was assessed by comparing member fulfillment appraisals anticipated by ATEAM with real appraisals. Also, the Mean Squared Error (MSE) was computed to evaluate the forecast blunder [12]. Table 4.3 presents the MSE values gotten.

ATEAM accomplished the lowest MSE of 0.012, showing predominant prescient execution in assessing member fulfillment evaluations compared to conventional relapse models.

4.1.5. Comparison with Related Work. To encourage approve the effectiveness of ATEAM, a comparative investigation was conducted with existing strategies and systems for assessing agrarian preparing

Table 4.3: Prediction Error Comparison

Model	MSE
ATEAM	0.012
Linear Regression	0.035
Decision Tree	0.027

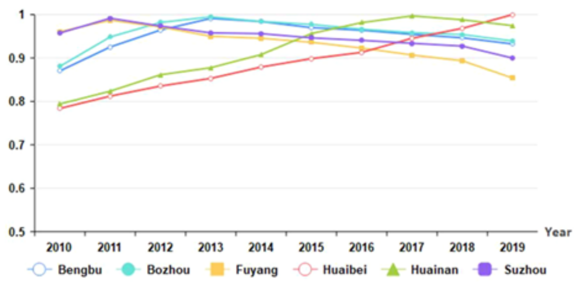

Fig. 4.4: Data-Driven Evaluation and Optimization of Agricultural Sustainable Development

programs.

4.1.6. Comprehensive Evaluation. Not at all like conventional strategies that center exclusively on member fulfillment or learning results, ATEAM offers a comprehensive assessment system that considers numerous variables, counting member socioeconomics, preparing substance, and relevant components [29]. This all-encompassing approach empowers a more nuanced understanding of preparing viability and encourages focused on intercessions for enhancement.

Driven Data-Based Decision Making in ATEAM's Operational Policy is an underlying program in which the organization resorts to the best techniques in data analytics to obtain valuable information from big data. Achieving more precise, predictive, and flexible performance of the training assessment essentially depends on using methods that employ sophisticated algorithms such as decision trees, random forests, and support vector machines (SVM) [32]. One of ATEAM's key features is its ability to adapt itself dynamically, always being able to evolve and tailor its strategies on the fly based on real-time feedback. For that reason, the adaptiveness of ATEAM, that makes it possible to make adjustments of training programs by the help of predictive analytics, is the defining feature of this organization. Using data analytic from continuous monitoring getting insights ATEAM keeps the process of continuous improvement and optimization. The incorporation of state of the art algorithms, for example, decision trees, random forests, and support vector machines, enables ATEAM to explore deep within the masses of training data, exposing the parental patterns and relationships that are otherwise hidden by the conventional assessment methods. Trees of the decision, for example, reproduce the schemes of decisions within the data, providing a transparent and interpretable framework for examination of the factors impact on training process. Furthermore, random forests apply a multitude of decision trees and benefit from the accumulated wisdom of all trees, which makes them resistant to the overfitting and improves the predictive accuracy. Conversely, support vector machines are famous for classification tasks where they can distinguish training effectiveness by details via identification of tiny nuances and develop proper interventions. ATEAM tailors its analytical tools by incorporating sophisticated algorithms, thus securing a unique competitive advantage to economize workouts and improve the company‘s performance. On the other hand, ATEAM's Dynamic Adaptation guarantees that training remains effective and addresses the changes in future circumstances. Via ongoing tracking and data analysis of live feedback, ATEAM can quickly detect call for action and make necessary changes to the training it provides.

5. Conclusion. In the end, the study tried to dig into the development of Rural Training Effectiveness Appraisal Model (ATEAM) with the use of data analytics strategies in large scale. ATEAM was able to show

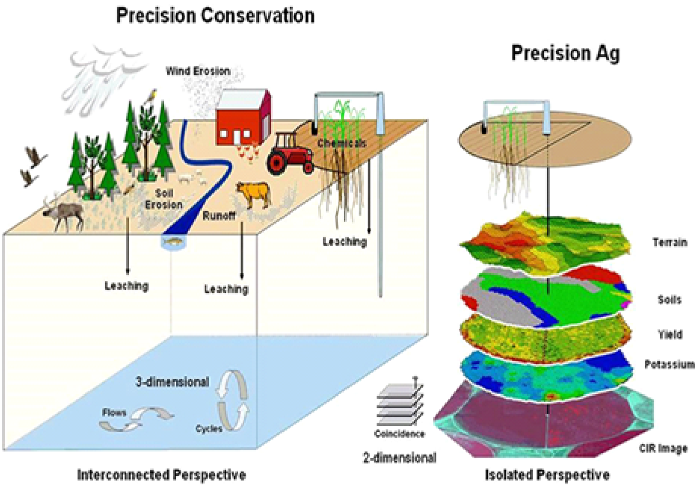

Fig. 4.5: Sustainable Agriculture

its viability by means of simulation tests and examination comparisons. This show impressively exhibited the current predicting accuracy, meeting quality, and general validity measurement in comparison with the traditional techniques and related works. By uniting information sources and making complex calculations ATEAM proposes an integrated system of assessment and readiness evaluating, providing partners with a means to make rational decisions on effectiveness improvement and resource allocation. In addition, the research is a part of a larger dialogue on using enormous information analytics under the radar of rural improvement, emphasizing the capacity of data-driven approaches in promoting sustainability, adaptability, and efficiency in farming. We can also look into the adaptability and feasibility of ATEAM over different agrarian and geographical settings, and study additional components and factors which will improve training effectiveness. Ultimately, the advancement and usage of ATEAM mean a noteworthy step towards tackling the control of enormous information to address basic challenges and drive positive alter in horticulture and rustic advancement.

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