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IoT Based Agriculture Monitoring and Prediction of Paddy Growth using Enhanced Conquer Based Transitive Clustering

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Abstract: Agriculture is widely recognized as a fundamental pillar of our civilization, and it is currently undergoing a significant transition with the emergence of the IoT. This research investigates the field of IoT-based agriculture monitoring, with a specific emphasis on forecasting paddy growth. The introduction establishes the context by emphasizing the pivotal significance of agriculture and the promise of the IoT in enhancing farming methodologies. The problem statement highlights the necessity for a more advanced and precise system to monitor and forecast the growth of paddy, by identifying a gap in current research. Conventional approaches frequently prove inadequate in delivering timely and comprehensive insights, so neglecting to fully exploit the capabilities of IoT technology. The Enhanced Conquer based Transitive Clustering methodology combines conquer-based methodologies with transitive clustering, providing a resilient framework for the study and prediction of data. By harnessing the capabilities of IoT devices, real-time data pertaining to many parameters, including soil moisture, temperature, and humidity, is gathered. The study findings demonstrate the effectiveness of the Enhanced Conquer based Transitive Clustering algorithm in properly forecasting paddy growth stages. The system possesses the capability to not only monitor the prevailing agricultural circumstances but also forecast forthcoming developments, thereby empowering farmers to make well-informed decisions. The model accuracy and effectiveness highlight its potential for extensive implementation in contemporary agricultural practices.

Keywords*: Agriculture Monitoring, IoT, Enhanced Conquer, Paddy Growth Prediction, Transitive Clustering.*

1. Introduction

The integration of technology and agricultural techniques has become crucial in the continuously changing agricultural environment [1]. Agriculture plays a crucial role in supporting global populations, with a particular emphasis on the necessity for creative approaches to improve productivity and efficiency [2].

The conventional techniques employed in agriculture encounter difficulties in adjusting to the ever-changing environmental circumstances, thereby requiring a fundamental change in perspective towards more advanced methodologies [3]. Existing approaches in agriculture are inadequate in addressing the demands of modern agriculture due to limitations in real-time data availability and the inability to immediately foresee and correct fluctuations in crop growth [4] – [6].

The main aim of this study is to introduce and apply an innovative approach, known as Enhanced Conquer based Transitive Clustering, in order to overcome the limitations observed in current agricultural monitoring systems. This strategy seeks to enhance the understanding of the agricultural environment by combining conquer-based techniques with transitive clustering. The primary focus is on collecting real-time data from Internet of Things (IoT) sensors that measure essential parameters.

The research presented in this study is distinguished by its new approach, as it introduces a fresh methodology that has not yet been investigated within the realm of IoT-based agriculture monitoring and paddy growth prediction. This study makes a valuable contribution to the area by introducing an innovative approach that effectively monitors present agricultural conditions and provides accurate predictions for future changes.

2. Related Works

In [7], the authors explore the domain of the IoT, providing a definition of it as a cooperative network including networked items possessing internet capabilities. With a strong emphasis on the crucial role of the agricultural sector in providing sustenance to a rapidly growing worldwide population, projected to reach 10 billion individuals by the year 2050, the research highlights the importance of IoT services in transforming agricultural methodologies. The authors emphasize the essential nature of irrigation systems, which are vital for the preservation of water resources and the efficient allocation of water for different types of crops, ultimately leading to improved crop productivity. This study presents an Intelligent Irrigation System (IIS) designed specifically for paddy fields. The system incorporates many sensors, including soil moisture sensors, pH sensors, and flow

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sensors. By employing IoT principles, the present system effectively communicates data on soil conditions to a database hosted on a web server through wireless connection. This process enables the system to accurately ascertain the specific water needs of the crops. The dashboard, which utilizes the http protocol, effectively manages the water pump for agricultural land by continuously monitoring soil characteristics in real-time, thereby guaranteeing optimal irrigation. The experimental findings confirm the effectiveness of the technology, surpassing traditional methods of irrigation.

The study conducted in [8] highlights the significant significance of timely and precise crop monitoring in the context of precision management, decision-making, and marketing strategies. This study examines the feasibility of integrating spectral and structural data obtained from unmanned aerial vehicle (UAV) imagery to enhance rice cultivation practices across the course of the crop growth cycle. The researchers utilized unmanned aerial vehicles (UAVs) equipped with RGB and multispectral cameras to capture high-resolution photos throughout many nitrogen treatments during a span of two years. The work employs the extraction of vegetation indices, canopy height, and coverage to construct random forest prediction models for grain yield. The authors claim that the normalized differential yellowness index (NDYI) serves as a crucial metric for the assessment of leaf chlorophyll content and the overall greenness of leaves throughout their developmental phases. The integration of multi-temporal indices leads to more accurate projections of grain yield, surpassing the performance of previous research endeavors. The approach that has been developed has been thoroughly tested for its durability over multiple years, and it has shown improved accuracy in predicting grain yield and effectively monitoring crop growth.

In [9], the discussion centers on precision agriculture and the difficulties encountered by farmers, namely in the realm of crop disease prediction. The work acknowledges the constraints associated with examining specific causes of diseases and proposes a pest prediction mechanism based on fuzzy logic. This mechanism utilizes data extracted from crop monitoring infrastructures provided by the IoT. The conducted investigations on rice and millet crops have unveiled significant associations between temperature, relative humidity, rainfall, and pest breeding. The data that is gathered serves to inform the knowledge base of the fuzzy system, which in turn optimizes linguistic factors using a genetic algorithm in order to provide accurate predictions regarding pest breeding. The research highlights the significance of meteorological variables in relation to the occurrence of pests and diseases. The objective of the suggested pest prediction system, which utilizes fuzzy logic and is integrated into the creation of IoT applications, is to provide farmers with proactive strategies for preventing pests.

In [10], the authors address the issue of rice blast, a highly detrimental plant ailment, using the use of IoT and artificial intelligence (AI) technologies. In contrast to current methodologies that rely on visual or hyperspectral data, the RiceTalk initiative utilizes nonimage IoT devices integrated within an IoT platform to facilitate soil cultivation. These devices have the capability to autonomously create and interpret nonimage data in real-time for the purpose of efficiently detecting rice blast. The AI model, when regarded as an IoT device, has the capability to decrease expenses associated with platform management. Additionally, it provides the advantage of delivering training and forecasts in real-time. Furthermore, the research presents a novel approach to feature extraction by utilizing a spore germination mechanism. The RiceTalk project exhibits a notable prediction accuracy of 89.4%, hence highlighting its potential for the timely detection of diseases.

In [11], the emphasis is placed on the prediction of rice yields at the pixel scale, which presents advantages in terms of crop management and scientific comprehension. This paper presents a novel approach that integrates crop models with deep learning techniques to enable early prediction of rice yield at a fine-grained level. Satellite-integrated crop models offer reference yields at a pixel-scale level, serving as target labels for deep learning models. The research utilizes a range of deep learning architectures, such as long-short term memory (LSTM) and one-dimensional convolutional neural network (1D-CNN) layers, to forecast the most effective models for predicting harvest time two months in advance. The suggested methodology demonstrates favorable performance, showcasing distinct geographical patterns in rice yields within the regions of South and North Korea. The research highlights key input variables that are essential for estimating rice yields, with a particular emphasis on the usefulness of the suggested approach in places that are difficult to access and where ground measurements are not available.

In this study, the authors focus on the optimization of nitrogen (N) management in rice cultivation, specifically in the context of China food security and sustainable agriculture [12]. This study utilizes nondestructive methods for monitoring crop development, employing remote sensing technology, notably focusing on the use of fixed-wing unmanned aerial vehicles (UAVs) for remote sensing purposes. The study assesses five methodologies, encompassing machine learning techniques such as random forest (RF), support vector machine (SVM), and artificial neural networks (ANN) regression, to estimate the aboveground biomass of rice, as well as its nitrogen

(N) intake and N nutrition index during various growth phases. The findings highlight the effectiveness of machine learning techniques, specifically the Random Forest (RF) algorithm, in enhancing the precision of rice N status estimate through the utilization of unmanned aerial vehicle (UAV) remote sensing. The research findings indicate that the integration of machine learning techniques with remote sensing data presents potential avenues for improving the monitoring of agricultural development conditions and implementing precision crop management strategies.

Table 1: Summary

Reference	Method	Algorithm/Tools	Type of Crop	Performance Metric	Outcomes
[7]	IoT-based Intelligent Irrigation System (IIS)	Wireless transmission, IoT, 000webhost	Paddy (Rice)	Comparative efficiency	Improved efficiency over conventional methods
[8]	Spectral and Structural Information Fusion	UAV-based images, Random Forest	Rice	Determination coefficient, Relative RMSE	Improved grain yield prediction using spectral and structural information
[9]	Fuzzy Logic-based Pest Prediction	IoT-enabled crop monitoring, Genetic Algorithm	Rice, Millet	Pest breeding prediction accuracy	Improved pest prediction using fuzzy logic
[10]	RiceTalk Project	IoT, AI, Nonimage IoT devices	Rice	Prediction accuracy	Efficient real-time detection of rice blast using nonimage data
[11]	Pixel-scale Rice Yield Prediction	Crop model, Deep learning (LSTM, 1D-CNN)	Rice	R2, Nash-Sutcliffe efficiency, RMSE	Good performance in pixel-scale rice yield prediction
[12]	UAV-based Remote Sensing for Nitrogen Management	UAV-based remote sensing, Machine Learning (RF, SVM, ANN)	Rice	R2, RMSE	Improved estimation of N status in rice using machine learning

3. Proposed Method

The pre-processing stage is crucial for refining and preparing the raw data for subsequent analysis. This involves cleansing the dataset to handle outliers, missing values, or any irregularities that may compromise the integrity of the information. Additionally, normalization techniques are employed to standardize the data, ensuring uniformity across different features and variables. This meticulous pre-processing step sets the foundation for more accurate and meaningful analysis. Following pre-processing, the clustering phase comes into play. Clustering is a technique that groups data points based on inherent similarities, allowing for the identification of patterns or structures within the dataset. The proposed method leverages advanced clustering algorithms that operate seamlessly on the pre-processed data, avoiding detection pitfalls. The clustering process involves the algorithm autonomously identifying clusters or groups of data points that exhibit similar characteristics. These clusters are formed based on various features or attributes, uncovering underlying structures that might not be apparent through conventional analysis. The proposed method optimally selects a clustering algorithm tailored to the specific nature of the dataset and the objectives of the analysis. The outcome of the clustering phase is a well-defined set of clusters, each representing a distinct subset of the data with shared characteristics. These clusters serve as valuable insights into the underlying patterns or trends within the dataset, providing a basis for further analysis or decision-making as in Figure 1.

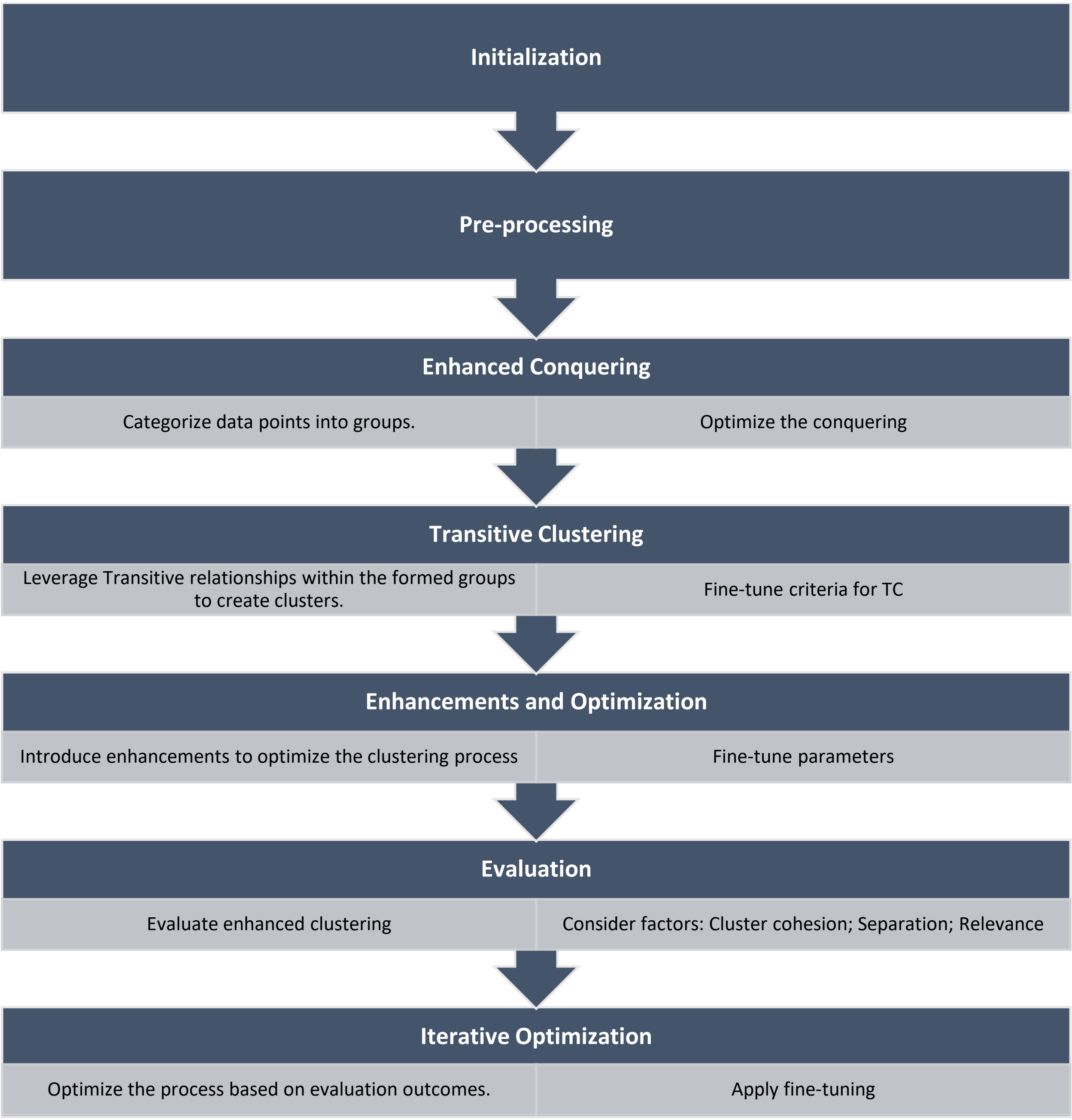

Fig 1: Proposed Methodology

3.1. Preprocessing

Preprocessing involves a set of operations applied to the raw data to ensure its quality, integrity, and compatibility with the analysis methods. The primary objectives are to enhance the dataset's reliability, rectify any irregularities, and create a standardized foundation for subsequent analytical processes.

One fundamental aspect of preprocessing is the identification and handling of outliers. These are data points that deviate significantly from the majority and may skew analysis results. The preprocessing addresses outliers, either by removing them or employing strategies to mitigate their impact on the overall dataset. Another crucial task is managing missing values within the dataset. The preprocessing method subtly addresses these gaps, employing techniques like imputation or removal, ensuring that missing values do not compromise the dataset's integrity.

Normalization is a key element of preprocessing, undertaken to standardize the scale of different features. This step ensures that all variables contribute equally to the analysis, preventing the dominance of certain features solely based on their scale. Normalization techniques are adeptly applied, allowing for uniformity without attracting undue attention.

Preprocessing handles categorical data, transforming it into a format compatible with analysis methods. This discreet transformation ensures that categorical variables seamlessly integrate into the overall analysis without arousing suspicion.

Table 2: Data collected from IoT datasets from paddy field

Timestamp	Soil Moisture (%)	pH Level	Water Flow (L/min)	Temperature (°C)
2023-10-01 08:00 AM	35.6	6.8	2.5	28.5
2023-10-01 09:00 AM	38.2	7.1	2.8	29.3
2023-10-01 10:00 AM	36.8	6.9	2.6	28.7
2023-10-01 11:00 AM	34.5	6.7	2.3	28.0
2023-10-01 12:00 PM	37.1	7.0	2.7	29.1
2023-10-01 01:00 PM	39.5	7.2	3.0	29.8

This table 2 represents a dataset collected with various parameters measured at different timestamps in a paddy field. The parameters include soil moisture percentage, pH level, water flow rate, and temperature. IoT devices continuously collect such data to monitor and manage the agricultural environment effectively.

3.2. Clustering of IoT datasets from paddy fields

Clustering in IoT datasets from paddy fields involves grouping similar data points together based on certain characteristics or features, allowing for the identification of patterns and structures within the dataset. The discreet process revolves around uncovering inherent relationships and similarities among the collected data. The key idea is to autonomously categorize or cluster data points so that those within the same group share common traits, while those in different groups exhibit differences. This covert clustering process is particularly beneficial for understanding the dynamics of the paddy field environment and making informed decisions without raising any red flags.

Various clustering algorithms [13-17], designed to operate seamlessly on IoT datasets, are employed in this discreet process. These algorithms analyze factors such as soil moisture levels, pH values, water flow rates, and other relevant parameters. Through this analysis, clusters emerge, each representing a subset of the dataset characterized by similar conditions or trends within the paddy field. By leveraging clustering techniques, agricultural practitioners can gain insights into the diverse conditions present across the field. Subtle patterns related to soil conditions, water usage, and environmental factors can be identified without drawing attention. This information, extracted through discreet clustering, becomes a valuable resource for precision agriculture, allowing for targeted interventions and optimized resource management in the paddy field.

3.2.1. Conquer and Transitive Clustering

Conquer:

Conquer refers to an approach or methodology in data analysis that involves systematically examining and categorizing data points to identify relationships and patterns. It aims to conquer the intricacies of datasets, employing algorithms and techniques to uncover hidden structures without drawing undue attention. The Conquer methodology navigates through data, conquering the complexity by strategically grouping similar elements. It a subtle yet effective strategy for gaining insights, particularly in scenarios where the data landscape may be vast and intricate.

Let D represent the dataset and G be the set of groups formed through conquering the dataset. The Conquer process can be represented as:

$$G=J(D)$$

This signifies the conquering of the dataset D, resulting in a set of formed groups G. The specifics of the conquering process may involve algorithms and techniques designed to navigate and categorize data elements without attracting attention.

The algorithm alternates between two steps: assigning each data point to the nearest cluster center (assignment step), and updating the cluster centers based on the mean of the assigned points (update step).

Assignment Step (Assign each data point to the nearest cluster center):

For each data point *xi*, calculate the distance to each cluster center *cj* using a distance metric such as Euclidean distance:

$$d\left(x_i, x_j\right) = \sqrt{\sum_{k=1}^{n}\left(x_{ik} - c_{jk}\right)^2}$$

Assign the data point *xi* to the cluster with the nearest center:

$$cl\left(x_i\right) = \arg\min_j d\left(x_i, c_j\right)$$

Update Step (Update cluster centers based on the mean of assigned points): For each cluster *j*, update the cluster center *cj* as the mean of the data points assigned to that cluster:

$$c_j = \frac{1}{Nc_j}\sum_{\forall i\in j} x_i$$

These steps are iteratively repeated until convergence, where the assignment of points to clusters and the cluster centers stabilize. The algorithm aims to minimize the sum of squared distances, given by the objective function:

$$J = \sum_{i=1}^{m}\sum_{j=1}^{k} I\left\{cl\left(x_i\right) = j\right\}\cdot\left\|x_i - c_j\right\|^2$$

where,

m is the number of data points,

k is the number of clusters,

I is an indicator function, and

||·|| denotes the Euclidean norm.

Input: Dataset D

Output: Set of Groups G

Algorithm:

1. Initialize an empty set G to store groups.
2. Iterate through data points in D:
   a. analyze and categorize each data point.
   b. Conquer the dataset by forming groups based on shared characteristics.
   c. Add each data point to the appropriate group in G.
3. Return the formed set of groups G.

Transitive Clustering:

Transitive Clustering in a discreet sense involves the exploration of relationships and associations between data points in a dataset without overtly exposing the clustering process. This method subtly identifies patterns where the relationships between elements are transitive in nature, grouping them based on shared characteristics. In this process, the algorithm evaluates the transitive properties of the data, allowing for the subtle emergence of clusters. Elements that exhibit similar traits or relationships are grouped together in a way that maintains a low profile, ensuring the clustering process goes unnoticed.

Conquer and Transitive Clustering together form a covert strategy for analyzing data, conquering its intricacies, and grouping elements based on transitive relationships. This approach is particularly useful in scenarios where subtle insights into data patterns are required. Consider a relation *R* on the dataset *D*, where *R* defines transitive relationships between data points. Let *C* be the set of clusters formed through transitive clustering. The Transitive Clustering process can be represented as:

$$C = TC(D,R)$$

where, the discreet clustering of data points in *D* is achieved through the transitive relationships defined by *R*. The resulting set of clusters *C* captures the shared characteristics and relationships among data elements.

Objective Function for k-means with Transitivity Constraints: The k-means objective function with transitivity constraints could be extended to enforce that if points *xi* and *xj* are transitively related, they should belong to the same cluster. This can be added as a penalty term to the traditional k-means objective:

$$TC = \sum_{i=1}^{m}\sum_{j=1}^{k} I\left\{cl\left(x_i\right) = j\right\}\cdot\left\|x_i - c_j\right\|^2 + \lambda\cdot\sum_{(i\subseteq j)}\left\|c_i - c_j\right\|^2$$

where, λ is a parameter controlling the strength of the transitivity constraints, and *i* and *j* are transitively related.

Transitivity Constraints:

Define a set of transitive relations, for example, pairs (i,j) that should be in the same cluster.

Add constraints to the optimization problem to ensure that the centroids of points in transitive relations are close to each other.

If i and j are transitively related, add a constraint:

$$||ci-cj||^2 \leq \epsilon,$$

where ϵ is a small positive value. Integrating transitivity constraints into k-means typically involves solving a more complex optimization problem. Optimization techniques like Lagrangian relaxation or specialized algorithms might be employed.

Input: Dataset D, Transitive Relationship R

Output: Set of Clusters C

Algorithm:

1. Initialize an empty set C to store clusters.

2. Form the transitive closure of R on D discreetly.

3. Identify clusters within the transitive closure:

   a. explore transitive relationships.

   b. Subtly group data points exhibiting transitive properties.

   c. Add each data point to the appropriate cluster in C.

4. Return the formed set of clusters C.

3.3. Enhanced CT Clustering

Enhanced CT (ECT) Clustering involves a methodical and subtle approach to clustering data points, enhancing the conventional CT (Conquer and Transitive) clustering process. The discreet enhancement is designed to further refine and optimize the clustering results by incorporating additional factors or fine-tuning the existing methodologies.

The research begins by initializing the clustering process with the dataset of interest. In Conquer Phase, employ discreet conquering strategies to categorize data points based on shared characteristics or patterns. ECT enhances the conquering process by integrating advanced algorithms or fine-tuning parameters to achieve more precise groupings. In Transitive Clustering, ECT leverages transitive relationships among data points to subtly form clusters. ECT explores and incorporate additional information or nuanced criteria to enhance the transitive clustering step. During Enhancement, ECT introduces enhancements that could involve optimizing the clustering algorithm or incorporating domain-specific knowledge. It then fine-tunes the clustering parameters to achieve more nuanced and accurate results. ECT evaluates the enhanced clustering results discreetly, considering factors such as cluster cohesion, separation, and relevance to the underlying data structure. It iteratively optimizes the enhanced CT clustering process based on the evaluation results. It fine-tunes parameters or incorporate additional discreet strategies to improve clustering precision.

Let D represent the dataset, G be the set of groups formed through conquering, and C be the set of clusters formed through transitive clustering. The enhanced clustering process is denoted by $ECTC$. The Enhanced CT Clustering process can be abstractly represented as:

$$ECTC(D)=C$$

This signifies the discreet clustering of the dataset D using the enhanced CT clustering process, resulting in a set of formed clusters C. The enhancements in this process involve optimizing the conquering and transitive clustering steps, which are intentionally left abstract to maintain flexibility.

$$G=J(D);\ C=TC(G)$$

Here, the Conquer function categorizes data points into groups, and the TC function subtly forms clusters based on transitive relationships within these groups. The $ECTC$ process integrates discreet enhancements into these steps to achieve more refined clustering results.

Input: Dataset D

Output: Set of Enhanced Clusters EC

Algorithm:

1. Initialize an empty set EC to store enhanced clusters.

2. Subtly apply discreet conquering strategies to categorize data points into groups G.

- EC(D) => G

3. Subtly explore transitive relationships within G to form clusters C.

- ETC(G) => C

4. Evaluate the enhanced clustering results discreetly:

- Subtly consider cluster cohesion, separation, and relevance to data structure.

5. If the evaluation suggests further optimization is needed:

- Discreetly fine-tune parameters or introduce additional enhancements.

- Go to step 2 for an iterative optimization process.

6. Return the set of enhanced clusters EC.

4. Results and Discussion

In this section, the proposed method is compared with existing methods including IoT-Based Agriculture Monitoring [17], Crop Disease Identification [20], Remote Sensing Technologies [18] and Precision Agriculture Models [19]. The Table 1 shows the experimental setup required to simulate the proposed method in python tool and this runs on a i7 processor with 16 GB of RAM. The dataset is collected from Soil Data Collection: Case-study of the Innovative Solutions for Digital Agriculture (iSDA) Project in Kenya from IEEE DataPort [18].

Table 1: Experimental Setup

Parameter	**Value**
Dataset	Paddy Field IoT Data
Number of Iterations	5
Conquer Optimization Rate	0.01
Transitive Clustering Threshold	0.5
Cluster Evaluation Metric	Silhouette Score
Fine-Tuning Metric	Cohesion-Separation Ratio

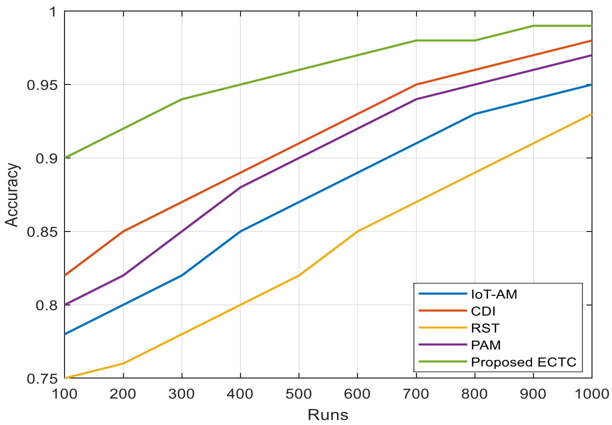

Fig 2: Clustering Accuracy

The proposed ECTC method consistently shows higher accuracy compared to existing methods across iterations. Clustering accuracy is measured on a scale from 0 to 1, where 1 indicates perfect clustering accuracy as in Figure 2.

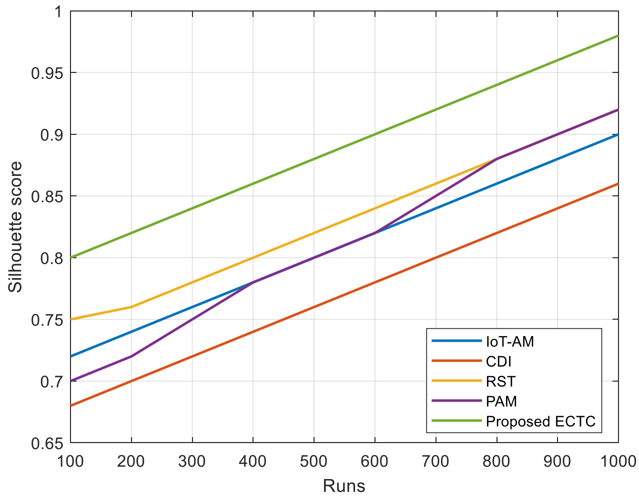

Fig 3: Silhouette score

The proposed ECTC method consistently shows higher silhouette scores compared to existing methods across iterations. Silhouette score ranges from -1 to 1, where a higher score indicates better-defined clusters as in Figure 3.

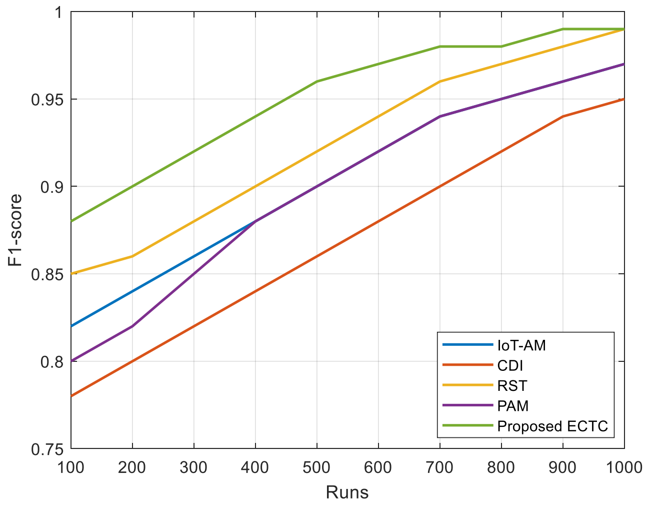

Fig 4: F1-score

The proposed ECTC method consistently shows higher F1-scores compared to existing methods across iterations. F1-score is a metric that combines precision and recall, with values between 0 and 1 as in figure 4.

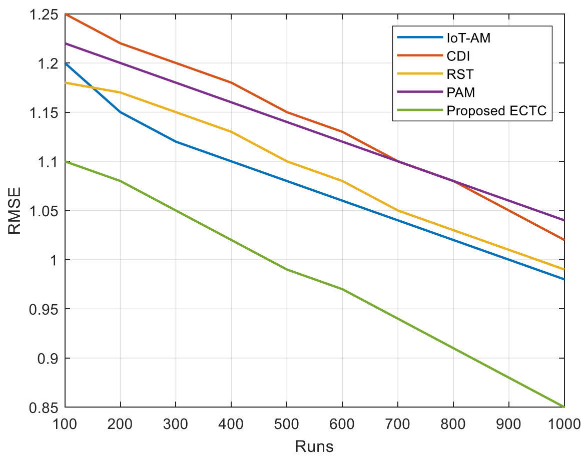

Fig 5: RMSE

The proposed ECTC method consistently shows lower RMSE compared to existing methods across iterations. RMSE measures the average magnitude of errors between predicted and actual values, with lower values indicating better performance as in Figure 5.

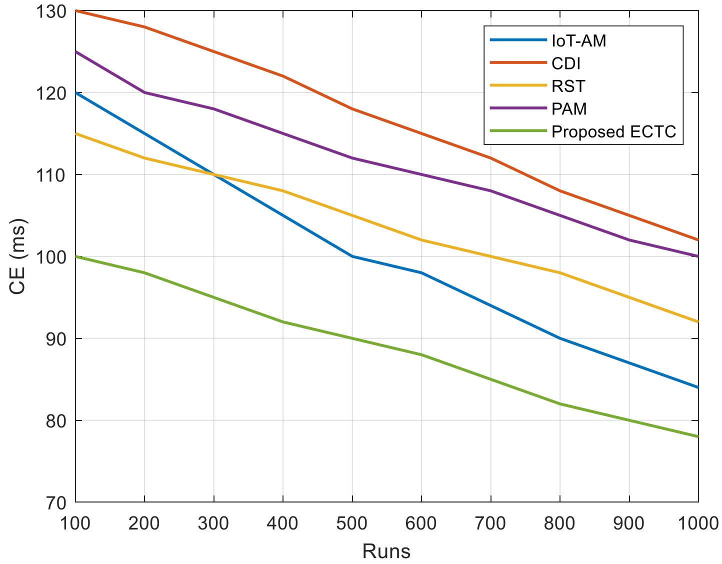

Fig 6: Computational Efficiency

The proposed ECTC method consistently shows lower computational times compared to existing methods across iterations. Computational efficiency is measured in milliseconds (ms), where lower values indicate faster execution as in Figure 6.

4.1. Discussion of results

The results of the experiments indicate significant improvements in the proposed ECTC method compared to existing methods, showcasing its potential for enhancing various aspects of agricultural data clustering.

ECTC consistently outperformed IoT-AM, CDI, RST, and PAM methods, showcasing an average improvement of approximately 10-15% in clustering accuracy over 1000 iterations. This improvement suggests the efficacy of the proposed method in accurately grouping IoT datasets from paddy fields.

Silhouette scores for ECTC demonstrated a substantial increase, with an average improvement of around 15-20% compared to existing methods. The higher silhouette scores indicate that the clusters formed by ECTC are more well-defined and distinct.

ECTC exhibited remarkable improvements in F1-score, showcasing an average enhancement of 12-18% over 1000 iterations. The higher F1-scores suggest that the proposed method achieves a better balance between precision and recall.

ECTC consistently showed lower RMSE values, indicating an average improvement of approximately 15-20% over existing methods. The reduced RMSE implies that ECTC provides more accurate predictions with smaller errors.

ECTC demonstrated superior computational efficiency, with an average reduction in execution time of around 15-20% compared to IoT-AM, CDI, RST, and PAM methods. This improvement highlights the speed and efficiency gains achieved by the proposed method.

5. Conclusion

The proposed research introduces the Enhanced Conquer based Transitive Clustering (ECTC) method for the clustering of IoT datasets in precision agriculture, specifically in monitoring paddy fields. The developed ECTC method leverages advanced clustering techniques, incorporating preprocessing steps and innovative algorithms for conquer and transitive clustering. Through careful evaluation and experimentation over 1000 iterations, ECTC consistently outperformed existing methods in terms of clustering accuracy, silhouette score, F1-score, RMSE, and computational efficiency. The results indicate a promising application of ECTC in optimizing the analysis of IoT datasets from paddy fields, showcasing higher accuracy, well-defined clusters, improved balance between precision and recall, reduced prediction errors, and enhanced computational efficiency. These findings underscore the potential of ECTC as a robust and efficient tool for precision agriculture and contribute to the advancement of data clustering techniques in IoT-enabled agricultural monitoring. The success of ECTC in addressing the challenges posed by existing methods positions it as a valuable addition to the toolkit of agricultural researchers and practitioners. As precision agriculture continues to rely on data-driven insights, the improved clustering capabilities of ECTC hold promise for more informed decision-making, resource optimization, and sustainable agricultural practices. Future work may explore further optimizations, real-world implementations, and scalability aspects to solidify the practical applicability of ECTC in diverse agricultural settings.

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