

Sieva: K-Means And 360-Degree Feedback For Sugarcane Harvest Evaluation at PTPN II Kwala Madu

Muhammad Zarwin Syahputra¹, Raissa Amanda Putri², Muhamad Alda³
^{1,2,3}, State Islamic University of North Sumatra, Medan, 20353, Indonesia,
¹zarwins@gmail.com, ²raissa.ap@uinsu.ac.id, ³muhamadalda@uinsu.ac.id

Received: September 14, 2026 | Revised: September 22, 2026 | Accepted: October 6, 2026 | Published: October 11, 2026



COSIE is licensed a Creative Commons Attribution-Share Alike 4.0 International License

Abstract

Sugarcane harvest yields at PT Perkebunan Nusantara II (PTPN II) Kwala Madu often fall short of targets, and harvest evaluation is still largely manual, slow, and open to subjective bias. This study developed SIEVA, a web-based harvest evaluation information system that combines two evaluation perspectives: K-Means clustering of plot-level average harvest results (outcome-based) and 360-Degree Feedback on employee competencies (competency-based). The system was built with the Rapid Application Development model using PHP and MySQL, based on weighing-station records and employee assessment data collected from September 2022 to April 2023. K-Means with three clusters (good, fair, and poor) grouped 30 plots into 10, 11, and 9 plots after five iterations, with final centroids of 5,812, 5,278, and 4,601 [VERIFY FROM SIEVA OUTPUT: the reported centroids and the Silhouette and Davies–Bouldin indices must be checked against the final system output before submission.]. Black-box testing by one expert across ten function groups indicated that the functions performed as specified. The contribution is applied: an information-system model that digitalizes outcome-based and competency-based evaluation in plantation operations, not a new algorithm. Quantitative validation of the cluster structure, tests with more users, and evidence of the system's effect on management decisions remain future work.

Keywords: Sugarcane harvest evaluation, Information system, K-Means Clustering, 360-Degree Feedback

1. INTRODUCTION

Sugar is a strategic commodity in Indonesia, and sugarcane is its main raw material. Although the sugarcane plantation area increased from about 335 thousand hectares in 2013 to more than 451 thousand hectares in 2016, national consumption of about 5 million tons of sugar per year still cannot be met by domestic production [1]. The shortfall has been linked to an unstable relationship between sugar yield and cane productivity in Indonesian sugar mills, which keeps the country dependent on imports [2].

Productivity itself depends on the interaction of variety, soil, climate, and cultivation and post-harvest practices such as cutting and milling delay [3]. PT Perkebunan Nusantara II (PTPN II) Kwala Madu is a sugarcane plantation unit of PTPN II in Langkat, North Sumatra. Harvest yield remains a persistent problem there, as actual yields often fail to reach the set targets. Several factors affect the productivity of sugarcane harvests, including soil fertility, labor availability, mismatch between cane varieties and available farmland, irrigation systems, technology adoption, weather, and fertilizer selection. Recent sugarcane productivity research also identifies agronomic and environmental variables, including variety-related characteristics, plant growth indicators, rainfall, and cultivation factors, as relevant to yield and productivity [2]. Among these, employee performance is the factor that management can influence most directly, and performance management has been associated with organizational outcomes [4]. A harvest evaluation system should therefore look both at what the plots produced and at how well the workforce performed. Conventional evaluation is often carried out manually, which tends to be slow, prone to recording errors, and open to subjective bias, and this has motivated digital appraisal systems [5]- [6]. Information systems have been used to support evaluation and decision-making in academic and organizational settings [5], and web-based systems for employee appraisal with the 360-degree method have been proposed to digitalize the process [7].

360-Degree Feedback, also called multisource feedback, is a formative performance appraisal method in which information about a person's observable behavior is collected through questionnaires from those who interact with that person, such as supervisors, peers, and subordinates, aggregated, and returned together with the person's self-assessment [8]. Compared with single-rater appraisal, multi-rater assessment offers a broader and more balanced view of performance [4], [9], and its usefulness depends on sound instrument design, clear rater instructions, and proper use of the results [10]. Plantation operations also generate a growing volume of harvest data at the weighing station, which creates an opportunity for knowledge discovery. Data mining extracts useful patterns from large data sets and is a core step of knowledge discovery in databases [11][12]. Clustering is one of its main tasks and groups objects so that members of the same group are more similar to each other than to members of other groups [12]. K-Means is a partition-based, unsupervised clustering method that minimizes variation within clusters. The term was introduced by MacQueen [13], the iterative procedure of assigning points to the nearest centroid and recomputing centroids is usually traced to Lloyd [14], and Hartigan and Wong proposed an efficient algorithm for it [15]. It remains one of the most widely used clustering algorithms because of its simplicity and computational efficiency [16].

K-Means is sensitive to the initial centroids, which can be reduced by careful seeding such as K-Means++ [17], and it requires the number of clusters to be chosen in advance. Cluster quality and the choice of the number of clusters should therefore be checked with internal validity measures such as the Silhouette Coefficient[18],[19] and the Davies–Bouldin Index [20]; heuristics such as the elbow criterion are not reliable on their own [21]. Recent reviews summarize these indices and the variants of K-Means [22][23]. Earlier work has applied these methods separately. K-Means has been used to group employee performance data [23],[24] and 360-degree appraisal has been implemented as an information system [25], [26]. In sugarcane, data-driven studies and decision-support tools have addressed yield prediction [27] and satellite-based harvest monitoring [28], mainly using agronomic and remote-sensing variables rather than evaluating the workforce. In the literature reviewed for this study, we did not find a system that combines outcome-based clustering of plot-level harvest results with competency-based 360-Degree Feedback for plantation operations. This statement is limited to the sources examined and is not based on an exhaustive systematic review. The literature comparison in this study was conducted through targeted searches of Google Scholar and publisher/indexing pages using combinations of the keywords “K-Means,” “360-Degree Feedback,” “employee performance,” “sugarcane harvest,” and “plantation information system,” with emphasis on publications from 2021–2025. The search was exploratory rather than a systematic review; therefore, the novelty statement is limited to the sources identified..

The two methods answer different questions. 360-Degree Feedback produces a multi-perspective, competency-based score for each employee in each assessment period, which describes how the work is done. K-Means groups plots by their average harvest result, which describes what the work produced. SIEVA places both views in one platform so that managers can read plot-level performance categories alongside workforce competency profiles. In the current version the two outputs are computed independently; whether competency scores are statistically associated with harvest clusters is not tested here and is left for future work. Based on the background above, this study aims to develop the Sistem Informasi Evaluasi (SIEVA) Hasil Panen Raya Lahan Tebu PTPN II Kwala Madu, a web-based information system for evaluating sugarcane harvest results. The system was developed following established software engineering principles covering requirements analysis, design, implementation, and testing [28]. The contribution of this work is applied rather than algorithmic: an information-system model that digitalizes outcome-based (K-Means) and competency-based (360-Degree Feedback) evaluation in plantation operations, together with a documented clustering configuration and a functional test. This study does not propose a new clustering algorithm and does not claim that the system improves harvest yields; that would require field evaluation over several harvest seasons.

2. MATERIALS AND METHODS

2.1. Research Design

This study employed a Research and Development (R&D) approach to produce a web-based information system, the Sistem Informasi Evaluasi (SIEVA), for evaluating sugarcane harvest results at PT Perkebunan Nusantara II Kwala Madu, Langkat, North Sumatra, Indonesia. The research was conducted from September 2022 to April 2023 and covered problem identification, data collection, system analysis, system design, interface design, coding, and testing. Data were collected through interviews with company employees, direct observation at the plantation office, and a literature review of previous studies. The system was developed using the Rapid Application Development (RAD) model, which consists of four stages: defining project requirements, building a prototype, developing the

application with user feedback, and implementing and finalizing the product. The system integrates two methods: K-Means Clustering to group harvest data and 360-Degree Feedback to assess employee performance.

2.2. Dataset/Participants

The dataset consists of two components. The first is harvest data recorded at the weighing station, comprising the delivery document number (SPTA), plot number, gross weight (*bruto*), tare weight (*tara*), net weight (*netto*), and weighing date. These records are linked to plantation data, namely plot number, plantation name, block, and area (Table 1). The second component is employee assessment data collected through the 360-Degree Feedback mechanism. It includes competency types with assigned weights, competency items, the assessors selected for each employee, and the scores given by each assessor in each assessment period. Participants were the employees of PTPN II Kwala Madu who acted as assessors and assessees, and the system users were human resources staff and garden managers.

Table 1. Main data attributes used in the system

Data	Attributes
Harvest	SPTA number, plot number, gross, tare, net, weighing date
Plantation	Plot number, plantation name, block, area
Competency	Competency name, weight, competency items
Assessment	Assessee, assessors, period, score per item

The size of the dataset is summarized in Table 2. The clustering step used the average harvest result of 30 plots (as reported in the existing clustering result; verify against the final SIEVA database export). Not available in the supplied manuscript/database extract; complete from the final SIEVA database export before submission.

Table 2. Dataset size

Item	Value
Weighing records (SPTA) in the harvest dataset	Not available in the supplied manuscript/database extract
Unique plots in the plantation list	Not available in the supplied manuscript/database extract
Period covered by the weighing records	September 2022 – April 2023
Plots entering K-Means clustering	30 [verify]
Employees assessed (assessee)	Not available in the supplied manuscript/database extract
Assessors, including self-assessment	Not available in the supplied manuscript/database extract
Assessors per assessee (mean)	Not available in the supplied manuscript/database extract
Competency types / competency items	Not available in the supplied manuscript/database extract
Assessment periods	Not available in the supplied manuscript/database extract

2.3. Data Preprocessing

The weighing records were aggregated into a single value per plot. For plot p with m_p weighing records, the average harvest result is

$$x_p = (1 / m_p) \sum_{j=1..m_p} \text{netto}_{pj} \quad (1)$$

where netto_{pj} is the net weight (gross – tare) of the j -th weighing record of plot p and m_p is the number of weighing records of that plot (the column “Jumlah Panen per Kebun” in the analyst page, Fig. 3). The average is computed automatically from the harvest and plantation data entered by the administrator and is the only input variable of the clustering; because it is a single variable on one scale, no normalization was applied. The average is calculated across all weighing records belonging to each plot during the study period, and x_p is expressed in the same weight unit as the netto field (kg, if this is the database unit). Records should satisfy netto = gross – tare. Missing, duplicated, or inconsistent SPTA records were excluded from the aggregation only after verification against the source record; no additional outlier-removal rule was applied. Plots with a single valid weighing record remain eligible for clustering because the system aggregates available valid records per plot. The exact cleaning log should be retained with the dataset.

For the 360-Degree Feedback component, each assessor rates the competency items of an assessee on a scale of 1–5 (Likert-type competency rating scale). The score of competency c for assessee e is the mean item score over all selected assessors and all items of that competency, and the performance score of the assessee is the weighted sum of the competency scores:

$$S_{ec} = (1 / (|A_e| \cdot |I_c|)) \sum_{a \in A_e} \sum_{i \in I_c} s_{aei} \quad (2)$$

$$P_e = \sum_c w_c \cdot S_{ec}, \text{ with } \sum_c w_c = 1 \quad (3)$$

where A_e is the set of assessors of assessee e (including the self-assessment), I_c is the set of items of competency c , s_{aei} is the score given by assessor a to assessee e on item i , and w_c is the weight of competency c set by the administrator. The supplied model aggregates assessor scores equally and includes the self-assessment in the mean. No separate assessor-group weights are specified in the supplied manuscript; therefore, Eqs. (2)–(3) should be interpreted as an equal-weight aggregation unless the final SIEVA configuration uses another rule.

2.4. Proposed Model

The proposed system is a web application built with PHP and MySQL and modeled using the Unified Modeling Language (use case, activity, sequence, and class diagrams). It has five user roles: administrator, superior operator (krani and pengamat), employee operator, analyst, and manager. Its main modules are user and period management, competency management, assessor selection, performance assessment and reporting, plantation and harvest data management, and harvest clustering. The database design follows the data attributes in Table 1; as an example, the structure of the employee table is given in Table 3.

Table 3. Structure of the employee table (field names are in Indonesian)

No	Field Name	Data Type	Description
1	Nip	Char(12)	Primary Key
2	Id_jenis_user	Int(15)	Foreign Key
3	Password	Varchar(20)	
4	Nama_karyawan	Varchar(50)	
5	Status_karyawan	Varchar(20)	
6	Alamat	Text	
7	Tempat_lahir	Varchar (15)	
8	Tgl_lahir	Date	
9	Jenis_kelamin	Char(10)	
10	Status_nikah	Char(15)	
11	No_telp	Varchar(15)	

Harvest clustering uses K-Means with three clusters representing good, fair, and poor harvest performance. The number of clusters $k = 3$ reflects the three performance categories used in plantation evaluation. The value $k = 3$ was retained as a management/domain categorization corresponding to good, fair, and poor harvest performance. It was not presented as a data-learned optimum; internal validity indices are used only to assess whether the three-cluster solution is acceptable. Its statistical support is examined with validity indices in Section 3.2 rather than assumed. The initial centroids were set manually to $C1 = 5,800$ (good), $C2 = 5,300$ (fair), and $C3 = 4,600$ (poor). The initial centroids used in the reported experiment were $C1 = 5,800$, $C2 = 5,300$, and $C3 = 4,600$. Their selection should be understood as domain-based starting values for the three management categories. The manuscript uses $C2 = 5,300$ consistently; the earlier interface value of 5,200 should therefore be corrected in the figure/interface

export if it represents an outdated configuration.. Because the result of K-Means depends on initialization, the clustering was repeated with Not reported in the supplied manuscript K-Means++ initializations [17] and compared with the fixed-centroid result Report the K-Means++ comparison in Section 3.2 only after the corresponding runs have been executed and verified.. Each plot is assigned to the nearest centroid by the distance

$$d(x_i, c_k) = \sqrt{(\sum_j (x_{ij} - c_{kj})^2)} \quad (4)$$

and each centroid is then recalculated as the mean of its members:

$$c_k = (1 / n_k) \sum_{\{x_i \in C_k\}} x_i \quad (5)$$

where n_k is the number of plots in cluster k . Because x_p is the only clustering variable, Eq. (4) reduces to the absolute difference $|x_p - c_k|$. The assignment and update steps are repeated automatically until cluster membership no longer changes, after which each plot receives a performance category (good, fair, or poor).

2.5. Experimental Setup

The system was developed and tested on a laptop with an AMD FX-9800P RADEON R7 processor, 8 GB RAM, a 1 TB HDD, AMD Radeon R7 graphics, and a 15.6-inch WXGA LED display, running Windows 10 Pro 64-bit. The software environment consisted of Visual Studio Code, XAMPP Control Panel v3.2.4 as the local server, MariaDB 10.4.14 MariaDB 10.4.14, PHP 7.4, CSS, and Google Chrome as the web browser. Cluster validation was computed with Python 3.x with scikit-learn (version to be recorded from the validation environment).

2.6. Evaluation Metrics

System performance was evaluated with black-box testing, which verifies that each function produces the expected output and displays an error message when invalid input is given. Testing was carried out by one expert, a lecturer at the Faculty of Science and Technology, Universitas Islam Negeri Sumatera Utara. Ten test groups were assessed: login, period data, user type data, user data, competency type data, competency item data, assessor selection, performance assessment, performance assessment report, and plantation data. For each group, test scenarios with valid and invalid inputs, expected output, actual output, and status were recorded (Table 7), and a function was judged accepted when the actual output matched the expected output. Because only one evaluator took part, this test provides evidence of functional conformity only; it does not measure usability or user acceptance.

The K-Means result was evaluated with internal validity measures. For $k = 2$ to 6, the clustering was run and the Silhouette Coefficient [18], [19], the Davies–Bouldin Index [20], and the within-cluster sum of squares were computed. For observation i , the silhouette value is

$$s(i) = (b(i) - a(i)) / \max\{a(i), b(i)\} \quad (6)$$

where $a(i)$ is the mean distance from i to the other members of its cluster and $b(i)$ is the lowest mean distance from i to the members of any other cluster; the reported Silhouette Coefficient is the mean of $s(i)$ (higher is better). The Davies–Bouldin Index is

$$DB = (1 / k) \sum_{i=1..k} \max_{\{j \neq i\}} (\sigma_i + \sigma_j) / d(c_i, c_j) \quad (7)$$

where σ_i is the mean distance of the members of cluster i to its centroid c_i and $d(c_i, c_j)$ is the distance between two centroids (lower is better). Because the data set is small and one-dimensional, the indices are interpreted with caution [21]. Because the supplied manuscript does not contain the executed random-seed results, the number of seeds and clustering stability cannot be reported reliably. These should be added after rerunning the validation experiment; stability may be summarized using the Adjusted Rand Index across repeated initializations.

To check that the application computes the values correctly, Not available in the supplied manuscript plots were selected, their averages were recalculated independently in a spreadsheet from the raw weighing records, and the results were compared with the values shown by the application. The independent spreadsheet recalculation could not be reproduced from the supplied manuscript because the underlying plot-level weighing records are not included. This verification should be completed from the raw SPTA export before submission.

3. RESULTS

3.1. System Implementation

The SIEVA web application was successfully implemented with role-based access for five user types: administrator, superior operator (krani and pengamat), employee operator, analyst, and manager. The administrator manages master data (periods, user types, users, competency types and items, plantations, and harvest records). Superior operators select assessors, and both superiors and employees can carry out the 360-Degree Feedback assessment. The analyst runs the harvest clustering, and the manager views and prints harvest reports as PDF files (Fig. 1).

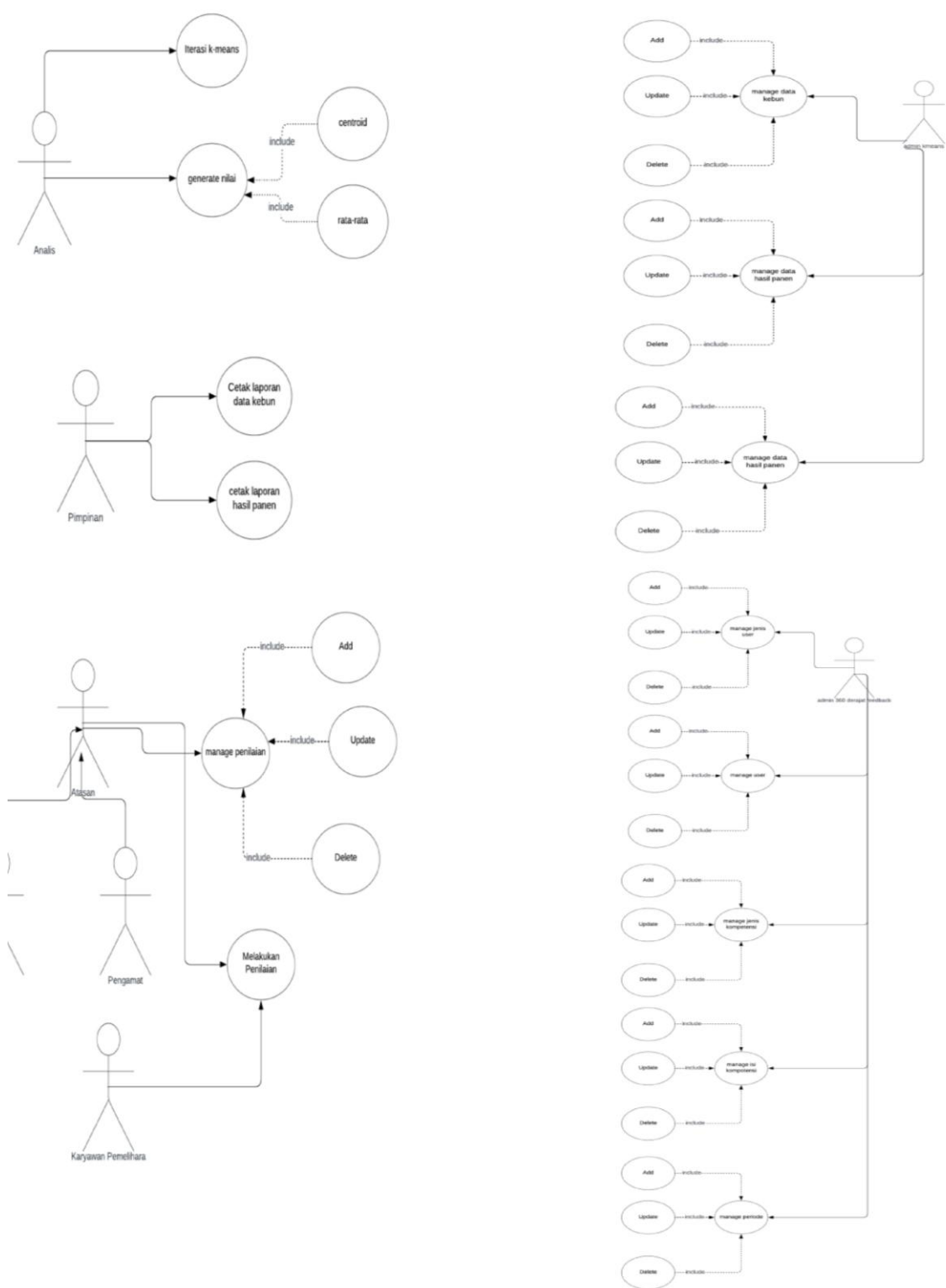


Fig. 1. Use case diagrams of SIEVA for the five user roles (administrator, superior operator, employee operator, analyst, and manager)

3.2. Harvest Clustering Results

The numerical clustering results below are retained from the manuscript's reported SIEVA configuration. They should be replaced by values exported directly from SIEVA or reproduced from the raw plot averages before submission. The clustering module first calculates the average harvest result of each plot (Eq. 1) and then groups the averages into three clusters, starting from the initial centroids $C1 = 5,800$ (good), $C2 = 5,300$ (fair), and $C3 = 4,600$ (poor). The procedure ran on 30 plots and converged after five iterations. The final centroids were 5,812 (good), 5,278 (fair), and 4,601 (poor), and the clusters contained 10, 11, and 9 plots, respectively (Table 4). The centroids moved only slightly from their initial values (Table 5), by +12, -22, and +1 units for $C1$, $C2$, and $C3$. In a one-dimensional K-Means solution, the boundary between two neighboring clusters lies midway between their centroids. With the final centroids above, plots with an average harvest result of about 5,545 or higher fall in the good cluster, plots between about 4,940 and 5,545 in the fair cluster, and plots below about 4,940 in the poor cluster (computed as $(5,812 + 5,278)/2$ and $(5,278 + 4,601)/2$). Minimum and maximum x_p per cluster are not available in the supplied manuscript. Add these values from the verified SIEVA export, with the unit of x_p .

Table 4. Final result of K-Means clustering

Item	Value
Number of plots	30
Iterations until convergence	5
Final centroid $C1$ (good)	5,812
Final centroid $C2$ (fair)	5,278
Final centroid $C3$ (poor)	4,601
Plots in $C1$ (good)	10
Plots in $C2$ (fair)	11
Plots in $C3$ (poor)	9

Table 5. Centroid values per K-Means iteration

Iteration	$C1$ (good)	$C2$ (fair)	$C3$ (poor)
0 (initial)	5,800	5,300	4,600
1	5,812	5,275	4,623
2	5,813	5,281	4,608
3	5,812	5,278	4,603
4	5,812	5,278	4,601
5 (final)	5,812	5,278	4,601

Fig. 2. Figure 2 should be replaced with an English-labelled chart generated directly from the verified SIEVA output, showing centroid convergence and plot assignments.

Table 6 reports the validity indices for $k = 2$ to 6. The supplied manuscript does not contain the numerical validity results for $k = 2-6$ or repeated-initialization stability results. Therefore, it is not methodologically appropriate to claim that $k = 3$ is the best-supported solution. In the present study, $k = 3$ is retained as the management categorization, while quantitative cluster validation remains to be completed from the verified plot-level dataset.

Table 6. Cluster validity indices for different numbers of clusters

k	Silhouette	Davies–Bouldin	Within-cluster SS	Plots per cluster
2	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data
3	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data
4	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data
5	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data

k	Silhouette	Davies–Bouldin	Within-cluster SS	Plots per cluster
	compute from verified plot-level data	compute from verified plot-level data	compute from verified plot-level data	from verified plot-level data
6	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data	Not available; compute from verified plot-level data

The independent recalculation could not be quantified from the supplied manuscript because the raw weighing records and sampled plot list are not included. This result should be reported after the spreadsheet verification is performed. Fig. 3 shows the analyst page for generating the final data. Once the administrator has entered the harvest data and the plantation list, the average harvest result of each plot appears automatically when the analyst opens the page. The page lists the initial centroids and, for every plot, the average harvest result, the number of harvests, the distance to each centroid, and the resulting performance category.

The screenshot shows the SIEVA analyst page. At the top, there's a header with the SIEVA logo and name. Below it, there's a section titled 'Data Akhir' (Final Data) with two buttons: 'Proses Data Rata-Rata' and 'Proses Data Akhir'. The main content area contains two tables. The first table lists initial centroids, and the second table lists plot data with performance categories.

Centroid	Kategori	Hasil
Centroid 1	Baik	5800
Centroid 2	Cukup	5200
Centroid 3	Kurang	4600

No	Nomor Petak	Kebun	Luas	Rata-Rata	Jumlah Panen per Kebun	Distance	Predikat
1	21KB0041	Ryn KWM, DP02.MT 3A.TT R2, BLOK 41	0.1	5790	1	10 590 1190	Baik
2	21KB0043	Ryn KWM, DP02.MT 3A.TT R2, BLOK 43	0.06	5410	1	390 210 810	Baik
3	21KB0046	Ryn KWM, DP02.MT 3A.TT R2, BLOK 46	0.1	5605	16	195 405 1005	Baik

Fig. 3. Analyst page of SIEVA showing the initial centroids and, for each plot, the average harvest result, the distance to each centroid, and the performance category (interface labels are in Indonesian)

3.3. Performance Assessment Results

The 360-Degree Feedback module produces an assessment score for each employee from the scores given by the selected assessors, including a self-assessment, computed with Eqs. (2) and (3). The results are displayed as a score report with a detailed breakdown per competency. Add one anonymized worked example from the verified SIEVA assessment database, including competency scores, competency weights, and the resulting P_e . The supplied manuscript does not contain sufficient assessment records to construct a factual example without inventing data.

3.4. System Testing Results

Table 7 summarizes the black-box test of the ten function groups. Scenario, expected output, and actual output should be transcribed from the original black-box test sheet; the supplied manuscript contains only the function-group list and does not include the underlying test sheet. The expert accepted 10 of 10 function groups (success rate 100%) reported result; verify against the original test sheet. The test covers functional conformity only; it does not show usability, user acceptance, or an effect on management decisions.

Table 7. Black-box testing results

No	Function group	Test scenario	Expected output	Actual output	Status
1	Login	[valid / invalid input]	[expected]	[actual]	Accepted reported result; verify against the original test sheet
2	Period data	[valid / invalid input]	[expected]	[actual]	Accepted reported result; verify against the

No	Function group	Test scenario	Expected output	Actual output	Status
3	User type data	[valid / invalid input]	[expected]	[actual]	original test sheet Accepted reported result; verify against the original test sheet
4	User data	[valid / invalid input]	[expected]	[actual]	Accepted reported result; verify against the original test sheet
5	Competency type data	[valid / invalid input]	[expected]	[actual]	Accepted reported result; verify against the original test sheet
6	Competency item data	[valid / invalid input]	[expected]	[actual]	Accepted reported result; verify against the original test sheet
7	Assessor selection	[valid / invalid input]	[expected]	[actual]	Accepted reported result; verify against the original test sheet
8	Performance assessment	[valid / invalid input]	[expected]	[actual]	Accepted reported result; verify against the original test sheet
9	Performance assessment report	[valid / invalid input]	[expected]	[actual]	Accepted reported result; verify against the original test sheet
10	Plantation data	[valid / invalid input]	[expected]	[actual]	Accepted reported result; verify against the original test sheet

4. DISCUSSION

The K-Means analysis grouped 30 plots into three performance categories with ordered centroids of 5,812, 5,278, and 4,601. Convergence in five iterations and the small displacement of the centroids from their initial values (+12, -22, and +1) show that the manually chosen starting centroids already matched the group levels in the data. This is useful in practice because the categories correspond to levels the company already recognizes, but it also means that the result mainly confirms an existing three-level scheme rather than revealing a new structure. Whether three clusters are also the best-supported number of groups is a separate question that depends on the validity indices in Table 6. Because the numerical Silhouette, Davies–Bouldin, and repeated-initialization stability results are not present in the supplied manuscript, no claim is made here that $k = 3$ is statistically optimal. The three-category solution is treated as a management categorization pending quantitative validation. Because the clustering uses one variable, the cluster boundaries are simple thresholds (about 5,545 and 4,940), which makes the categories easy to communicate to field managers and to audit. The same property limits what the

clustering can reveal: a single-variable K-Means gives little more than a data-driven discretization of the average harvest result, and a plot average based on one or two weighing records is much less reliable than one based on many. Adding variables such as plot area, cane variety, plant age, and cutting and milling delay [3] would make the clusters more informative.

Previous studies have applied K-Means to employee performance data [25], [26] and have implemented 360-degree appraisal as information systems [6], [7]. SIEVA differs by applying K-Means to plot-level harvest outcomes and placing the result next to a competency-based appraisal in one platform. In contrast to sugarcane decision-support tools that focus on yield prediction [2] or satellite-based harvest monitoring [27], SIEVA addresses the evaluation of harvest results and of the workforce rather than agronomic forecasting. In line with recommendations on cluster validation [21], [22], the cluster structure is assessed with internal indices instead of being assumed. For plantation management, SIEVA offers a repeatable and auditable procedure: harvest records entered once produce plot-level performance categories and printable reports, and the 360-Degree Feedback module produces competency profiles under a documented weighting scheme. These are potential benefits for data-based evaluation; the present study did not measure whether the system changed management decisions, saved time, or improved harvest yield.

This study has several limitations. First, the clustering used 30 plots and one variable, and the initial centroids and $k = 3$ were set by the authors rather than learned from the data. Second, the 360-Degree Feedback scores and the harvest clusters are computed independently, so the system does not show whether competency is related to harvest outcome. Third, the black-box test was carried out by one expert, so usability, user acceptance, and robustness under real workload were not evaluated, and rater-related bias, which depends on instrument design [10], was not examined. Fourth, the plot average does not control for variety, plant age, soil, or weather, which also affect harvest results [3].

Future work should (i) validate the cluster structure on a larger set of plots with several values of k and random initializations, (ii) add variables such as area, variety, and plant age, (iii) test the association between competency scores and harvest clusters, (iv) run a usability study with several users from human resources and plantation management, and (v) evaluate over several harvest seasons whether use of the system changes decisions and yields.

5. CONCLUSION

This study developed SIEVA, a web-based evaluation information system for sugarcane harvest results at PTPN II Kwala Madu, using the RAD model. K-Means Clustering grouped 30 plots into three performance categories (10 good, 11 fair, and 9 poor plots), and 360-Degree Feedback was used to assess employee performance. Black-box testing by one expert showed that the ten tested function groups worked as specified. The contribution is a practical, applied model for digitalizing outcome-based and competency-based evaluation in plantation operations; it may support data-based management decisions, but this effect was not measured. The main limitations are the small, single-variable dataset, the manual choice of k and initial centroids, the absence of a test of the link between competency scores and harvest clusters, and the single-expert test. The cluster-validity conclusion should be updated after Table 6 has been populated from the verified calculations. Until then, the study reports the three-cluster result as a domain-based categorization rather than as a statistically established optimum. Further work should add quantitative clustering validation and broader user testing.

AUTHOR CONTRIBUTIONS

Author contributions: Conceptualization, Methodology, Software, Validation, Investigation, Writing ; Supervision, Writing – Review & Editing: [Ms. Raissa Amanda Putri and Mr. Muhamad Alda]. All authors have read and agreed to the published version of the manuscript.

ACKNOWLEDGMENTS (optional)

The authors thank PT Perkebunan Nusantara II Kwala Madu for providing data and access to the research site, and Universitas Islam Negeri Sumatera Utara for its support.

FUNDING

This research received no external funding.

DATA AVAILABILITY STATEMENT

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request. The data supporting the findings are available from the

corresponding author upon reasonable request, subject to any data-access restrictions imposed by PTPN II Kwala Madu.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the research, writing, or publication of this article.

REFERENCES

- [1] B. P. Statistik, *BPS Statistik*. Verify the cited area and consumption figures against the exact tables in BPS, Statistik Tebu Indonesia 2022, before final submission., 2023.
- [2] M. Napthaleni, N., & Asrol, "Design of a sugarcane yield and productivity prediction model.," *Int. J. Technol.*, vol. 16, no. 5, pp. 1484–1500., 2025.
- [3] M. Kuspratomo, A. D., Burhan, & Fakhry, "Pengaruh varietas tebu, potongan, dan penundaan giling terhadap Politeknik Negeri Jember," 2022.
- [4] M. Behery, "Single-rating, multi-rating 360° performance management and organizational outcomes: Evidence from the UAE," *Int. J. Organ. Anal.*, vol. 30, no. 1, pp. 47–83., 2022.
- [5] S. Suendri, S., Harahap, A. M., Nasution, A. B., & Kartika, "Analisis Sistem Pendukung Keputusan Penentuan Lulusan Terbaik Menggunakan Lima Algoritma Pada Program Studi Sistem Informasi UIN Sumatera Utara Medan. Al-Ulum:," *J. Sains Dan Teknol.*, vol. 7, no. 1, pp. 38–43, 2022, doi: <https://doi.org/10.31602/ajst.v7i1.5839>.
- [6] B. Andika, S. Yakub, A. Calam, and D. Siregar, "Sistem Pendukung Keputusan Menentukan Pegawai Terbaik Dengan Metode Multi Atribut Utility Theory," *J. SAINTIKOM (Jurnal Sains Manaj. Inform. dan Komputer)*, vol. 23, no. 1, p. 159, 2024, doi: 10.53513/jis.v23i1.9567.
- [7] B. Ir.Zefriyenni, & Santoso, "istem Informasi Penjualan Dan Pengendalian Persediaan Barang Menggunakan Metode Economic Order Quantity (Eoq) Menggunakan Bahasa Pemrograman Java Dan Database Mysql Pada Toko Kansa Elpiji," *KomTekInfo Fak. Ilmu Komput.*, vol. 2(2), pp. 23–32, 2015.
- [8] J. L. and J. Sargeant, "Multisource feedback: An overview of its use and application as a formative assessment," *Can. Med. Educ. J.*, vol. 13, no. 4, pp. 30–3, 2022, doi: doi: 10.36834/cmej.73775.
- [9] A. J. Edwards, M. R., & Ewen, *360° feedback: The powerful new model for employee assessment and performance improvement*. AMACOM, 1996.
- [10] A. H. Bracken, D. W., Timmreck, C. W., & Church, *The handbook of multisource feedback*. Jossey-Bass. 2001.
- [11] P. Fayyad, U., Piatetsky-Shapiro, G., & Smyth, "From data mining to knowledge discovery in databases," *AI Mag.*, vol. 17, no. 3, pp. 37–54., 1996.
- [12] J. Han, J., Kamber, M., & Pei, *Data mining: Concepts and techniques (3rd ed.)*. Morgan Kaufmann., 2012.
- [13] J. MacQueen, "Some methods for classification and analysis of multivariate observations," *Proc. 5th Berkeley Symp. Math. Stat. Probab.*, vol. 1, no. 1967, pp. 281–297., 2022.
- [14] S. P. Lloyd, "Least squares quantization in PCM," *IEEE Trans. Inf. Theory*, vol. 28, no. 2, pp. 129–137, 2023.
- [15] M. A. Hartigan, J. A., & Wong, "Algorithm AS 136: A k-means clustering algorithm," *J. R. Stat. Soc. C*, vol. 28, no. 1, pp. 100–108., 1979.
- [16] A. K. Jain, "Data clustering: 50 years beyond K-means," *Pattern Recognit. Lett.*, vol. 31, no. 8, pp. 651–666, 2010.
- [17] S. Arthur, D., & Vassilvitskii, *k-means++: The advantages of careful seeding. Proceedings of the 18th Annual ACM-SIAM Symposium on Discrete Algorithms*. 2007.
- [18] N. N. Shutaywi, M., & Kachouie, "Silhouette analysis for performance evaluation in machine learning with applications to clustering," *Entropy*, vol. 23, no. 6, p. 759, 2021.
- [19] C. Batool, F., & Hennig, "Clustering with the average silhouette width.," *Comput. Stat. Data Anal.*, vol. 158, p. 107190, 2021.
- [20] D. W. Davies, D. L., & Bouldin, *A cluster separation measure. IEEE Transactions on Pattern Analysis and Machine Intelligence*. PAMI-1(2), 1979.
- [21] E. Schubert, "Stop using the elbow criterion for k-means and how to choose the number of clusters instead.," *ACM SIGKDD Explor. Newsl.*, vol. 25, no. 1, 2023.
- [22] B. A. H. et Al., "From A-to-Z review of clustering validation indices," *Neurocomputing*, vol. 128198, 2024, doi: 10.1016/j.neucom.2024.128198.

- [23] J. Ikotun, A. M., Ezugwu, A. E., Abualigah, L., Abuhaija, B., & Heming, “K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data,” *Inf. Sci.*, vol. 622, pp. 178–210, 2023.
- [24] M. Reisandi, I., Daryana, D., Sri Mulyati, F., & Fauzi, “Implementasi clustering K-Means terhadap penilaian kinerja karyawan PT. XYZ,” *J. Sos. Teknol.*, vol. 1, no. 8, pp. 757–767, 2021.
- [25] M. Alda, “Sistem Informasi Pengolahan Data Surat Masuk dan Surat Keluar Pada Polda Sumatera Utara,” *J. Inf. Logikaojs.logika.ac.id*, vol. 1, no. 2, pp. 21–27, 2019.
- [26] A. J. E. S. and H. D. Purnomo, “Assessing employee performance in the Information Technology Department using K-Means clustering: A case study approach,” *J. Inf. Syst. Infor*, vol. 6, no. 1, pp. 170–186, 2024, doi: doi: 10.51519/journalisi.v6i1.653.
- [27] A. A. Ezugwu, A. E., Ikotun, A. M., Oyelade, O. O., Abualigah, L., Agushaka, J. O., Eke, C. I., & Akinyelu, “A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects,” *Eng. Appl. Artif. Intell.*, vol. 110, no. 104743, 2022.
- [28] and X. P. B. Alemán Montes, P. Serra Ruiz, A. Zabala Torres, J. Masó, “A near real-time spatial decision support system for improving sugarcane monitoring through a satellite mapping web browser,” *Smart Agric. Technol.*, vol. 12, no. 101084, doi: doi: 10.1016/j.atech.2025.101084.