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Implementation of the C4.5 Decision Tree Algorithm in a Decision Support System for Employee Payroll at PT Hesed

Paulus Erwin Gulo[1]; Abdul Rohman[2]
[1,2] Faculty of Computer Science and Education, Ngudi Waluyo University, Indonesia
e-mail: erxgulo09@gmail.com
*Correspondence: erxgulo09@gmail.com

Abstract: *Payroll management is a critical business process because it directly affects employee compensation and organizational administration. PT Hesed still encounters challenges in payroll verification, including calculation errors, limited visibility of payroll components, and sequential verification procedures. This study implements the C4.5 Decision Tree algorithm in a web-based payroll Decision Support System and evaluates both software functionality and classification performance. The study employed a Design and Creation strategy using qualitative analysis for system requirement identification and quantitative analysis for model evaluation. Historical payroll data consisted of 12 verified records from January to April 2026, with payroll period, attendance, years of service, employment status, and tardiness as predictor attributes and payroll recommendation as the class label. C4.5 attribute selection used entropy, information gain, split information, and gain ratio, while LOOCVevaluated predictive performance. Tardiness achieved the highest gain ratio (1.0000) and became the root node in the full dataset and in every LOOCV fold. LOOCV produced 7 correctly classified Appropriate records and 5 correctly classified Inappropriate records, yielding 100% accuracy, macro-precision, macro-recall, and macro-F1, compared with a 58.33% majority-class baseline accuracy. Black-box testing recorded outputs that matched the specified functions, while logic-level white-box verification reproduced the reference C4.5 calculations. Because the dataset is limited and no processing-time, usability, payroll-error reduction, or field-impact study was conducted, these results should be interpreted as evidence of functional conformity and internal classification consistency rather than demonstrated operational efficiency or broad generalizability.*

Keywords: *C4.5 Decision Tree, Decision Support System, Payroll Verification, Leave-One-Out Cross-Validation, Payroll Information System*

1. Introduction

The rapid advancement of information technology has encouraged companies to manage business processes in a faster, more accurate, and more integrated manner. Organizations require information systems to support administrative processes and decision-making activities. One of the most critical processes in corporate management is employee payroll. Payroll encompasses wage payment, attendance data processing, job position, allowances, overtime, deductions, performance evaluation, and the company's internal policies. Conventional payroll systems may lead to recording errors, calculation inaccuracies, reporting delays, and inconsistencies in employee data [1]. Therefore, companies require payroll systems capable of generating accurate, accountable, and efficient information.

PT Hesed requires a payroll system capable of effectively supporting the decision-making process. The company's payroll system involves numerous interrelated variables, including employee data, attendance records, overtime, allowances, deductions, job positions, years of service, and performance evaluation results. Suboptimal data management may result in payroll calculation errors and employee dissatisfaction. Faisal et al. 2024 stated that a web-based payroll system can assist organizations in managing attendance records, payroll data, payslips, allowances, and reporting processes more efficiently and in real time [2].

A payroll system is a system used by organizations to manage employee compensation data based on the applicable payroll components. The system processes employee records, attendance, job positions, overtime, allowances, deductions, and other components related to salary payments [3]. An inadequately designed payroll system may result in recording errors, calculation inaccuracies, delayed salary payments, and inconsistencies in employee data [4]. Syukron & Abdurrazaq, 2021 explained that a web-based payroll system can help organizations reduce payroll administration problems [5]. Likewise, Tandrio and Fianty 2026 reported that web-based payroll systems facilitate more efficient management of attendance records, payroll data, payslips, allowances, and reports [6].

A Decision Support System (DSS) can assist organizations in producing more objective and measurable decisions. A DSS supports decision-makers in solving semi-structured and unstructured problems through the utilization of data, analytical models, and specific decision-making processes [7]. In payroll management, a DSS can process employee data, analyze payroll components, determine salary increment eligibility, and provide decision recommendations based on predetermined criteria. A Decision Support System is a computer-based system that assists users in selecting decision alternatives based on specific data, criteria, and analytical models. Pratama et al., 2025 explained that a DSS facilitates the resolution of semi-structured and unstructured problems through data analysis. Within payroll management, a DSS can be utilized to evaluate salary increase eligibility, bonus allocation, allowance assessment, and the analysis of other payroll components [7]. Hutahaean et al., 2023 stated that a DSS must be properly designed to assist users in determining the most appropriate decision alternative [9].

The advancement of artificial intelligence has created opportunities for organizations to improve the quality of decision-making systems. Machine learning can enhance a system's capability to recognize data patterns and support payroll evaluation processes. Machine learning enables systems to learn from historical data, identify relationships among variables, and perform prediction or classification based on the available data [10]. In the field of human resource management, machine learning can support employee data management, turnover analysis, data analytics, and the prediction of specific trends in decision-making processes [11]. The implementation of machine learning in human resource management is also highly relevant because the technology enables large-scale data analysis across various human resource functions [12]. Machine learning is a branch of artificial intelligence that enables systems to learn patterns from data. Dargan et al., 2020 explained that machine learning can be employed to develop systems capable of learning from data, making predictions, and supporting classification tasks [13]. In human resource management, machine learning can facilitate employee data management, performance analysis, employee behavior prediction, and data-driven decision-making [14]. Ersöz, 2023 further explained that integrating machine learning into Human Resource Information Systems (HRIS) can support predictive analysis of employee-related data [15].

Organizations need to evaluate machine learning-based decision-making systems in payroll management processes. System evaluation can assess system effectiveness, decision accuracy, data processing efficiency, and the extent to which the system satisfies user requirements. Hutahaean et al., 2023 explained that a Decision Support System should be properly designed and implemented to assist users in selecting the most appropriate decision alternative [16]. Such evaluation enables organizations to identify the strengths, weaknesses, and future development opportunities of the payroll system implemented at PT Hesed. The C4.5 Decision Tree algorithm constructs a decision tree by calculating entropy, information gain, split information, and gain ratio. The attribute with the highest gain ratio is selected as the decision node, which reduces the bias that information gain may have toward attributes with many categories. The resulting rules are interpretable and can be inspected by payroll administrators [17].

Classification performance can be evaluated using a confusion matrix, accuracy, precision, recall, and the F1-score.

Previous studies on web-based payroll systems mainly focus on automating payroll administration, attendance, salary calculation, payslip generation, and reporting to improve efficiency and reduce errors [2], [5], [6]. Some studies use Decision Support Systems for payroll-related decisions based on predefined criteria and analytical models [7], [9]. However, most emphasize payroll calculation or employee evaluation rather than transparent payroll verification using interpretable classification models. Limited reporting of decision targets, predictor variables, validation procedures, and decision rules also reduces the transparency, interpretability, and reproducibility of payroll decision models, making their reliability difficult to audit and evaluate. Previous studies on web-based payroll systems mainly emphasize automation and calculation, while limited attention is given to transparent payroll verification using interpretable decision models. Likewise, Decision Support Systems and machine learning in human resource management mostly focus on performance, turnover, and recruitment rather than payroll verification. This study addresses these gaps by developing a web-based payroll Decision Support System using the C4.5 Decision Tree to generate auditable payroll recommendation rules through data preparation, target definition, rule generation, validation, and system implementation. The decision problem is defined as classifying payroll recommendations as appropriate or not appropriate based on payroll-related attributes, supporting transparent payroll verification before salary approval.

Accordingly, this study addresses the following research questions: RQ1. How can the C4.5 Decision Tree algorithm be integrated into a web-based decision support system for payroll verification at PT Hesed? RQ2. Which payroll-related attributes contribute most significantly to payroll recommendation decisions? RQ3. How accurately can the proposed C4.5 model classify payroll recommendations using historical payroll data? RQ4. To what extent can the proposed system improve payroll verification through interpretable decision rules and an auditable web-based implementation? This study develops a web-based payroll decision support system that integrates the C4.5 Decision Tree algorithm to support payroll verification at PT Hesed. The proposed model utilizes historical payroll data to classify payroll recommendations based on payroll-related attributes, generates interpretable decision rules for auditing purposes, and evaluates classification performance through appropriate validation procedures. By integrating an interpretable machine learning model into an operational payroll information system, this study aims to provide a transparent, consistent, and auditable payroll verification framework for organizational decision-making.

2.Methods

Research Design

This study employed a Design and Creation research strategy with a mixed-methods approach. Qualitative analysis of observations, interviews, and literature reviews was used to formulate system requirements, while quantitative analysis of historical payroll data was used to develop and evaluate the C4.5 Decision Tree model. The Design and Creation strategy was selected because the study focuses on developing and evaluating an information technology artifact, such as a system or application [23]. A scientific approach was applied through systematic, rational, and empirical procedures to obtain valid data [18], covering problem identification, data collection, requirements analysis, system design, model development, application testing, and evaluation of the employee payroll decision support system at PT Hesed.

Research Stages

a. System Processing and Analysis Techniques

This study employed qualitative analysis to formulate system requirements and quantitative analysis to evaluate the C4.5 Decision Tree. Qualitative data from observations, interviews, and literature reviews were analyzed through data condensation, display, and conclusion drawing [19]. Quantitative analysis used 12 historical payroll records to calculate entropy, information gain, split information, gain ratio, and classification performance, with the highest gain ratio determining the decision node. Due to the limited dataset, LOOCV was conducted 12 times, using one record for testing and 11 for training in each iteration. Model performance was evaluated using accuracy, precision, recall, F1-score, and a confusion matrix, with macro-averaged metrics and a majority-class baseline for comparison. The analysis also examined payroll processes, system limitations, variable relationships, and user requirements to define the proposed system's workflow, data requirements, functional requirements, and decision-making process.

b. System Development Method and Design

This study employed the Waterfall model, a structured and sequential approach consisting of requirements analysis, system design, implementation, testing, and maintenance [20]. Requirements analysis identified system needs, while design covered the architecture, database, interface, and decision-making process. The system was then implemented, tested, and refined through maintenance. Alongside Waterfall development, the C4.5 Decision Tree analyzed historical payroll data based on payroll period, attendance, years of service, employment status, and tardiness [10], classifying payroll recommendations as "Appropriate" or "Inappropriate" for verification against company policies.

c. Ground-truth labeling

The target classes were defined from PT Hesed's verified historical payroll decisions before model development. "Appropriate" indicated an accepted payroll record, while "Inappropriate" indicated a record requiring correction or rejection. These labels were treated as pre-existing ground truth rather than generated through weighting, normalization, scoring, or ranking. The labels were verified by the payroll administrator based on company procedures. Since the records had undergone internal verification, no additional expert annotation or inter-rater agreement analysis was conducted. Thus, the model learned patterns between payroll attributes and previously verified organizational decisions.

d. System Testing Techniques

This study distinguished software testing from C4.5 model evaluation. White-box testing verified the implemented calculations for entropy, information gain, split information, gain ratio, root-node selection, and branch execution by comparing outputs with independently recomputed values from the 12-record dataset, without claiming exhaustive code coverage [20]. Black-box testing evaluated user-visible functionality, including login, employee data, attendance, payroll, machine learning evaluation, payroll verification, payslip, and reporting, with tests marked Passed when observed outputs matched requirements [21]. The evaluation focused on functional conformity and C4.5 predictive performance through LOOCV. Processing time, usability, payroll-error reduction, and field impact were not evaluated.

e. Attribute Selection

This study used primary and secondary data. Primary data were collected through observation and interviews at PT Hesed to identify payroll processes, components, data management, and system requirements, while secondary data from scholarly sources supported the theoretical foundation and system design [22]. The C4.5 dataset comprised 12 payroll records from January–April 2026, with seven "Appropriate" and five "Inappropriate" classifications. Each record included payroll period, attendance, years of service, employment status, tardiness, and recommendation, without personal identifiers. The unit of analysis was one payroll evaluation per employee per period, supporting record-level payroll verification rather than long-term employee prediction.

f. Dataset Scope and Limitation

The historical payroll dataset comprised all records meeting the study's inclusion criteria during January–April 2026. The period reflected the available verified records and was considered sufficient to evaluate the proposed payroll verification framework at PT Hesed. The study focused on assessing the feasibility of integrating an interpretable C4.5 Decision Tree into a web-based payroll decision support system rather than developing a broadly generalizable model. Thus, the findings represent an organizational case study, while future research should use larger datasets, longer observation periods, and multiple organizations to assess external validity and generalizability.

3. Results and Discussion

Results

a. Analysis of the Existing System

The findings of this study indicate that the payroll calculation process currently implemented at PT Hesed can be illustrated as follows:

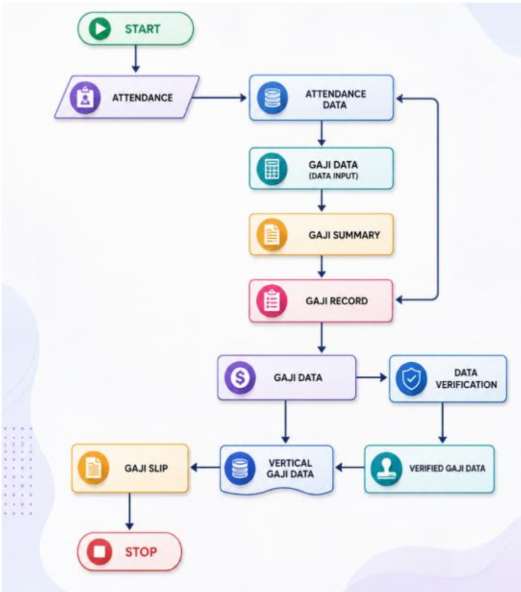

Figure 1. Existing Payroll System

The existing system analysis examined PT Hesed's payroll workflow to identify processes and system requirements. Employees record attendance daily, after which the treasurer collects attendance and payroll data at the end of each month to prepare payroll summaries. Payroll is calculated based on attendance, basic salary, allowances, incentives, overtime, and deductions, then submitted to management for verification. After approval, the treasurer generates payslips and processes salary payments. This workflow indicates that payroll processing still relies heavily on manual data compilation and sequential verification.

b. Analysis of the Proposed System

The existing payroll system faces limitations in accuracy, efficiency, and transparency due to manual calculations and limited payroll information. Employees receive only total salary information without detailed deductions. To address these issues, this study proposes a web-based Payroll Decision Support System using the C4.5 Decision Tree to classify payroll recommendations as "Appropriate" or "Inappropriate" [7]. The system integrates attendance, employee data, payroll components, and decision rules into a single interface for transparent payroll verification.

c. System Design

The system design phase developed the workflow, database, user interface, and payroll decision-making process to meet user requirements [22]. The system processes employee data, attendance, overtime, allowances, deductions, and performance information, and generates payroll summaries, classification results, payslips, and reports. The C4.5 model analyzes historical data to produce interpretable payroll verification recommendations. System quality was assessed through functional testing and model validation, without measuring processing speed, user satisfaction, payroll-error rates, or organizational efficiency.

d. System Testing Results

Software testing and model evaluation were conducted separately to distinguish application functionality from predictive performance. Black-box testing assessed whether user actions produced the expected outputs, while white-box verification checked the C4.5 calculation flow against reference values from the 12-record dataset. Predictive performance was independently evaluated using LOOCV and classification metrics.

1) Black-Box Testing

Black-box testing covered the login, employee data management, attendance management, payroll components, C4.5 evaluation, payroll verification, payslip, and payroll reporting modules.

Table 1. Black-Box Functional Test Results

Input / Action	Expected Output	Observed Output	Status
User login	Main dashboard is displayed according to access privileges.	Dashboard opened and role-based menu access was displayed.	Passed
Select Employee Data	Employee records are displayed.	Employee record list opened and records were displayed.	Passed
Select Attendance	Attendance input and summary are displayed.	Attendance input form and attendance summary were displayed.	Passed
Select Payroll Components	Salary components are displayed.	Basic salary, allowances, overtime, incentives, and deductions were displayed.	Passed
Select Machine Learning Evaluation	Payroll classification results are displayed.	C4.5 recommendation and decision rule were displayed from historical data.	Passed
Select Payroll Verification	Records requiring managerial review are displayed.	Payroll records and recommendation were presented for managerial verification.	Passed
Select Payslip	Detailed payslip is displayed.	Payslip with detailed payroll components was displayed.	Passed
Select Payroll Report	Report for selected payroll period is displayed.	Payroll report for the selected period was displayed.	Passed

2) White-Box Logic Verification

White-box logic verification compared the reported C4.5 outputs with independently recomputed reference values from the same dataset. The checks focused on the arithmetic and branch logic that determine the root node and final class. The results are presented in Table 2.

Table 2. White-Box Logic Verification Results

Logic Unit	Test Input / Condition	Expected Reference	Observed Result	Status
Total entropy	7 Appropriate; 5 Inappropriate	Entropy = 0.9799	0.9799	Passed
Tardiness split	<=2: 7 A / 0 I; >2: 0 A / 5 I	Gain = 0.9799; SplitInfo = 0.9799; GainRatio = 1.0000	0.9799; 0.9799; 1.0000	Passed
Root-node selection	Compare gain ratio of all predictors	Tardiness has the highest gain ratio (1.0000)	Tardiness selected	Passed
Branch <= 2	Tardiness <= 2 occurrences	Appropriate	7 of 7 records classified Appropriate	Passed
Branch > 2	Tardiness > 2 occurrences	Inappropriate	5 of 5 records classified Inappropriate	Passed

All recorded black-box cases produced observed outputs that matched the specified functional outputs. The white-box logic checks also reproduced the reference C4.5 values used in the analysis. These findings support functional conformity and calculation consistency within the tested cases only. They do not constitute evidence of usability, faster processing, reduced payroll errors, or exhaustive code coverage because those evaluations were outside the scope of this study.

a) Internal Payroll Control System

At PT Hesed, payroll responsibilities are separated among employees, the treasurer, and management. Employees record attendance, the treasurer compiles attendance and payroll components and prepares the payroll summary, and management verifies the payroll data before salary authorization. The proposed system preserves this role separation by maintaining distinct data-entry, payroll-processing, and verification functions. This description represents the designed control workflow; the study did not perform a separate audit of fraud prevention or control effectiveness.

b) Authorization and Recording System

In the proposed workflow, management reviews payroll information after the treasurer prepares the payroll data. Attendance, overtime, allowances, deductions, and other payroll components are stored in the application and can be reviewed together with the generated C4.5 recommendation. Employees can access their detailed payslips, while management can review the data used during payroll verification. The study evaluates whether these functions are available and operate as specified, not whether they improve control effectiveness in field deployment.

c) C4.5 Classification Scope

The analytical model in this study is a C4.5 classification model, not a hybrid C4.5-MCDM model. Criterion weights, benefit-cost normalization, alternative scoring, and ranking are therefore not used. The historical payroll decisions serve only as class labels, while payroll period, attendance, years of service, employment status, and tardiness serve as predictors. This separation ensures that the reported results correspond directly to the 12-record training and validation dataset.

d) Data Selection

The classification dataset consisted of 12 historical payroll evaluation records from January to April 2026. The predictor attributes were payroll period, attendance, years of service, employment status, and tardiness; the target was the verified payroll recommendation. No employee identifier was used as a predictor. Table 3 presents the complete dataset used for C4.5 construction and LOOCV.

Table 3. Historical Payroll Dataset Used for C4.5

Payroll Period	Attendance	Years of Service	Employment Status	Tardiness	Class Label
January 2026	≥ 26 days	> 1 year	Permanent	≤ 2 occurrences	Appropriate
January 2026	≥ 26 days	> 1 year	Permanent	≤ 2 occurrences	Appropriate
January 2026	≥ 26 days	< 1 year	Contract	≤ 2 occurrences	Appropriate
February 2026	< 26 days	> 1 year	Permanent	> 2 occurrences	Inappropriate
February 2026	≥ 26 days	> 1 year	Permanent	≤ 2 occurrences	Appropriate
February 2026	< 26 days	< 1 year	Contract	> 2 occurrences	Inappropriate
March 2026	≥ 26 days	> 1 year	Permanent	≤ 2 occurrences	Appropriate
March 2026	< 26 days	> 1 year	Permanent	≤ 2 occurrences	Appropriate
March 2026	< 26 days	< 1 year	Contract	> 2 occurrences	Inappropriate
April 2026	≥ 26 days	< 1 year	Contract	> 2 occurrences	Inappropriate
April 2026	≥ 26 days	> 1 year	Permanent	≤ 2 occurrences	Appropriate
April 2026	< 26 days	> 1 year	Permanent	> 2 occurrences	Inappropriate

e) C4.5 Entropy, Information Gain, and Gain Ratio Calculation

Entropy was calculated for the class distribution of each attribute value. Information gain measured the reduction in entropy after a split, while split information measured the intrinsic information of the partition. C4.5 selected the root node using gain ratio rather than information gain alone. The corrected entropy values are shown in Table 4, and the attribute-level selection results are summarized in Table 5.

Table 4. Entropy Calculation Results

Attribute / Value	Number of Records	Appropriate	Inappropriate	Entropy
Total	**12**	**7**	**5**	**0.9799**
January 2026	3	3	0	0.0000
February 2026	3	1	2	0.9183
March 2026	3	2	1	0.9183
April 2026	3	1	2	0.9183
Attendance >= 26 days	7	6	1	0.5917
Attendance < 26 days	5	1	4	0.7219
Years of Service > 1 year	8	6	2	0.8113
Years of Service < 1 year	4	1	3	0.8113
Permanent Employment	8	6	2	0.8113
Contract Employment	4	1	3	0.8113
Tardiness <= 2 occurrences	**7**	**7**	**0**	**0.0000**
Tardiness > 2 occurrences	**5**	**0**	**5**	**0.0000**

Table 4 shows that tardiness divides the 12 records into two pure subsets: all seven records with ≤ 2 tardiness occurrences are classified as “Appropriate,” while all five records with >2 are “Inappropriate.” Attendance also reduces uncertainty but produces mixed subsets, resulting in tardiness having the highest C4.5 gain ratio. These calculations reflect associations within the dataset, not causal relationships, and attribute importance may change with larger datasets or different organizations.

Table 5. C4.5 Attribute Selection Results

Attribute	Information Gain	Split Information	Gain Ratio	Rank
Payroll Period	0.2911	2.0000	0.1456	5
Attendance	0.3339	0.9799	0.3408	2
Years of Service	0.1686	0.9183	0.1836	3
Employment Status	0.1686	0.9183	0.1836	3
Tardiness	0.9799	0.9799	1.0000	1

f) Decision Tree Construction

The decision tree in Table 5 selected tardiness as the root node because it had the highest gain ratio (1.0000). Both branches were pure, so no further splitting was required. The resulting rules classify payroll as “Appropriate” when tardiness is ≤ 2 occurrences and “Inappropriate” when it is >2 occurrences. Although these rules completely separate the 12 available records, this result is specific to the dataset and does not establish tardiness as a universally dominant payroll variable. Further validation using larger and longer-term datasets is required to assess rule stability.

g) Model Validation Using Leave-One-Out Cross-Validation

LOOCV was performed in 12 iterations. In each fold, one record was withheld and the model was rebuilt from the remaining 11 records. Tardiness retained the highest gain ratio (1.0000) in every fold, and each withheld record was classified correctly. Table 6 reports the fold-level predictions.

Table 6. LOOCV Prediction Results

Fold	Test Record	Actual Class	Predicted Class	Result
1	R1	Appropriate	Appropriate	Correct
2	R2	Appropriate	Appropriate	Correct
3	R3	Appropriate	Appropriate	Correct
4	R4	Inappropriate	Inappropriate	Correct
5	R5	Appropriate	Appropriate	Correct
6	R6	Inappropriate	Inappropriate	Correct
7	R7	Appropriate	Appropriate	Correct
8	R8	Appropriate	Appropriate	Correct
9	R9	Inappropriate	Inappropriate	Correct
10	R10	Inappropriate	Inappropriate	Correct
11	R11	Appropriate	Appropriate	Correct
12	R12	Inappropriate	Inappropriate	Correct

Aggregating the 12 held-out predictions produced the confusion matrix in Table 7. Using Appropriate as the positive class, the model produced 7 true positives, 5 true negatives, 0 false positives, and 0 false negatives.

Table 7. LOOCV Confusion Matrix

Actual / Predicted	Appropriate	Inappropriate
Appropriate	7	0
Inappropriate	0	5

The resulting accuracy, macro-precision, macro-recall, and macro-F1 were all 100.00%. For comparison, the majority-class baseline always predicts Appropriate, the most frequent class (7 of 12 records), and therefore achieves 58.33% accuracy. The observed accuracy difference is 41.67 percentage points, but statistical generalization cannot be inferred from only 12 records.

Table 8. Classification Performance and Baseline Comparison

Evaluation Measure	Value
LOOCV Accuracy	100.00%
LOOCV Macro-Precision	100.00%
LOOCV Macro-Recall	100.00%
LOOCV Macro-F1	100.00%
Majority-Class Baseline Accuracy	58.33%
Accuracy Difference	+41.67 percentage points

Discussion

The C4.5 results show an unusually simple decision structure: tardiness alone separates all 12 historical labels. Its gain ratio of 1.0000 is substantially higher than attendance (0.3408), years of service (0.1836), employment status (0.1836), and payroll period (0.1456). This pattern means that, within the observed January-April 2026 records, the historical verification outcome is perfectly aligned with the tardiness threshold used in the stored data. The result is interpretable, but its simplicity also indicates that the dataset contains limited variation.

LOOCV produced perfect classification because the same separation remained present after each single record was withheld. The 100% metrics should therefore be read together with the sample size and class structure. With only 12 observations, LOOCV reduces the loss of training data relative to a fixed holdout set, but it cannot substitute for external validation. A small dataset can yield optimistic performance when one attribute deterministically matches the labels, and new records may introduce combinations that are absent from the current sample.
The majority-class baseline provides a minimum comparison for the classification task. A rule that always predicts Appropriate would be correct for 7 of 12 records, or 58.33%. The C4.5 model is therefore more consistent with the available historical labels than this naive baseline. However, the 41.67 percentage-point difference describes only internal predictive performance; it does not show that the application reduces salary errors, accelerates payroll processing, improves user satisfaction, or produces financial benefits.

The software tests address a different question from the model metrics. Black-box testing shows that the tested user actions produced the specified outputs, while the logic-level white-box checks reproduce the reported C4.5 calculations and branch behavior. These results support functional conformity of the tested cases, but the study did not measure execution time, usability, reliability under load, security, or exhaustive path coverage. Claims about efficiency and effectiveness should therefore remain outside the conclusions of this dataset.

Methodologically, removing the previous weighting, normalization, alternative scoring, and ranking analysis makes the analytical pipeline consistent with the stated C4.5 method. The payroll decision is treated as a supervised class label rather than as an MCDM score. This distinction improves reproducibility because the dataset in Table 3, the gain-ratio calculations in Tables 4-5, the decision rule, and the LOOCV results now refer to the same 12 records.

Future studies should expand the observation period, include more payroll records, test the stability of the root attribute, and conduct external or prospective validation before making operational claims.

4. Conclusion

This study implemented a web-based payroll Decision Support System at PT Hesed using a C4.5 classification pipeline based on 12 verified historical payroll records. The analysis uses payroll period, attendance, years of service, employment status, and tardiness as predictors and a pre-existing Appropriate/Inappropriate payroll recommendation as the target. Weighting, normalization, alternative scoring, and ranking are not part of the model. Black-box testing recorded expected and observed outputs for eight principal application functions and all reported cases passed. Logic-level white-box verification reproduced the reference entropy, information gain, split information, gain ratio, root selection, and branch outcomes. These tests demonstrate conformity within the reported test cases; they do not establish usability, processing-speed improvement, payroll-error reduction, or exhaustive source-code coverage.

Tardiness achieved the highest gain ratio (1.0000) and formed a one-node decision tree in the full dataset. LOOCV correctly classified all 12 held-out records, producing 100.00% accuracy, macro-precision, macro-recall, and macro-F1, compared with a 58.33% majority-class baseline accuracy. Because the dataset is small and the labels are perfectly separated by one attribute, these findings are preliminary and specific to the observed PT Hesed records. Larger datasets, longer observation periods, external validation, and field-based usability and operational studies are required before the model can be generalized or used to support claims of improved payroll efficiency or effectiveness.

References

[1] A. Syukron and M. H. Abdurrazaq, "Perancangan sistem informasi penggajian karyawan berbasis website dengan metode waterfall," *Jurnal Sistem Informasi Akuntansi (JASIKA)*, vol. 1, no. 2, pp. 74–83, 2021, https://doi.org/10.31294/jasika.v1i2.624.
[2] M. Faisal, M. Rifansyah, U. Radiyah, and S. Marlina, "Rancang sistem informasi penggajian berbasis website dengan model waterfall di PT Astro Teknologi Indonesia," *Jurnal Minfo Polgan*, vol. 12, no. 2, pp. 2818–2832, 2024, https://doi.org/10.33395/jmp.v12i2.13406.
[3] A. M. Ahmed, C. N. Mohammed, and A. M. Ahmad, "Web-based payroll management system: Design, implementation, and evaluation," *Journal of Electrical Systems and Information Technology*, vol. 10, no. 1, Art. no. 17, 2023, https://doi.org/10.1186/s43067-023-00082-5.
[4] P. Chima, J. Ahmadu, and O. G. Folorunsho, "Implementation of digital integrated personnel and payroll information system: Lesson from Kenya, Ghana and Nigeria," *Governance and Management Review*, vol. 4, no. 2, pp. 1–17, 2019.
[5] K. Ekasari, A. Afandi, and A. H. A. Yolandra, "Enhancing payroll systems for accountability and user experience: A case study at Kanindo Cooperative, Malang," *Journal of Applied Business, Taxation and Economics Research*, vol. 4, no. 2, pp. 327–340, 2024, https://doi.org/10.54408/jabter.v4i2.421.
[6] F. Tandrio and M. I. Fianty, "Web-based payroll system development using the prototyping method and structured database design," *JITK (Jurnal Ilmu Pengetahuan dan Teknologi Komputer)*, vol. 11, no. 3, pp. 851–863, Feb. 2026, https://doi.org/10.33480/jitk.v11i3.7044.
[7] T. Limbong, Muttaqin, A. Iskandar, A. P. Windarto, J. Simarmata, Mesran, O. K. Sulaiman, D. Siregar, D. Nofriansyah, D. Napitupulu, and A. Wanto, *Sistem Pendukung Keputusan: Metode & Implementasi*. Medan, Indonesia: Yayasan Kita Menulis, 2020.
[8] V. Pratama, I. S. Gana, F. D. Idris, I. Nasrudin, and A. Setiawan, "Decision support system in attendance and payroll as a part of IT governance," in *2025 19th International Conference on Telecommunication Systems, Services, and Applications (TSSA)*, 2025, pp. 1–5, https://doi.org/10.1109/TSSA65978.2025.11140540.
[9] J. Hutahaean, F. Nugroho, D. Abdullah, Kraugusteeliana, and Q. Aini, *Sistem Pendukung Keputusan*. Medan, Indonesia: Yayasan Kita Menulis, 2023.

[10] A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*, 2nd ed. Sebastopol, CA, USA: O'Reilly Media, 2019.
[11] J. R. Pomperada, "Human resource information system with machine learning integration," *Qubahan Academic Journal*, vol. 2, no. 2, pp. 5–8, 2022, https://doi.org/10.48161/qaj.v2n2a120.
[12] S. Garg, S. Sinha, A. K. Kar, and M. Mani, "A review of machine learning applications in human resource management," *International Journal of Productivity and Performance Management*, vol. 71, no. 5, pp. 1590–1610, 2022, https://doi.org/10.1108/IJPPM-08-2020-0427.
[13] S. Dargan, M. Kumar, M. R. Ayyagari, and G. Kumar, "A survey of deep learning and its applications: A new paradigm to machine learning," *Archives of Computational Methods in Engineering*, vol. 27, no. 4, pp. 1071–1092, 2020, https://doi.org/10.1007/s11831-019-09344-w.
[14] Q. Hossain, M. Z. Ikbal, and M. M. Rahman, "A meta data-driven decision support in human capital management: Reviewing HRIS and predictive analytics integration," *ASRC Procedia: Global Perspectives in Science and Scholarship*, vol. 1, no. 1, pp. 215–246, 2025, https://doi.org/10.63125/xgew7q22.
[15] T. Ersöz, F. Ersöz, and E. Bedir, "Predictive analytics in human resources using machine learning and data mining," *International Journal of 3D Printing Technologies and Digital Industry*, vol. 7, no. 3, pp. 602–613, 2023, https://doi.org/10.46519/ij3dptdi.1341376.
[16] J. Hutahaean, F. Nugroho, D. Abdullah, Kraugusteeliana, and Q. Aini, *Sistem Pendukung Keputusan*. Medan, Indonesia: Yayasan Kita Menulis, 2023.
[17] J. R. Quinlan, C4.5: Programs for Machine Learning. San Mateo, CA, USA: Morgan Kaufmann, 1993.
[18] Sugiyono, *Metode Penelitian Kuantitatif, Kualitatif, dan R&D*. Bandung, Indonesia: Alfabeta, 2019.
[19] M. B. Miles, A. M. Huberman, and J. Saldaña, *Qualitative Data Analysis: A Methods Sourcebook*, 4th ed. Thousand Oaks, CA, USA: SAGE Publications, 2018.
[20] R. S. Pressman and B. R. Maxim, *Software Engineering: A Practitioner's Approach*, 9th ed. New York, NY, USA: McGraw-Hill Education, 2020.
[21] R. Sholehurrohman, S. Q. A'yuni, D. Sakethi, I. S. Ilman, and M. Muhaqiqin, "Implementation of black-box testing on the information system for the Smart Indonesia Card college recommendation," *JESII: Journal of Elektronik Sistem Informasi*, vol. 3, no. 1, pp. 1–11, 2025, https://doi.org/10.31848/JESII.V3I1.4038.
[22] J. W. Creswell and J. D. Creswell, *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 5th ed. Thousand Oaks, CA, USA: SAGE Publications, 2018.
[22] A. Dennis, B. H. Wixom, and D. Tegarden, *Systems Analysis and Design: An Object-Oriented Approach with UML*, 6th ed. Hoboken, NJ, USA: John Wiley & Sons, 2020.
[23] T. S. Carlson, "Information Artifact Evaluation and Iterative Design: A Novel Mixed-Method Approach," Ph.D. dissertation, Information School, Univ. of Washington, Seattle, WA, USA, 2017.