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Classification of Construction Worker Productivity Levels Using the C4.5 Algorithm

Michael Sergio Vernandez Sinurat[1,*],Teguh Hady Nurwahid[1],Agin Dinata[1], Agus Perdana Windarto[2]

[1] Information Systems Study Program, Sekolah Tinggi Ilmu Komputer Tunas Bangsa, Pematangsiantar, Indonesia
Jl. Jenderal Sudirman Street, Block A No. 1/2/3, Pematangsiantar 21127, North Sumatra, Indonesia
[2] Master of Informatics Study Program, Sekolah Tinggi Ilmu Komputer Tunas Bangsa, Pematangsiantar, Indonesia
Jl. Jenderal Sudirman Street, Block A No. 1/2/3, Pematangsiantar 21127, North Sumatra, Indonesia
Email: [1,*]keelsergio91@gmail.com, [2]teguhnurwahid2@gmail.com, [3]agin20570@gmail.com, [4]agus.perdana@amiktunasbangsa.ac.id.
Correspondence Author Email: keelsergio91@gmail.com
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Abstract−Construction worker productivity is a critical factor determining time efficiency, cost, and quality in construction project implementation. Productivity assessments are often conducted subjectively; therefore, a data-driven approach is needed to produce more objective and measurable evaluations. This study aims to classify the productivity levels of construction workers on a bathroom renovation project at MBK Tanjung Pinggir using the C4.5 algorithm. The dataset consists of 20 construction workers with three primary evaluation attributes: working hours, attendance, and skill level. Through entropy and information gain calculations, the skill attribute was identified as the most dominant factor with the highest gain value, thus becoming the root node in the formation of the decision tree. The model results produced a series of classification rules that describe the relationship between attributes and worker productivity levels, and indicate a tendency that technical skills have the greatest influence compared to other attributes. The implementation of the C4.5 algorithm proved effective in generating a classification model that is easy to understand and can support more objective project management decision-making. These findings are expected to serve as a foundation for human resource management in construction projects and encourage further research with a larger data scope.

Keywords: Productivity; Labor; Data Mining; C4.5 Algorithm; Classification; Decision Tree

1.INTRODUCTION

Construction worker productivity is one of the primary factors determining the success and efficiency of construction project implementation. Productivity focuses on two aspects: efficiency and effectiveness (Gde et al., 2023). Productivity will inevitably decline if a worker lacks the necessary skills or expertise (Yandi, 2022). Worker productivity levels directly impact project completion time, project costs, and the quality of the resulting construction, all of which require analysis. Classification plays a crucial role at various stages of data analysis. Through the classification process, a deeper understanding of the data can be gained, leading to more informed and accurate decisions (Reynaldi Valerian et al., 2025). This study focuses on classifying the productivity of construction workers during bathroom renovations in each room at Maria Bunda Karmel Tanjung Pinggir. With performance evaluations in place, it is hoped that employee work quality will improve, thereby enabling targets to be met (Capah et al., 2024). Job dissatisfaction and declining motivation can arise as a result of improper management, which ultimately reduces productivity levels (Nurhendi & Bastam, 2025). Therefore, measuring and managing construction workers' productivity is a critical aspect of project management in accordance with established plans. Productivity describes the comparison between the results obtained and the resources used, namely the ratio of output to input (Productivity et al., n.d.). Greater output can be produced in a project when the same input is managed by a workforce with a high level of productivity (Ningsih, 2024). Assessments of construction worker productivity on-site are often conducted subjectively by foremen or project supervisors based on direct observation. Such subjective assessments have the potential to lead to unfairness, as they are not based on measurable and verifiable data. Quality, fatigue, discomfort, stress, illness, and productivity are strongly interrelated with performance (Program et al., n.d.). Many algorithms can be used to measure worker productivity, but such measurements are difficult to implement due to their subjective nature. Therefore, we require a systematic, data-driven approach to measure construction workers' productivity. Productivity data serves as a strong foundation for assessing workers' productivity levels (Rizky et al., 2022); a widely used approach in complex data analysis is data mining.

Data mining is the process of examining and analyzing large-scale data to identify patterns, important information, or new insights that can be utilized in the decision-making process. Data mining can be used to improve the quality of data and information management, thereby supporting better and more accurate decision-making (Firda, 2023). One effective data mining algorithm for classification tasks is the C4.5 algorithm. This algorithm is an extension of ID3 and is capable of generating *decision tree* models that are easy to understand and can handle both numerical and categorical attributes (Asa Noyari et al., 2024). The C4.5 algorithm creates an effective decision tree construction system thanks to improvements over the ID3 algorithm. Some of these improvements include tree pruning, handling of missing data, and management of continuous data (Rahayu & Farlina, 2021). In the context of construction worker productivity, the application of data mining enables the identification of key factors influencing construction worker performance as well as the creation of a classification model to group productivity levels. According to previous research, the C4.5 algorithm outperforms other algorithms such as ID3, CART, and Random Forest due to its ability to handle numerical attributes, its capability to address missing data, and the use of the gain ratio to split data in a balanced manner(Sukri & Handrianto, 2024). Based on prior research conducted to make a comparison, it can be concluded that the C4.5 algorithm demonstrates superior performance compared to the K-Nearest Neighbor algorithm. This is evident when comparing the results produced by the C4.5 algorithm, which achieved an accuracy of 74.95%. Meanwhile, the K-Nearest Neighbor algorithm only achieved an accuracy of 71.79% (Prediksi et al., 2024; Fakih et al., 2025). This suggests that the C4.5 algorithm is more advantageous for prediction and classification due to its higher accuracy. Another advantage of this algorithm is its ability to handle data with *missing values*, as well as its capacity to generate efficient models for decision-making.

This study uses a case study from the MBK Tanjung Pinggir Project, specifically the bathroom renovation activities in each room. Data collected from this project includes various variables related to construction workers' performance, such as daily working hours, attendance, and workers' ability to complete a project. Using the C4.5 method, this study classifies the relationships among these variables and generates a classification model capable of mapping construction workers' productivity levels more accurately and measurably. The primary objectives of this study are to: (1) identify factors influencing construction workers' productivity in the MBK Tanjung Pinggir project, (2) implement the C4.5 algorithm to classify workers' productivity levels based on the collected data, and (3) generate a classification model that can serve as a basis for decision-making in construction worker management. In addition to providing practical benefits for project management, the results of this study are also expected to contribute scientifically to the development of data mining applications in the field of Information Systems. The resulting classification model can serve as a reference for further research with different project scopes and methods, as well as a foundation for the development of computer-based decision support systems. Thus, this study is expected to offer a new contribution to the development of productivity analysis methods with a high level of accuracy.

2. RESEARCH METHODOLOGY

2.1 Research Stages

In the research phase, this study aims to classify the productivity levels of construction workers using data mining and the C4.5 algorithm, with a case study of a bathroom renovation project in every room at Tanjung Pinggir MBK. The research stages are illustrated in Figure 1:

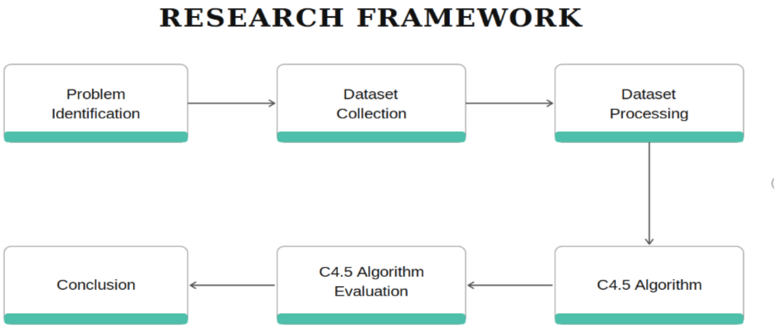

Figure 1. Research Framework

This study began with problem identification to understand the factors influencing labor productivity in construction projects as well as the project management's need to accurately classify labor productivity levels. Research data was collected through field observations, interviews with foremen and workers, and documentation of daily and weekly work reports. The data used included working hours, work experience, the number of tasks completed, work quality, and work challenges. Subsequently, the obtained data was processed through data cleaning, normalization, productivity labeling (high, medium, and low), and data transformation to make it suitable for applying the C4.5 algorithm.

The C4.5 algorithm was then used to build a decision tree that classifies workers' productivity levels based on the available attributes. The classification results were analyzed to determine the accuracy and alignment with on-site conditions. An evaluation phase was conducted to measure the accuracy and effectiveness of the resulting classification model. The research findings were then compiled into a report detailing the research methodology, analysis results, worker productivity classifications, and recommendations for improving construction worker productivity on the MBK Tanjung Pinggir Project.

2.2 Data Mining and Classification

In data mining, various statistical, mathematical, artificial intelligence, and machine learning techniques are applied to extract patterns or information from a selected dataset (Anastassia Amellia Kharis & Haqqi Anna Zili, 2022). Through a structured series of steps, data mining enables the discovery of added value in the form of knowledge that could not previously be identified manually (Department of Computer Science and Informatics Education et al., n.d.). Data mining involves searching for desired patterns or trends within big data to assist decision-makers in the future (Gusti Maulid et al., n.d.). The chosen techniques consider data characteristics, variable complexity, and the purpose of the analysis so that the resulting model can provide deep insights and support a more structured and evidence-based decision-making process.

Classification is a method used to categorize various data into predefined groups based on patterns or characteristics present in the data (Yogianto et al., 2024). The purpose of classification is to identify patterns based on the

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characteristics of a class, which can subsequently be used to assess other characteristics (Ramadhon et al., 2024). Classification facilitates data analysis and grouping, such as categorizing productivity into high, medium, and low based on its attributes. Various algorithms can be used to build classification models, particularly decision trees using the C4.5 algorithm (Muriyatmoko et al., n.d.).

2.3 C4.5 Algorithm

In this study, the C4.5 algorithm was used due to its ability to handle both continuous and categorical attributes, as well as its capacity to generate rules that result in a simpler decision tree. The C4.5 algorithm constructs a decision tree from a set of training data, similar to the ID3 algorithm. Training samples are used as input in this algorithm to form a verified tree; the data fields in these samples are then used as parameters in the classification process. The C4.5 algorithm calculates entropy and gain for each attribute that will become a node or branch in the decision tree. The entropy criterion is used to measure how pure a dataset is. The gain criterion is used to determine which features act as node separators in the resulting decision tree. This decision is then organized into a hierarchical structure resembling a decision tree. In this structure, each attribute is represented as a branch that must be traversed sequentially until the process reaches its endpoint (Ifaru et al., 2024)(Musa et al., 2024)(Aulifia Riski Putra Wahyu et al., n.d.).

Steps of the C4.5 Algorithm:

a. Defining and Grouping Datasets
b. Calculating the Entropy and Gain for Each Attribute
c. Attribute selection and root node selection
d. Forming branches and decision trees

The formulas used in the C4.5 algorithm employ the entropy formula to calculate data uncertainty and the information gain formula to determine the most influential attribute in the formation of *the decision tree*.

Entropy Formula: $$Entropy\ (S) \sum_{i=1}^{n} \frac{|s_i|}{|s|} - pi * log2pi \quad (1)$$

Explanation: S : S: Set of cases; N: Number of partitions of S; Pi: proportion of Si relative to S.

Information Gain Formula: $$Gain\ (S, A) = Entropy(S) - \sum_{i=1}^{n} \frac{|s_i|}{|s|} * Entropy\ (Si) \quad (2)$$

Definitions: S: data set; A: attribute; n: number of partitions of attribute A; |Si|: number of cases in the i-th partition;

|S|: number of cases in S.

3. RESULTS AND DISCUSSION

This section discusses the results of data processing and analysis using the C4.5 algorithm to categorize the productivity levels of construction workers on a bathroom renovation project at MBK Tanjung Pinggir. The research was structured by following the research stages from dataset processing, entropy and gain calculations, decision tree creation, to classification results. Each research stage produced findings that describe the relationship between construction workers' attributes and their productivity

3.1 Initial dataset analysis

The dataset in this study consists of 20 construction workers who were the subjects of evaluation. Data was obtained through direct field observations from daily and weekly productivity records compiled by the project foreman or supervisor. The input variables used include working hours, attendance, and work ability, while the output variable is the productivity category of each worker. Productivity scores were calculated based on variable weightings: 30% for working hours, 30% for attendance, and 40% for work capacity. The final productivity score was then converted into three categories: low if the final score is < 65%, moderate if within the 65%–80% range, and high if > 80%. These categories are subsequently used as classes in the classification process. The data is then processed to create a dataset table, calculating entropy and gain for each attribute in the classification using the C4.5 algorithm. The following is the weighted dataset shown in Table 1.

Table 1. Construction Worker Productivity Dataset

No.	Working Hours	Attendance	Skill	Productivity
1	Duration	Good	Good	High
2	Long	Good	Good	High
3	Long	Good	Fair	High
4	Long	Fair	Good	High
5	Long	Fair	Good	High
6	Long	Poor	Good	High
7	Long	Good	Good	High

No.	Working Hours	Attendance	Skill	Productivity
8	Medium	Good	Fair	Moderate
9	Long	Good	Poor	Moderate
10	Long	Poor	Moderate	Moderate
11	Short	Moderate	That's	Moderate
12	Moderate	Good	Poor	Low
13	Moderate	Good	Poor	Low
14	Long	Good	Good	High
15	Short	Fair	Poor	Low
16	Long	Good	Good	High
17	Long	Fair	Low	Low
18	Long	Not enough	Good	High
19	Long	Good	Fair	High
20	Moderate	Good	Good	High

The research dataset consists of 20 construction workers evaluated based on three input attributes, namely:
a. Working Hours (Long, Moderate, Short)
b. Attendance (Good, Fair, Poor)
c. Skill (Good, Fair, Poor)
The output serving as the target class is Productivity, which is categorized as:
a. High
b. Moderate
c. Low
These categories are derived based on the following weighting:
a. Working Hours = 30%
b. Attendance = 30%
c. Skills = 40%
From 20 data points, the following results were obtained:
a. High Productivity = 12 workers
b. Moderate Productivity = 4 workers
c. Low Productivity = 4 workers

This category distribution indicates that the majority of workers have high productivity levels. Therefore, the classification system must still be able to accurately distinguish the minority groups (Medium and Low), so the best discriminating features are required using the entropy and gain methods.

3.2 Entropy and Gain Calculations

3.2.1 Calculation of Total Entropy and Gain

After the dataset is collected and productivity is grouped, the next step is data processing using the C4.5 algorithm. The initial step in determining the root of the decision tree is to calculate the total entropy of the dataset. The attribute with the highest gain value is then selected as the root of the tree (Vian Agesti et al., n.d.). The calculation results are shown in Table 2, Table 3, and Table 4.

Table 2. Calculation Results for Entropy and Gain

Node	Description	Total	High	Medium	Low	Entropy	Gain
Total		20	12	4	4	1.370950594	
Working Hours							0.108489539
	Duration	14	11	2	1	1.232087222	
	Moderate	4	1	1	2	1.5	
	Short	2	0	1	1	1	
Attendance							0.03949107
	Good	12	8	2	2	1.584962501	
	Enough	5	2	1	2	1.521928095	
	Less	3	2	1	0	0	
Ability							0.706564975
	Good	10	10	2	2	1.328771238	
	Enough	5	2	1	0	0	
	Less	5	2	1	0	0	

Table 3. Table of Capabilities Derived from Maximum Gain and Entropy for Good Inputs

No.	Working Hours	Attendance	Capacity	Productivity
1	Duration	Good	Good	High
2	Long	Good	Good	High

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No.	Working Hours	Attendance	Capacity	Productivity
3	Long	Fair	Good	High
4	Long	Fair	Good	High
5	Long	Poor	Good	High
6	Long	Good	Good	High
7	Long	Good	Good	High
8	Long	Good	Good	High
9	Long	Poor	Good	High
10	Medium	Good	Good	High

Table 4. Results of Iterative Entropy and Gain Calculations

Node	Description	Total	High	Medium	Low	Entropy	Gain
Overall		20	12	4	4	1.370950594	1.370950594
Total		10	10	0	0	0	
Business Hours							0
	Duration	9	9	0	0	0	
	Moderate	1	1	0	0	0	
	Short	0	0	0	0	0	
Attendance							0
	Okay	6	6	0	0	0	
	Enough	2	2	1	0	0	
	Less	1	1	1	0	0	

The attribute with the highest gain is the attribute most capable of separating the data based on productivity class. This process is repeated until each branch produces a homogeneous class (entropy = 0), resulting in the final decision tree. The total entropy of the dataset is:

$$Entropy(S) = 1.370950594$$

The gain calculation results based on Table 2 show:

a. Gain (Working Hours) = 0.108489539
b. Gain (Attendance) = 0.03949107
c. Gain (Skill) = 0.706564975

Of the three attributes, Ability has the highest gain value (0.7065), so it is selected as the root node in the decision tree. The selection of the Ability attribute as the basis is also consistent with the assessment scores given, where Ability received the highest score (40%). This makes perfect sense because workers' technical skills significantly influence overall work productivity.

3.3 Model and Accuracy

3.3.1 Model

The classification model in this study was built using the C4.5 algorithm with the help of RapidMiner software. The modeling process is shown in Figure 2, which illustrates the main flow starting from the data retrieval process in the dataset to the validation stage. The worker productivity dataset was included in the validation process to ensure that the resulting model could be systematically tested against the training and test data.

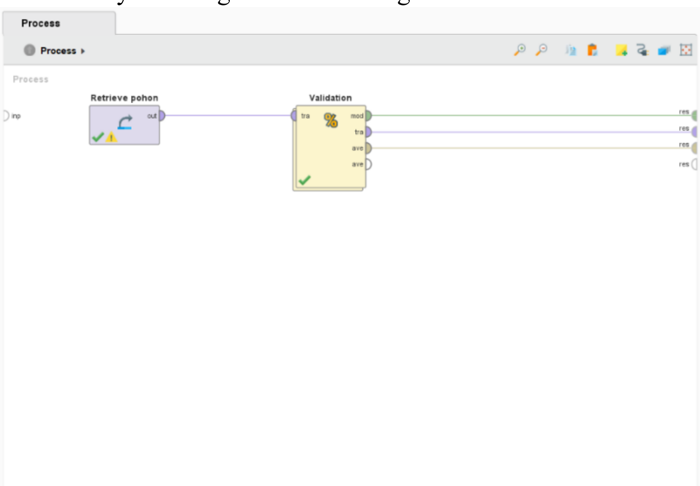

Figure 2. Data flow model

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Furthermore, the classification model structure is shown in Figure 3, where the Decision Tree (C4.5) algorithm is used during the *training* stage. The resulting model is then applied to the test data using the Apply Model process, and its performance is evaluated through the Performance module. This workflow ensures that the model is not only built but also tested for its accuracy in classifying construction worker productivity based on the attributes of working hours, attendance, and skills.

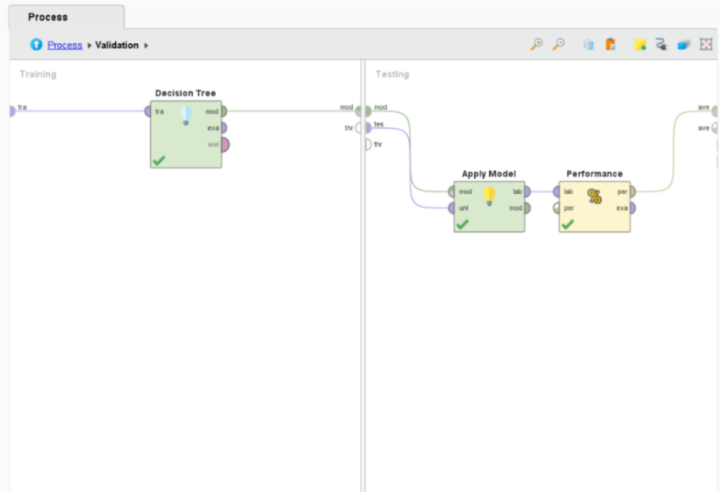
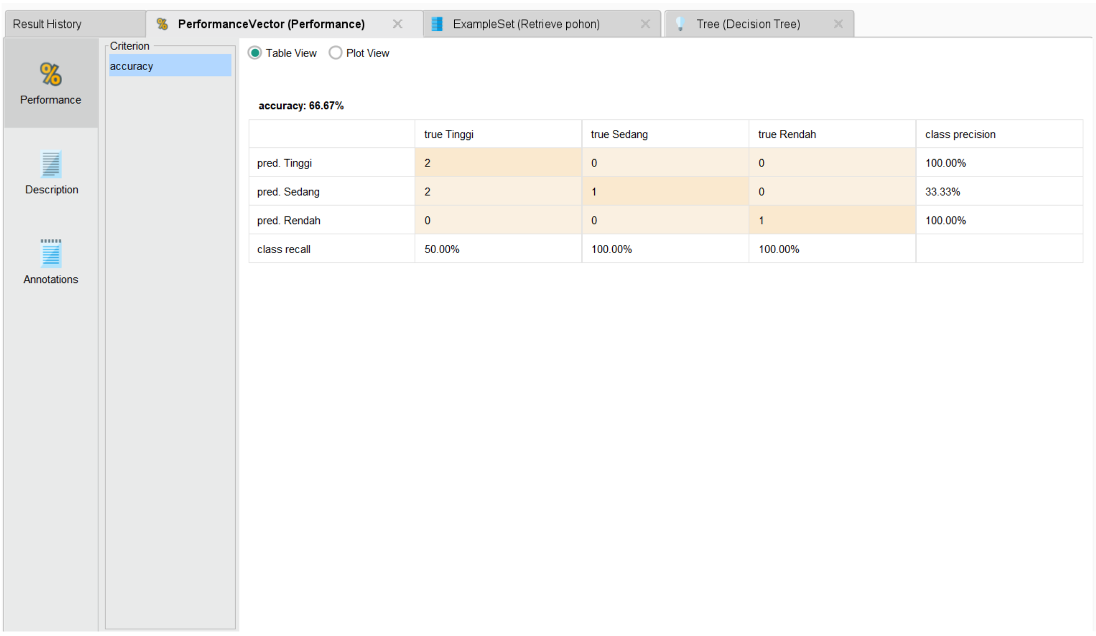


Figure 3. Data Flow Model

3.3.2 Accuracy

The results of the classification model accuracy test are shown in Figure 5. Based on the performance evaluation results, the C4.5 model achieved an accuracy rate of 66.67%. This value indicates that the majority of worker data was successfully classified into the appropriate productivity categories: high, medium, and low.



	true Tinggi	true Sedang	true Rendah	class precision
pred. Tinggi	2	0	0	100.00%
pred. Sedang	2	1	0	33.33%
pred. Rendah	0	0	1	100.00%
class recall	50.00%	100.00%	100.00%	

Figure 4. C4.5 Data Accuracy

3.4 Decision Tree Construction

After the Ability attribute was selected as the root node, a decision tree was constructed to identify rules for classifying data based on Ability, Working Hours, and Attendance.

3.4.1 Decision Tree

The decision tree resulting from the application of the C4.5 algorithm is shown in Figure 6. The tree structure indicates that the Ability attribute was selected as the root node, signifying that this attribute is the most dominant factor in determining the productivity level of construction workers. Subsequent branches are formed based on the Working Hours and Attendance attributes until the final productivity class is reached

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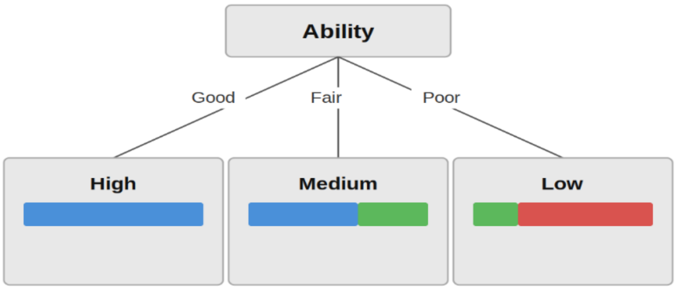

Figure 5. Dominant Decision Tree

This decision tree illustrates that workers with good ability are directly classified into the high productivity category. Meanwhile, workers with adequate and poor ability require further consideration through the working hours and attendance attributes. A more complete decision tree is shown in the flowchart below.

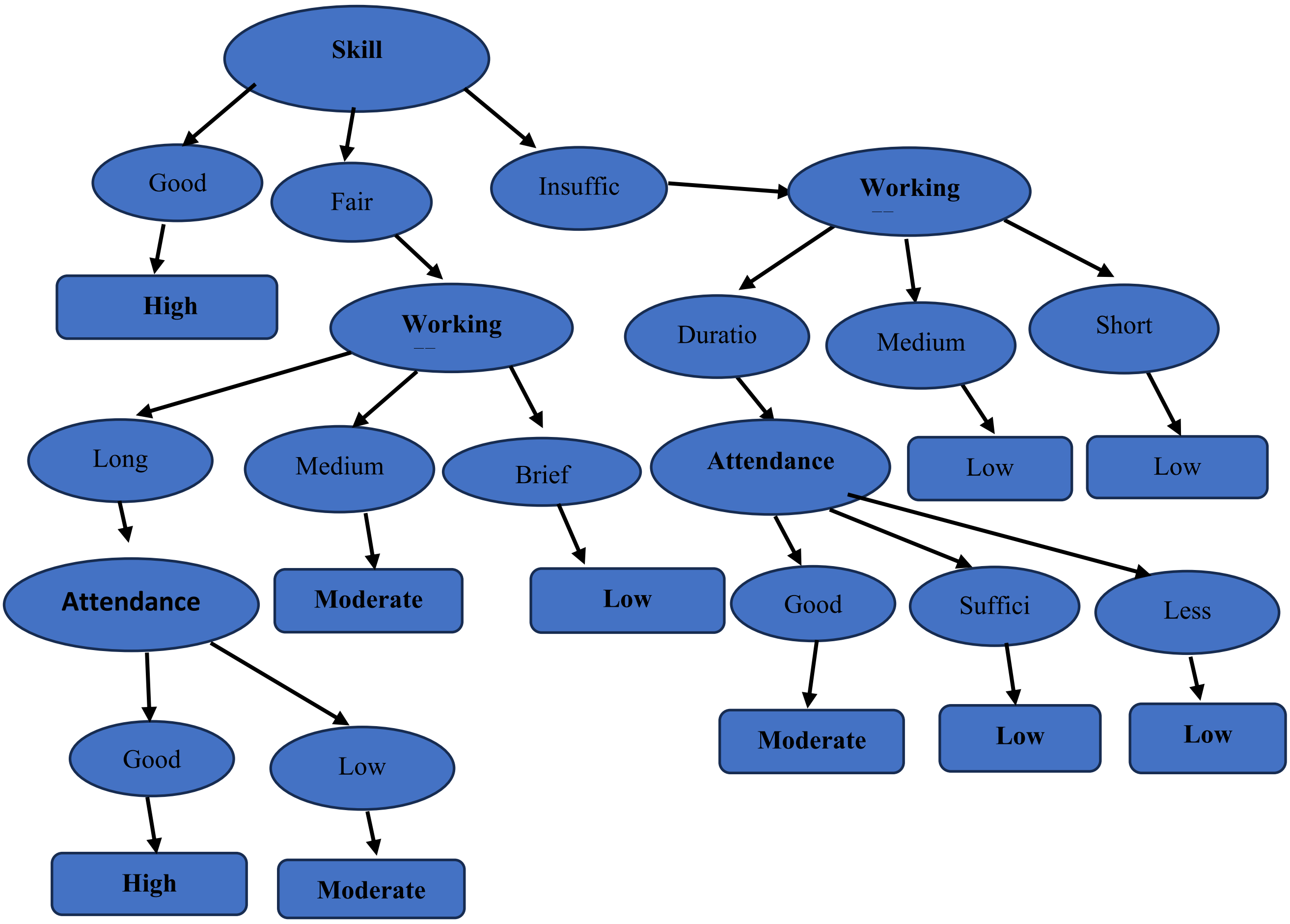

Figure 6. Flow Diagram

3.5 Final Classification Rules

From the resulting decision tree, the generated rules reveal an important pattern, as follows:

a. IF Ability = Good THEN Productivity = High
b. IF Ability = Adequate AND Working Hours = Short THEN Productivity = Low
c. IF Ability = Adequate AND Working Hours = Moderate THEN Productivity = Moderate
d. IF Ability = Adequate AND Working Hours = Long AND Attendance = Good THEN Productivity = High
e. IF Ability = Adequate AND Working Hours = Long AND Attendance = Poor THEN Productivity = Moderate
f. IF Ability = Low AND Working Hours = Short THEN Productivity = Low
g. IF Ability = Insufficient AND Working Hours = Moderate THEN Productivity = Low
h. IF Ability = Low AND Working Hours = Long AND Attendance = Good THEN Productivity = Moderate
i. IF Ability = Low AND Working Hours = Long AND Attendance = Adequate THEN Productivity = Low
j. IF Ability = Low AND Working Hours = Long AND Attendance = Low THEN Productivity = Low

Based on the decision tree formed by the C4.5 algorithm, a pattern emerges showing that worker ability is the most dominant factor in determining productivity levels. Workers with *good* ability are almost always classified as having *high* productivity. At the *adequate* ability level, productivity is influenced by working hours and attendance. Short working hours tend to result in low productivity, while moderate working hours result in moderate productivity. For long working hours, productivity is determined by attendance: good attendance results in high productivity, while poor attendance results in moderate productivity. For workers with *low* skill levels, most conditions result in low productivity, except in cases of long working hours combined with good attendance, which can achieve moderate productivity. These patterns indicate that the combination of skill level, working hours, and attendance has a direct impact on the productivity levels of construction workers.

4. CONCLUSION

This study demonstrates that the use of the C4.5 algorithm is highly effective in providing effective and measurable solutions for classifying the productivity levels of construction workers on a bathroom renovation project at MBK Tanjung Pinggir. Based on the analysis of the three main attributes working hours, attendance, and skill it was found that the skill attribute plays the most dominant role in distinguishing workers' productivity levels, as indicated by the highest gain value in the entropy calculation. The C4.5 Algorithm also achieved a fairly accurate accuracy rate of approximately 66.67%. The resulting decision tree model clearly illustrates patterns and relationships among attributes through the formed classification rules, thereby serving as a guide for evaluating worker performance in a more objective and data-driven manner. This classification indicates that workers' skills have a significant impact on the quality of work outcomes, compared to the number of working hours or attendance. Furthermore, this study demonstrates that data classification, particularly using the C4.5 algorithm, can serve as an effective approach to aid decision-making in classifying construction worker productivity. However, this study has limitations related to the relatively small dataset and the scope of the case study, which focuses on a single project; therefore, the application of its results must be conducted carefully and appropriately. Furthermore, comparing the model's performance with other classification algorithms such as Random Forest, Naive Bayes, or methods based on neural networks could provide a more comprehensive understanding of the accuracy and effectiveness of the applied techniques. The development of an application-based decision support system could also be a focus of future research to facilitate the direct implementation of the model in the field. With this development, it is hoped that this study can make a greater contribution to improving the quality of construction worker productivity management in the construction project sector.

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