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Service Queue Optimization using Decision Tree and XGBoost Based on AHP Weighted Criteria

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ABSTRACT

The increasing use of electric vehicles, especially electric motorcycles produced by PT Hartono Istana Teknologi (Polytron), demands a better service queue management system. The current First-Come, First-Served (FCFS) method is considered inadequate because it ignores the level of service urgency and vehicle damage characteristics. This study proposes a priority-based queue system by combining the Analytical Hierarchy Process (AHP) method and machine learning classification algorithms, namely Decision Tree and XGBoost. Data were collected through interviews with workshop technicians, then AHP was used to determine the weights of three main criteria which were then used as features in the service priority level classification process. The evaluation results showed that both models were able to classify priority services well, but XGBoost showed superior and more stable performance than Decision Tree. Quantitatively, Decision Tree achieved an accuracy of 94.44% with an average prediction time of 0.00162 seconds, while XGBoost achieved a higher accuracy of 97.22% with an average prediction time of 0.00202 seconds. Thus, even though it requires slightly longer computation time, XGBoost is considered more suitable for application in service priority systems because it is able to provide more consistent and reliable classification results.

1. INTRODUCTION

Background

PT Hartono Istana Teknologi, or Polytron, is one of the leading electronic manufacturers in the country, which has also ventured into electric vehicle manufacturing, which has been well received by the population. Nevertheless, the service process of its electric motorcycles is still part of the general services, which causes problems with respect to proper queue management as well as technician assignment. At present, services are managed manually, following a first-come, first-served (FCFS) basis, which, although simple, is not always optimal, especially when different levels of services are required by the vehicle. This is because, under an FCFS basis, urgency as well as complexity of repair are not taken into consideration, although some service points are managed under a fastest job first (SJF) basis, which, although better, is not always optimal, especially when vehicles are to be repaired extensively. Moreover, technician assignment also causes workflow disruptions, which necessitates a more flexible queuing system where the Analytic Hierarchy Process (AHP) may be employed to determine weights of criteria such as damage level of vehicle, availability of technician, as well as waiting time of customers, although it must be emphasized that AHP alone is not enough without integration with intelligent data processing technologies.

The machine learning classification algorithm can also be used for the estimation of service priority levels. This study aims to compare the classification results of the Decision Tree and XGBoost algorithms with the AHP-weighted criteria as an input. The reason for choosing the Decision Trees algorithm is that it is simple and easy to understand and has been proven to be effective for classification problems, as presented in previous studies such as Charbuty and Abdulazeez [1]. The XGBoost algorithm is also chosen for this study due to its high accuracy and efficiency in training the model without the risk of over-fitting, which makes it one of the most popular machine learning algorithms, as presented by Chen and Guestrin [2]. This study aims to design a priority-based service queue system for electric motorcycles and compare the results of the AHP with the Decision Tree and the AHP with the XGBoost algorithms based on the accuracy of the algorithms and the processing time and their application in the real-world workshop environment.

Scope

This study is limited to the development of a service priority classification system for electric motorcycles with a focus on Polytron brand vehicles. This system utilizes the Analytic Hierarchy Process (AHP) method to provide weights for priority criteria, namely the level of vehicle damage, technician availability, and customer waiting time. The weighted results from the AHP are then used as input for the classification algorithm, namely Decision Tree and XGBoost, to predict the level of service priority. This study only compares the two algorithms based on accuracy and efficiency of process time, without discussing the development of a web-based system, comprehensive technician scheduling, or integration with real queuing systems in the field.

Objective

To improve service efficiency, this project aims to develop a priority scheduling queue management system for electric motorcycle repair shops. In determining service priorities in this system, several elements are considered, including waiting time, technician skills, and vehicle damage levels. Analytic Hierarchy Process (AHP) is used to assign weights to each criterion so that priority determination is not done randomly. These weight values are then used as input for classification models, namely Decision Tree and XGBoost, to predict service priority levels. To determine which model performs better for priority-based queuing systems, the two algorithms are compared based on accuracy, classification performance, and processing time.

LITERATURE STUDY

Queuing systems are important for managing how customers are served, whether it is simply based on arrival time or certain priority rules. Queuing theory itself has been used in many areas, including public services, hospitals, and repair workshops. In electric motorcycle workshops, a more adaptive queuing system is becoming necessary as the number of electric vehicle users keeps increasing while technician availability remains limited. Traditional approaches like First Come First Served (FCFS) are often no longer effective, since they do not consider the level of damage or urgent service conditions. Therefore, a priority scheduling system is needed that considers the complexity of the damage and the efficiency of the technician.

Several approaches have been investigated to improve service systems. Elshahed et al. [3] proposed a Prioritized Sorted Task-Based Allocation (PSTBA) method on an IoT-based cloud system for healthcare. The findings included improvement in the adaptability of the system, as well as a decrease in task delays and failure rates. Although the analysis was performed in the healthcare industry, the conclusion arising from the result reveals that priority-based algorithms have vast possibilities for optimizing the efficiency of service systems. The proposed solution has not yet addressed issues concerning human factors, such as the expertise of the technician and the preference of the customer, which can be considered important in the workshop environment.

Regarding emergency services, Sharif et al. [4] proposed an urgency scheduling approach that combined priority algorithms and edge computing in the healthcare context. This approach is useful for fast responses to life-critical situations, like that of patients in an emergency situation. The applicability of this approach is pertinent to the situation in the workshop, which occurs when a vehicle is damaged to an extent on the road. In this proposed work, the aspect of the ability of the technicians has not been used as a priority for consideration, despite its importance in the heavily skill-dependent system.

In regard to decision-making with respect to multiple criteria in a more structured way, among the best approaches is the Analytical Hierarchy Process (AHP) method. Yoo et al. [5] demonstrated the effectiveness of AHP in constructing a service hierarchy based on expert evaluation, for example in the agro-healing service classification system. This method has the potential to be applied in workshops to arrange queues based on the level of damage, waiting time, and technician experience. However, AHP faces certain challenges when applied in real-time systems.

Furthermore, research by Karimunnisa and Pachipala [6] combined AHP with a metaheuristic approach for scheduling optimization in cloud computing. The results strengthen the flexibility of AHP that can be combined with other computing techniques. Unfortunately, such research is still rarely applied directly in the service sector such as workshops, thus opening up opportunities for exploration in this study. Ghanbari [7] also proposed a priority scheduling algorithm based on AHP in a cloud environment with diverse criteria, which are job characterization, system performance criteria, and scheduling strategies. Their approach showed enhancement in system efficiency as compared to classical algorithms such as FCFS and Round Robin.

Interestingly, the combined approach of AHP and Decision Tree has also been developed by a study focusing on the feasibility of financing procurement for MSMEs by Setyadi et al. [8] This is an indication that the combination of these approaches is effective for identifying eligibility for loans and for identifying suitable financial institutions based on related criteria. Even though the application area is different, this kind of two-stage decision structure can still be adapted to a workshop environment. Apart from predicting service priority based on existing data patterns, this approach can also help group customers according to their needs and how urgent their cases are. The study also relies on direct observation data from MSMEs, which is fairly similar to the use of technician observations and customer surveys commonly found in workshop settings.

In addition, Deif et al. [9] introduced an automated triage system that combines XGBoost and AHP to determine ICU admission priority during the COVID-19 pandemic. Even though the study was carried out in a hospital environment, it clearly shows how these two methods can work together for priority-based decision making in critical conditions. The proposed model classifies patients using clinical data and assigns priority weights, achieving an accuracy of around 97%. Even though the context comes from healthcare, the approach can still be applied to an electric motorcycle repair shop queue system, since decisions there are also driven by urgency and the limited number of available technicians.

Closer to the context of electric vehicles, Zhang and Shi [10] designed a queuing system for charging stations based on M/G/s queuing theory with real data from various seasons. This model optimizes the number of terminals and power capacity to reduce operating costs by 28.12% and waiting time by 41.76%. Adjusting the number of terminals based on user priority shows that this model is flexible and relevant enough to be applied in electric motorcycle repair shops that have high customer arrival dynamics and service complexity.

In addition to the classification approach, prediction techniques also have the potential to be applied to support service scheduling. The and Herawati [11] showed that the Support Vector Regression (SVR) algorithm is more accurate than K-Nearest Neighbor (KNN) in predicting stock prices. Although the context is different, this principle of accurate prediction can be applied to estimate customer waiting time at the workshop, which can later be used as one of the supporting variables in determining service priorities.

This review can be combined with both major queuing systems with AHP approaches, decision trees, prediction methods, and other planning algorithms to draw the conclusion that there is a strong reason. However, most studies continue to be limited to public services such as healthcare and cloud computing, and do not explicitly examine the operational challenges of electric motor workshops. Therefore, this study develops a latency management system that prioritizes services based on customer illness, technician experience and delays, but ensures that technician allocation is more balanced and effective. This system is expected to meet the practical needs of electric motor workshops and improve services amidst the increasing demand for electric vehicles.

2. RESEARCH METHOD

Data Collection

The data used in this study were collected through surveys and technician interviews. Surveys involving customers and technicians were conducted to determine the weight of priority criteria using the Analytic Hierarchy Process (AHP). Interviews with Polytron motorcycle service technicians were also carried out to obtain descriptions of commonly encountered damage and operational conditions in the workshop. These interviews helped identify key factors influencing service prioritization, such as the type and severity of damage, estimated processing time, technician expertise requirements, and customer waiting time. The interview results were used to formulate criteria and sub-criteria in the AHP method and to ensure that the variables used in the system reflect real workshop conditions.

The priority criteria survey was designed to assess the relative importance of several factors in the electric motorcycle service queue system. Respondents included not only electric motorcycle users and technicians, but also those from conventional gasoline motorcycles to provide comparative perspectives. A pairwise comparison approach based on a simplified AHP scale was used to evaluate the importance of criteria such as damage level, technician expertise, and customer waiting time. The survey results were processed into pairwise comparison matrices and used to calculate the AHP weights that serve as the basis for priority determination in the proposed scheduling system.

In addition to survey data, a service dataset was constructed from technician interview information to support machine learning model training. The dataset includes variables such as damage description and level, need for specialized technicians, customer waiting time, and estimated service duration. Each criterion value was normalized and multiplied by the corresponding AHP weight to produce an AHP score. Priority labels (Low, Medium, High) were not assigned manually but generated based on the total AHP score using a quantile-based equal-frequency discretization approach. These labels were then used as target classes in the Decision Tree and XGBoost classification models and applied within a priority scheduling system to optimize the electric motorcycle service queue.

Data Pre-Processing

Before model training, several data pre-processing steps were performed to ensure consistency and suitability for machine learning. Repair time estimates obtained from technician interviews were originally expressed in different units, such as minutes, hours, days, and time ranges. To standardize the data, all repair time values were converted into hours. Time given in minutes was converted to hours, while time in days was converted assuming one working day equals eight hours, based on workshop operational conditions. For time ranges, the average value was used. This standardization prevents scale imbalance and ensures that repair duration can be processed uniformly in the modeling stage.

Categorical attributes were then encoded into numerical values because machine learning algorithms require numeric input. Variables such as damage category, difficulty level, and the need for specialized technicians were transformed using a consistent encoding scheme. Irrelevant text attributes, such as detailed damage descriptions, were removed to avoid redundancy and improve computational efficiency. These steps ensure that all input features are structured and suitable for model processing.

After preprocessing, an AHP-based composite score was calculated for each service record by combining normalized criteria values with their respective AHP weights. This score was used only to generate priority labels using a quantile-based approach, where the lowest 25% of scores were labeled as Low priority, the middle 50% as Medium, and the highest 25% as High. Once the labels were formed, the AHP score variable was removed from the dataset to prevent data leakage during model training. As a result, the classifiers were trained solely on the original service characteristics, ensuring fair evaluation and reliable performance measurement.

Analytical Hierarchy Process (AHP)

The AHP method is used to determine the weight of each criterion influencing the service priority for electric motor repair. This method was developed by Thomas L. Saaty and solves multicriteria decision problems by using pairwise comparisons. This study considered three factors: the degree of motor failure, the amount of time customers had to wait, and the need for skilled technicians.

The importance of each criterion is determined based on survey results from technicians and customers. Their responses reflect perceptions of what matters most in service prioritization. After the weights are established, a pairwise comparison matrix is created, with values based on the average of respondent assessments, as shown in **Table 1**.

The determination of the value for each pairwise comparison is obtained from the results of a survey completed by many respondents. Because each matrix element has more than one assessment value, a merging process is required to obtain a representative value for each comparison. Based on the Aggregation of Individual Judgments (AIJ) approach used in studies Todorova and Trifonov [14], the process of merging individual opinions is carried out using the Geometric Mean, because this method is able to maintain the multiplicative nature of the 1–9 comparison scale so that the results are more stable and consistent.

$$GM = (x_1 \cdot x_2 \cdot x_3 \cdot \ldots \cdot x_n)^{\frac{1}{n}} \quad (1)$$

Description:
- GM : Geometric Mean value
- $x_1 \cdot x_2 \cdot x_3 \cdot \ldots \cdot x_n$: assessment value of each respondent.
- n : number of respondents.

Table 1. Example of Pairwise Comparison Matrix Format between Criteria

Criteria	**TK**	**TTK**	**WT**
TK	1	a_{12}	a_{13}
TTK	$\frac{1}{a_{12}}$	1	a_{23}
WT	$\frac{1}{a_{13}}$	$\frac{1}{a_{23}}$	1

Description:
a. The values a_{12}, a_{13}, and a_{23} are the average results of respondents' assessments of the comparison of criteria
b. The diagonal value is always 1 because each criterion is compared to itself
c. The inverse ratio is used to maintain logical consistency in the matrix

After the pairwise comparison matrix is formed as shown in Table 1, the next step is to calculate the weight of each criterion. This calculation is done using the AHP method, namely by finding the normalized principal eigenvector of the comparison matrix. The priority weight $w = [w_1, w_2, \ldots, w_n]^T$ is obtained from the equation:

$$Aw = \lambda_{max} w \quad (2)$$

Where λ_{max} is the maximum eigenvalue of A.
To ensure the consistency of the respondents' judgments, the Consistency Index (CI) is calculated as:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (3)$$

Where n is the number of criteria.
Then, the Consistency Ratio (CR) is computed by:

$$CR = \frac{CI}{RI} \quad (4)$$

Where RI is the Random Index, a known value based on matrix size n.

A consistency ratio $CR \leq 0{,}1$ indicates acceptable consistency in the pairwise comparisons. The weights we get show how important each thing is. We will use these weights in the priority scheduling algorithm to decide when to service electric motorbikes.

Decision Tree

Decision Tree is one of the supervised learning algorithms used for classification and regression. Decision Tree works by dividing data into a tree structure based on the attribute that has the highest information gain, resulting in a decision on each leaf of the tree. According to Charbuty and Abdulazeez [1], Decision tree is considered as one of the most famous methods for data classification.

In this study, Decision Tree will be used to classify customers into three categories, namely high, medium, and low priority. This category is obtained from the calculation criteria score using the AHP method. The criteria used include the level of motor damage, the need for expert technicians, and the length of waiting time.

In general, the structure of the Decision Tree consists of several main components as shown in **Figure 1**. The most important part of a decision tree is the root node, which is where it all starts. Then the tree splits like a family tree into more branches. The result of how high the priority level of repairing the electric motor is will be displayed by the leaf node, which is the final answer at the end of several branches. Other branches lead to smaller decision points, helping to figure out the final answer step by step.

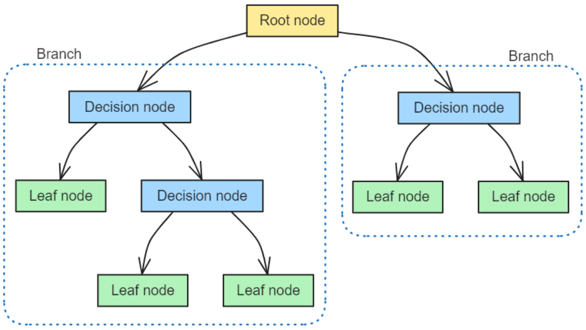

Figure 1. General Structure of Decision Tree

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This figure illustrates how data is classified in stages based on relevant attributes. In this study, the tree structure will be adjusted to the data used, namely the criteria for the level of motor damage, the length of customer waiting time, and the level of technician expertise, to determine the priority class of service. The formation of a decision tree in this algorithm is done by determining the best attribute used as a data separator at each node. The selection is based on the information gain value, which is the difference between the entropy of the initial data set and the average entropy of the data set formed after separation based on certain attributes.

Entropy is a measure of uncertainty or impurity in a data set and can be calculated using the following formula:

$$Entropy(S) = -\sum_{i=1}^{n} p_i log_2 p_i \tag{5}$$

Where p_i is the proportion of data in class i in the data set S.

Meanwhile, the information gain of an attribute A is formulated as:

$$Gain(S, A) = Entropy(S) - \sum_{v \epsilon Values(A)} \frac{|S_v|}{|S|} Entropy(S_v) \tag{6}$$

Where:

- S is the initial data set,
- A is the attribute being tested,
- S_v is a subset of S with attribute value $A = v$,
- and $|S_v|$ is the number of data in the subset S_v

The attribute that produces the highest information gain will be selected as the separator at that node. This process will be repeated recursively until all data can be classified optimally and meets the stopping criteria. In this study, Decision Tree is used to classify customer data based on three criteria, namely the level of motor damage, customer waiting time, and technician skill level, into service priority categories.

XGBoost

XGBoost (Extreme Gradient Boosting) is a decision tree-based ensemble algorithm that is included in the boosting technique. This method forms a tree gradually to correct prediction errors from the previous model. In this study, XGBoost is used to predict the priority of electric motor service based on damage data and AHP weights, as shown in **Figure 2.**

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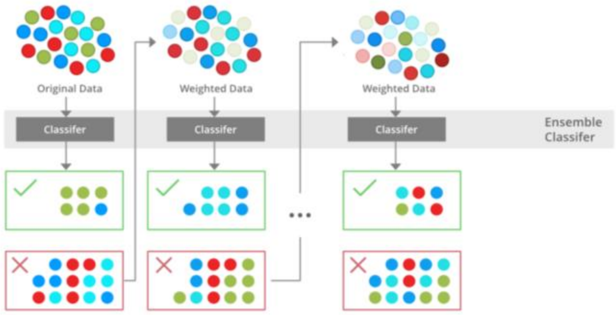

Figure 2. Boosting Process on XGBoost

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The preparation process in XGBoost not only relies on the selection tree structure, but also includes numerical calculations to slowly optimize the objective work. In each cycle, XGBoost will include unused demonstrations to shrink the expectation error of the previous demonstration using the corner approach. In general, this handling is defined in an objective framework consisting of two fundamental components, namely loss work and regularization work. Loss work is used to measure how big the prediction error is, while regularization work plays a role in controlling the complexity of the performance so that overfitting does not occur.

The training process in XGBoost aims to minimize the following objective function:

$$Obj(t) = \sum_{i=1}^{n} \quad l(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^{t} \quad \Omega(f_k) \tag{7}$$

Where:

- $l(y_i, \hat{y}_i^{(t)})$ is the loss function between the actual label y_i and the prediction $\hat{y}_i^{(t)}$ at the t iteration
- $\Omega(f_k)$ is the regularization function for the k model, which controls the complexity of the tree.
- f_k is the k decision tree
- t is the total number of iterations (number of trees)

The commonly used regularization function in XGBoost is formulated as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \quad w_j^2 \tag{8}$$

Where:

- T is the number of leaves in a tree
- w_j is the jth output score
- γ and λ is a parameter to set the penalty for the number of leaves and the size of the weight, to avoid overfitting.

To build each new tree, XGBoost uses a second-order Taylor expansion approximation of the loss function to speed up the optimization process. The estimated gain (accuracy improvement) of a split in the tree is calculated by the formula:

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} + \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}\right] - \gamma \tag{9}$$

Where:

- G_L, G_R is the sum of the gradients on the left and right sides of the split
- H_L, H_R is the sum of the hessians (second derivatives) on the left and right sides
- λ is a regularization parameter
- γ is a penalty for splitting

By utilizing this approach, XGBoost not only produces models with high accuracy, but is also efficient and stable against data with noise or outliers.

IMPLEMENTATION AND RESULT

Implementation

This section describes the overall implementation of the proposed service priority system, covering dataset construction, AHP weight calculation, data preprocessing, and model development. Since historical workshop data were not publicly accessible, the dataset was compiled based on structured interviews with Polytron electric motorcycle technicians to represent real service conditions. Each data record corresponds to one service case and includes key attributes such as damage category, difficulty level, estimated repair time, and the need for specialized technicians. These attributes were selected because they directly influence service priority determination and serve as input variables for both AHP weighting and machine learning classification.

The AHP method was implemented to determine the relative importance of priority criteria through pairwise comparisons. The resulting normalized weights were validated using a consistency check to ensure that the decision structure was logically reliable. These weights were then used to compute a composite AHP score for each service case. Before modeling, several preprocessing steps were conducted to standardize the data. Repair time values expressed in different units were converted into hours, categorical variables were encoded into numerical form, and irrelevant textual attributes were removed. Priority labels (Low, Medium, High) were generated from AHP scores using a quantile-based approach, after which the AHP score variable was excluded from the dataset to prevent data leakage during model training.

Two classification models, Decision Tree and XGBoost, were defined and trained to predict service priority levels. The Decision Tree model was configured with controlled depth and minimum sample constraints to maintain interpretability and reduce overfitting, while XGBoost was implemented as an ensemble boosting method with parameter settings designed to balance learning stability and model complexity. The dataset was split into training and testing sets using a 70:30 ratio with stratified sampling to preserve class distribution. Model performance was then evaluated based on classification accuracy, computational efficiency, and suitability for real workshop implementation, highlighting the comparative characteristics of both algorithms within the priority-based queue system.

Result

The questionnaire recapitulation indicates that respondents tended to prioritize waiting time over other criteria, preferring faster service even if handled by less experienced technicians, followed by technician experience and then the level of motorcycle damage as the least influential factor. Respondent assessments were aggregated using the geometric mean to represent the overall perception of criterion importance, forming a pairwise comparison matrix that was subsequently normalized to equalize scale differences. The resulting AHP weights show that waiting time has the highest weight (0.409), followed by technician experience (0.323) and level of damage (0.268). A consistency test was conducted using Saaty's Consistency Ratio approach, producing $\lambda max = 3.0987$, $CI = 0.0494$, and $CR = 0.0851$; since $CR < 0.1$, the matrix is considered consistent and the derived weights are valid for use in determining service priority.

The Decision Tree model demonstrated strong performance in classifying service priority levels, as shown by the confusion matrix where most predictions fall along the main diagonal, indicating correct classification across Low, Medium, and High priority classes. The model achieved 97.99% accuracy on the training data and 94.44% on the test data, with only a small difference between the two, suggesting good generalization and minimal overfitting. Precision, recall, and F1-score values for all classes were consistently high, confirming that each priority category was well distinguished with low misclassification rates. In terms of computational efficiency, the Decision Tree model required an average training time of 0.0033 seconds and prediction time of 0.0016 seconds, resulting in a total processing time of 0.0049 seconds, indicating that the model is highly efficient for practical service prioritization.

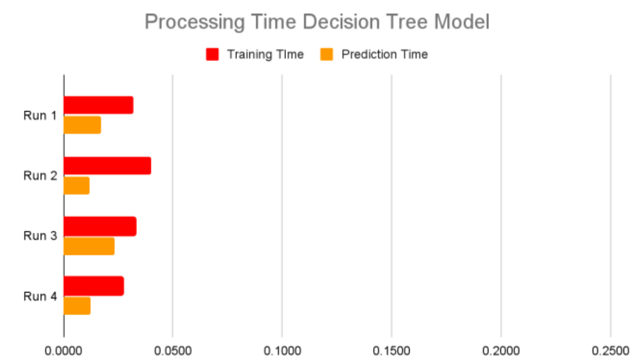

Figure 3. Processing Time Decision Tree Model 5 Times Run

Similarly, the XGBoost model showed excellent classification capability, with training accuracy of 97.99% and testing accuracy of 97.22%, again indicating strong generalization. The confusion matrix reveals that most instances were correctly classified, with only a small number of misclassifications, and evaluation metrics (precision, recall, and F1-score) remained consistently high across all priority classes, demonstrating stable and balanced performance. However, the processing time was higher compared to the Decision Tree model, with an average training time of 0.0215 seconds and prediction time of 0.0020

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Formatted: Font: (Default) Times, Font color: Auto seconds, leading to a total processing time of 0.0235 seconds. This difference reflects the higher computational complexity of XGBoost, which employs an ensemble boosting mechanism, but it also contributes to slightly better predictive performance.

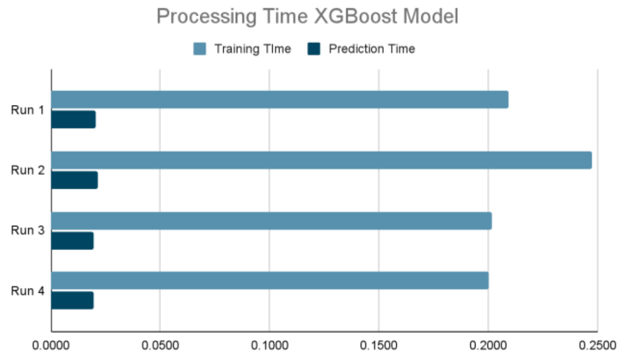

Figure 4. Processing Time XGBoost Model 5 Times Run

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Discussion

The classification results show that the integration of the Analytical Hierarchy Process (AHP) method with the Decision Tree and XGBoost algorithms is able to produce high accuracy values and evaluation metrics in determining service priorities. The performance comparison of the two models is carried out based on the evaluation results on test data using accuracy, precision, recall, and F1-score metrics. It is designed to analyze and evaluate the models with respect to their advantages and shortcomings in classifying service priority levels, especially in high-priority classes that have a greater level of urgency in the service queue system.

Generalization performance for the Decision Tree model is quite good, as can be seen from the fact that the accuracy difference between the training dataset and the testing data is small. Moreover, Decision Trees are explainable models that work well on simple data patterns. However, for the high-priority class (High), recall tends to be lower, even though precision reaches 100%. That means that for every High class prediction given by the model is always correct or there are no false positives, however, some high-priority data are still classified in the other class as false negatives. Therefore, this suggests the model is more conservative in assigning high-priority labels.

A similar pattern was also found in research conducted by Dani and Ginting [20], where very high evaluation metric values, including precision values reaching 100%, were associated with the possibility of imbalanced dataset distribution. In the current study, the implementation of class separation was done using the quantile based method, therefore, the potential for the occurrence of this condition exists. However, the results do not indicate the occurrence of the issue of overfitting since the performance of the other classes was consistent.

On the other hand, the XGBoost model performed with higher consistency for all classes with different priorities. The fairly balanced values of the evaluation metric with high priorities show that XGBoost can classify the data more reliably. This finding is in line with research conducted by Raihan et al. [21], which reported that the XGBoost model was able to achieve a precision value of up to 100% in the classification of chron ic kidney disease without directly indicating overfitting. These findings show that XGBoost may generate accurate and reliable predictions on well-structured data.

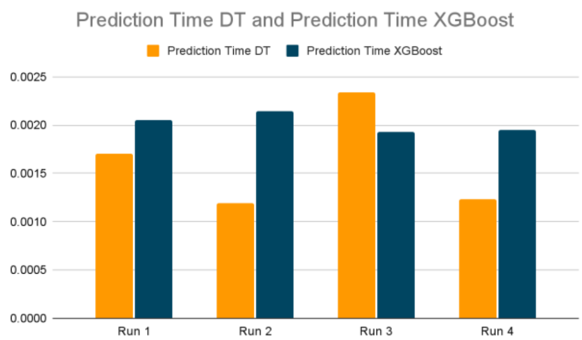

Figure 5. Comparison Of Prediction Time Decision Tree and XGBoost

The processing time shown in Figure 5 was not tested only once, as the computation time for the model can be affected by internal processes within the algorithm and the operational environment. Therefore, the test was performed four times to obtain a representative value for the average processing time. This helps to obtain a clear view free from subjective considerations as the testing time can affect the model, thus helping to objectively compare the two models.

In terms of processing time, the Decision Tree model demonstrates faster and more consistent prediction performance compared to XGBoost, making it more suitable for real-time service environments. Nevertheless, XGBoost exhibits stronger generalization ability and more stable classification performance, particularly for high-priority service cases. This indicates a trade-off between computational efficiency and predictive robustness. Therefore, although Decision Tree is more efficient, XGBoost is considered more appropriate for implementation when classification accuracy and reliability are prioritized in the service queuing system.

3. CONCLUSIONS

In this study, the Analytical Hierarchy process (AHP) approach was employed to establish the level of importance of each criterion in motorcycle services from respondents through comparison evaluations between criteria. In evaluating, the Saaty scale was employed, and comparisons were calculated utilizing the geometric mean, which generated a calculation matrix of collective evaluations. The calculation matrix was subjected to normalization, which generated parity weights of criteria. The level of consistency was evaluated utilizing the Consistency Ratio (CR) test, and findings established levels below 0.1, hence free from inconsistencies.

The weights of the AHP criteria are employed as the input variables in the service priority classification phase. The decision tree algorithm and the XGBoost algorithm are used. The data is presented in a numeric form, the data is then divided into the training data and test data. The training phase for the proposed system is performed using certain parameters, the correlation between the weighted variables and the levels of the services priority is found. Based on the test results, both systems have been able to determine the levels of services priority with high accuracy. The Decision Tree algorithm has high accuracy with shorter processing times, yet the XG Boost algorithm has higher accuracy with lower misclassification errors, especially for the high-priority services. The difference between them shows that the XG Boost algorithm can recognize more complex patterns out of the data with longer processing times compared to the Decision Tree algorithm.

These results can then be applied to optimize the algorithm selection according to the requirements of the system. Decision Tree is more suitably applied to systems that have low data complexity, as well as less computing capacity, whereas XGBoost is better suited to applications involving more complex data, which demand high accuracy irrespective of the processing time. Takeaways, this work has demonstrated that by applying the knowledge of the Decision Tree algorithm and XGBoost with the help of the AHP approach, an efficient approach for analyzing the importance of Electric Motor Maintenance can be obtained.

However, this study has limitations, such as the interview-based dataset used in this study and service prioritization criteria that are still not dynamic enough. In this regard, future research may be performed with actual operational data that is directly acquired from electric motorcycle repair shops to make the system model represent more dynamic and realistic conditions of service. Further research can also consider expanding priority criteria toward the technician and customer aspects, such as technician workload and customer urgency, so that the system becomes more comprehensive. Longer-term system testing is also needed in order to evaluate the stability of the model on an ongoing basis, as well as how a system may adapt to changing service patterns and the ongoing impacts such a system may have on both efficiency and service quality.

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