

Comparison of Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) in the Old Classification of Case Settlement in Religious Courts

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Abstract

The length of case settlement is one of the important aspects in the evaluation of the judicial process because it can provide an overview of the efficiency of case resolution. This study aims to compare the performance of the Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms in classifying the length of case settlement in the Religious Court into three categories, namely Fast, Normal, and Slow. The research data comes from the Religious Court case dataset consisting of 15,522 records and is then aggregated based on the case number so that data at the case level is obtained. The settlement time is calculated based on the difference between the registration date and the date of the verdict, then used as the basis for the formation of categories. The SVM and KNN models were tested using training and testing data with a ratio of 80:20, and hyperparameter tuning was carried out using 5-fold cross-validation. The evaluation was carried out using accuracy, precision, recall, and F1-Score. The test results showed that the KNN after tuning gave the best performance with an accuracy of 55.88%, precision of 55.40%, recall of 52.39%, and an F1-Score of 52.48%. The SVM after tuning obtained an accuracy of 53.35% and an F1-Score of 50.16%. These results showed that KNN Tuned was superior to SVM Tuned in the dataset used, although both models still faced difficulties in identifying the Slow category.

Keywords: classification, case resolution time, Religious Court, Support Vector Machine, K-Nearest Neighbor, machine learning

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Introduction

The development of information technology encourages the use of data as a basis to support the analysis and decision-making process in various fields. One of the widely used approaches is *machine learning*, especially classification methods that can study patterns from historical data to group an object into certain categories. The classification approach has been applied to various types of data, including public service data, health, image, and social data. The use of *machine learning* allows the grouping process to be carried out more systematically based on the patterns contained in the data. [1]

In the context of the judiciary, the length of settlement of cases is one of the information that can be used to describe the characteristics of the case settlement process. Information about the duration of settlement can be analyzed from historical data of the case, such as the date of registration and the date of the verdict, and then grouped into certain categories. This classification can provide an overview of the pattern of case settlement and is one of the approaches in the use of historical data to support the analysis of the judicial process. However, based on the references used in this study, the application of the comparison of SVM and KNN algorithms specifically for the classification of the length of case settlement in the Religious Court has not been discussed, so there is an opportunity to apply the two algorithms in the context of case data.

Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) are *supervised learning algorithms* that have different approaches to classification. KNN determines the class of a data based on the proximity of the data to a number of closest neighbors in the training data, while SVM determines the optimal separation boundary (*hyperplane*) between classes by maximizing *margins* [2]. These differences in characteristics cause the performance of the two algorithms to differ when applied to different datasets and feature characteristics.

A number of studies have compared the performance of SVM and KNN on various classification problems. Research on milk quality classification shows that KNN provides superior performance to SVM based on the evaluation of accuracy, precision, recall, and F1-Score. On the other hand, research on the sentiment analysis of JMO application reviews found that SVM has better performance than KNN, with an accuracy of 90.00% and 78.25%, respectively. These differences in results show that there is no one algorithm that always provides the best performance in all types of datasets. [3] [4]

The difference in the performance of SVM and KNN was also seen in other studies. In the classification of ear infection images, SVM produced an accuracy of 87.50%, while KNN obtained 72.50% in the final test. The study also applied *hyperparameter tuning* to both algorithms to obtain the best model configuration. Meanwhile, the diabetes classification research showed different results, namely KNN obtained an accuracy of 92.20% and an F1-Score of 0.93, while SVM obtained an accuracy of 88.39% and an F1-Score of 0.89. The study also showed that the selection of preprocessing techniques and model configuration can affect the performance of the algorithm. [5] [6]

Based on these studies, the performance of SVM and KNN is contextual and can be influenced by the characteristics of the dataset, the features used, and the configuration of the model parameters. Therefore, an empirical evaluation is needed to determine a more appropriate algorithm in the case dataset of Religious Courts, especially for the classification of the length of case settlement. This study uses historical case data aggregated based on case numbers and classifies the settlement time into three categories, namely Fast, Normal, and Slow. Furthermore, the SVM and KNN algorithms are compared through *baseline scenarios* and *hyperparameter tuning* with evaluation using accuracy, precision, recall, and F1-Score.

Model evaluation is also not enough to use accuracy alone. Flood risk classification research, for example, uses accuracy, precision, recall, F1-score, and AUC to obtain a more comprehensive picture of performance, especially when class distributions are unbalanced. A similar approach is used in pistachio classification studies that evaluate models using accuracy, precision, recall, F1-score, AUC-ROC, and confusion matrix. [7] [8]

Thus, this study aims to compare the performance of the Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms in classifying the length of case settlement in the Religious Court and determining the algorithm and model configuration that provides the best performance in the dataset used. The results of the study are expected to provide an empirical overview of the application of the two algorithms to case data and become a reference in the use of *machine learning* approaches for judicial data analysis.

Literature Review

Classification is one of the techniques in machine learning used to group data into classes or categories based on patterns contained in the data. In the classification process, a model is trained using labeled data so that it can learn the relationship between input characteristics or features and the target class. This approach is widely used in various problems, including social data, sentiment, image, and healthcare classification. Previous studies have shown that classification algorithms can be used to systematically group data and support data-driven decision-making processes . [9]

In this study, classification is used to group the case resolution duration of Religious Court cases into three categories, namely Fast, Normal, and Slow. These categories are determined based on the resolution duration calculated from the difference between the registration date and the decision date. Therefore, the research problem falls under multiclass classification, as the model must assign each case to one of three target categories.

Support Vector Machine (SVM) is a supervised learning algorithm that performs classification by finding an optimal hyperplane to separate data classes. The main principle of SVM is to maximize the margin, which is the distance between the separating boundary and the nearest data points from each class. For data that cannot be linearly separated, SVM can use a kernel function to map the data into a more suitable feature space, enabling separation between classes . [2]

K-Nearest Neighbor (KNN) is a distance-based classification algorithm that determines the class of a data point based on the classes of a number of its k nearest neighbors. The classification process is performed by calculating the distance between the data to be predicted and the training data, sorting the data based on distance, and then determining the class based on the nearest neighbors . [10]

The value of k is one of the main hyperparameters in KNN. In addition to the number of neighbors, the choice of distance metric can also affect classification results. Commonly used distance metrics include Euclidean distance and Manhattan distance.

In this study, the KNN configuration was determined through hyperparameter tuning by testing the number of neighbors ($n_neighbors$), weighting method ($weights$), and distance metric ($metric$). The best configuration obtained from the experiment was $n_neighbors = 31$, $weights = distance$, and $metric = Manhattan$. A summary of previous studies underlying this research is presented in Table 1.

Table 1. Summary of Previous Studies

No.	Domain	Methods	Main Findings
1	Milk quality	KNN, SVM	KNN achieved higher overall performance
2	Ear infection	KNN, SVM	SVM achieved higher performance after tuning
3	JMO sentiment	KNN, SVM	SVM 90.00%, KNN 78.25%
4	Diabetes	KNN, SVM	KNN 92.20%, SVM 88.39%
5	Regional songs	KNN, SVM, PCA	SVM RBF reached 79%; PCA improved KNN under certain configurations
6	Oil palm ripeness	KNN, SVM	Both achieved the same accuracy in one scenario

No.	Domain	Methods	Main Findings
7	Free Lunch Program sentiment	KNN, SVM	SVM 72%, KNN 48%
8	GoPay sentiment	KNN, SVM	SVM performed better on high-dimensional text data
9	Employee face recognition	KNN, SVM	SVM was relatively more stable under some conditions
10	Donor classification	SVM	Accuracy 89%, F1-score 90%
11	Pistachio classification	SVM, KNN, and other models	Tuning and cross-validation improved the modeling process
12	Flood risk	SVM, XGBoost	Demonstrated the importance of model selection and multi-metric evaluation

Overall, previous studies have produced inconsistent results regarding which algorithm performs better. KNN has shown superior performance on several datasets, such as milk quality and diabetes, whereas SVM has performed better in ear infection classification and several sentiment analysis problems. In other studies, the two algorithms have even achieved similar performance under certain conditions. [3] [10]

These findings strengthen the rationale for conducting this study, which does not assume from the outset that either SVM or KNN is the better algorithm, but instead evaluates both empirically on a Religious Court case dataset using the same preprocessing, data-splitting, and tuning schemes. Therefore, the contribution of this study lies in providing empirical evidence regarding the performance of the two algorithms for classifying case resolution duration, a topic that has not been specifically addressed in the references used.

Research Methodology

This study uses a comparative experimental method to compare the performance of Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms in classifying case resolution duration at Religious Courts. The research stages include dataset processing, formation of case resolution duration categories, feature engineering, preprocessing, data splitting, modeling, hyperparameter tuning, and model performance evaluation and comparison. A staged approach involving preprocessing, data splitting, modeling on the same dataset, and evaluation using multiple metrics has also been used in previous comparative studies of classification algorithms.

The dataset used in this study was obtained from Religious Court case data containing 15,522 records. The data were then aggregated by nomor_perkara, resulting in 6,405 unique cases. Case resolution duration was calculated as the difference between tanggal_putusan and tanggal_pendaftaran. Records with invalid or unavailable resolution durations were removed, resulting in 6,120 cases used for classification.

The target categories were formed based on the quartile values of the data, namely Q1 = 14 days and Q3 = 25 days. Cases were categorized as Fast when the resolution duration was ≤ 14 days, Normal when it was >14 to 25 days, and Slow when it was >25 days. The features consisted of the numerical features tahun_pendaftaran, bulan_pendaftaran, and hari_minggu, as well as the categorical features jenis_perkara_nama and dihadiri.

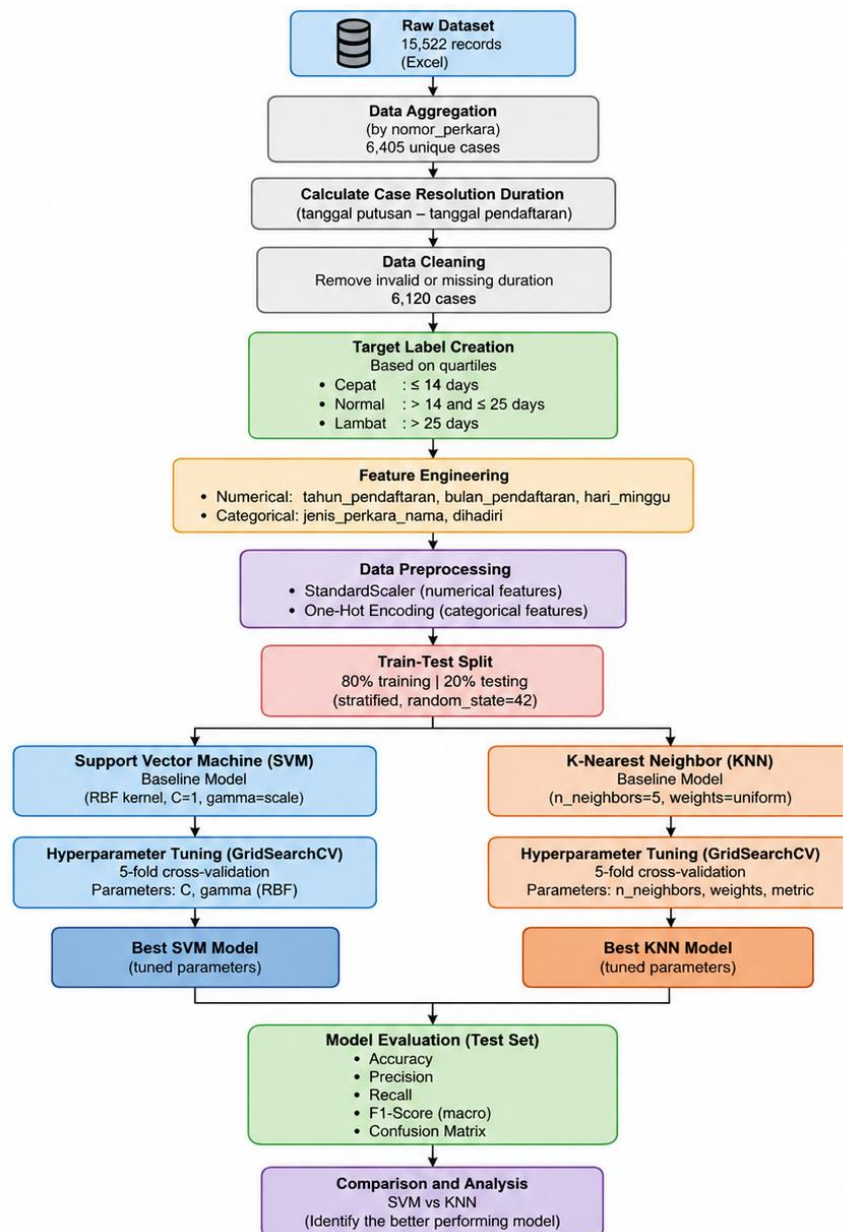


Fig. 1. Research flow of the proposed method.

Before modeling, numerical features were normalized using StandardScaler, while categorical features were transformed using One-Hot Encoding. The data were divided into 80% training data and 20% testing data using a stratified split with random_state=42. SVM and KNN were then tested using baseline configurations, followed by hyperparameter tuning using GridSearchCV with 5-fold cross-validation and F1-Macro as the primary scoring metric. The tested parameters included C and gamma for SVM, as well as the number of neighbors, weights, and distance metric for KNN.

The performance of both models was evaluated using accuracy, precision, recall, F1-Score, and a confusion matrix. Evaluation was performed on the same testing data so that the results of the two algorithms could be compared objectively. Multiple metrics were used so that the assessment would not depend solely on accuracy, particularly when the models differed in their ability to recognize individual classes.

Results

This study produced four model configurations for comparison: SVM Baseline, SVM Tuned, KNN Baseline, and KNN Tuned. All models were evaluated using the same testing data,

consisting of 1,224 cases, allowing their performance to be compared consistently. The testing data consisted of 448 Fast cases, 491 Normal cases, and 285 Slow cases.

Table 2. Distribution of Case Resolution Duration Categories

Category	Number of Cases	Percentage
Almost	2,240	36.60%
Normal	2,455	40.11%
Slow	1,425	23.28%
Total	6,120	100%

Based on this distribution, the Normal category contained the largest number of cases, with 2,455 cases or 40.11%, while the Slow category contained the fewest, with 1,425 cases or 23.28%. This difference in class distribution was considered in model evaluation. Therefore, the assessment used not only accuracy but also precision, recall, and F1-Score to provide a view of the models' ability to recognize each category. Initially, SVM and KNN were run using baseline configurations. SVM used an RBF kernel with $C = 1$ and $\gamma = \text{scale}$, while KNN used $k = 5$, $\text{weights} = \text{uniform}$, and $\text{metric} = \text{Minkowski}$.

Table 3. Baseline Model Performance

Model	Accuracy	Precision	Recall	F1-Score
SVM Baseline	52.53%	57.07%	49.03%	49.34%
KNN Baseline	54.66%	53.05%	51.86%	52.07%

The baseline results show that KNN achieved an accuracy of 54.66% and an F1-Score of 52.07%, while SVM achieved an accuracy of 52.53% and an F1-Score of 49.34%. KNN also achieved a higher recall of 51.86%, compared with 49.03% for SVM. In contrast, SVM produced higher precision at 57.07%. Thus, even under the baseline configuration, KNN demonstrated better overall performance in terms of accuracy, recall, and F1-Score.

Hyperparameter tuning was subsequently performed using GridSearchCV with 5-fold cross-validation and F1-Macro as the scoring metric. For SVM, the parameters tested included C , γ , and the RBF kernel. The tuning process resulted in the best configuration of $C = 10$, $\gamma = \text{scale}$, and $\text{kernel} = \text{RBF}$. For KNN, the parameters tested included the number of neighbors, weights, and metric. The best configuration obtained was $n_neighbors = 31$, $\text{weights} = \text{distance}$, and $\text{metric} = \text{Manhattan}$.

Table 4. Best Hyperparameters

Model	Best Parameters	CV F1-Macro
SVM	$C = 10$, $\gamma = \text{scale}$, $\text{kernel} = \text{RBF}$	0.4957
KNN	$n_neighbors = 31$, $\text{weights} = \text{distance}$, $\text{metric} = \text{Manhattan}$	0.5317

The tuning results show that the best KNN configuration uses a larger number of neighbors compared with the baseline configuration. Using 31 neighbors with distance weighting allows closer neighbors to have a greater influence on the classification process. Meanwhile, for SVM, increasing the value of C to 10 resulted in a better configuration compared with the baseline parameters. SVM parameter selection can affect the decision boundary formed by the model; therefore, parameter optimization is important for obtaining a configuration that is appropriate for the characteristics of the data. After the tuning process, both models were tested again using the same testing data. The comparison of the models before and after tuning is presented in Table 4.

Table 5. Comparison of Baseline and Tuned Models

Model	Accuracy	Precision	Recall	F1-Score
SVM Baseline	52.53%	57.07%	49.03%	49.34%
SVM Tuned	53.35%	58.16%	49.64%	50.16%
KNN Baseline	54.66%	53.05%	51.86%	52.07%

Model	Accuracy	Precision	Recall	F1-Score
KNN Tuned	55.88%	55.40%	52.39%	52.48%

Tuning improved the performance of both algorithms. For SVM, accuracy increased by 0.82 percentage points, from 52.53% to 53.35%. Precision increased from 57.07% to 58.16%, recall increased from 49.03% to 49.64%, and F1-Score increased from 49.34% to 50.16%.

For KNN, accuracy increased from 54.66% to 55.88%. Precision increased from 53.05% to 55.40%, recall increased from 51.86% to 52.39%, and F1-Score increased from 52.07% to 52.48%. Thus, the tuning process improved all evaluation metrics for both algorithms.

These results demonstrate the importance of hyperparameter selection in classification. A previous study on pistachio variety classification also showed that hyperparameter optimization can improve the performance of several models used.

Table 6. Final Performance Comparison

Metric	SVM Tuned	KNN Tuned	Difference
Accuracy	53.35%	55.88%	+2.53 pp
Precision	58.16%	55.40%	−2.76 pp
Recall	49.64%	52.39%	+2.75 pp
F1-Score	50.16%	52.48%	+2.32 pp

Based on the final results, KNN Tuned achieved higher overall performance. KNN obtained an accuracy of 55.88%, which was 2.53 percentage points higher than SVM. KNN also achieved a higher recall of 52.39%, while SVM obtained 49.64%. The difference in F1-Score also indicates higher performance for KNN, with 52.48% compared with 50.16% for SVM. However, SVM still achieved higher precision, at 58.16%.

Thus, KNN provided a better balance between the ability to identify data from each class and prediction accuracy on the study dataset. This result is consistent with a previous study on milk quality classification, which found that KNN achieved higher performance than SVM based on accuracy, precision, recall, and F1-Score. However, this result differs from a previous study on ear infection classification, which reported higher performance for SVM than KNN. These differences indicate that algorithm performance depends on the characteristics of the dataset, the features used, and the parameter configuration.

Class-level analysis shows that the two models exhibited relatively similar error patterns.

Table 7. Class-Level Performance

Model	Class	Precision	Recall	F1-Score
SVM Tuned	Fast	55.51%	57.37%	56.42%
SVM Tuned	Normal	49.16%	65.58%	56.20%
SVM Tuned	Slow	69.81%	25.96%	37.85%
KNN Tuned	Fast	58.35%	66.29%	62.07%
KNN Tuned	Normal	54.27%	62.12%	57.93%
KNN Tuned	Slow	53.59%	28.77%	37.44%

For the Fast category, KNN achieved an F1-Score of 62.07%, higher than SVM at 56.42%. KNN also achieved a recall of 66.29%, indicating that the model was able to correctly identify most cases that actually belonged to the Fast category. For the Normal category, both models achieved relatively high recall. SVM obtained a recall of 65.58%, while KNN obtained 62.12%. However, KNN achieved higher precision at 54.27%, compared with 49.16% for SVM. This resulted in a slightly higher F1-Score for KNN in the Normal category, at 57.93%.

The lowest performance was observed in the Slow category. SVM achieved a recall of only 25.96%, whereas KNN achieved 28.77%. Although KNN was slightly better at identifying

Slow cases, both models still experienced difficulties in distinguishing this category. Interestingly, SVM achieved a precision of 69.81% for the Slow category, indicating that its Slow predictions were relatively accurate; however, the model was able to identify only a small proportion of the cases that were actually classified as Slow.

This pattern can be observed more clearly through the confusion matrices.

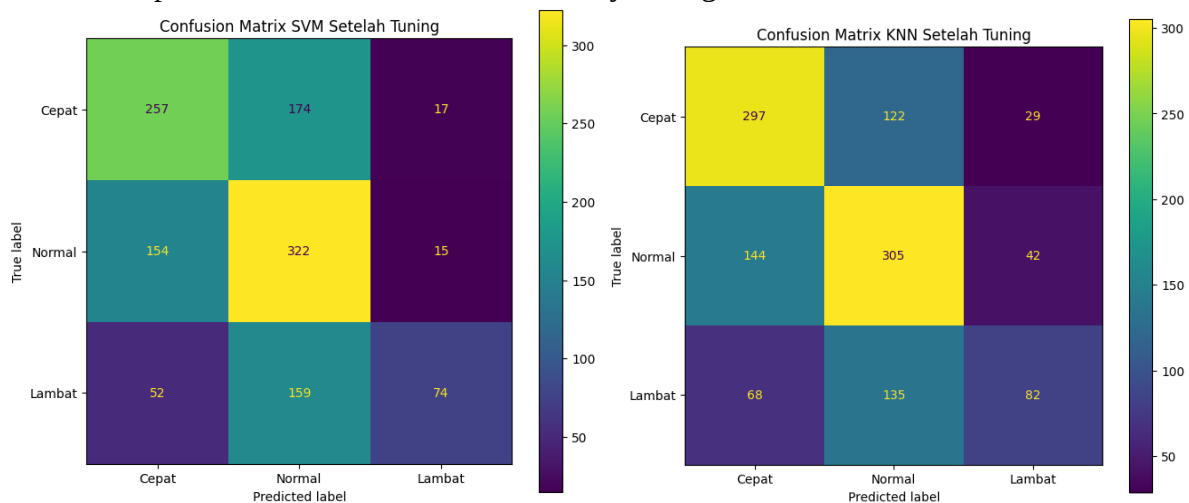


Figure 2. Confusion Matrix of SVM Tuned and KNN Tuned

For SVM Tuned, 257 Fast cases were correctly classified, while 174 Fast cases were classified as Normal. In the Normal category, 322 cases were correctly classified. Meanwhile, of the 285 cases that actually belonged to the Slow category, only 74 were correctly identified as Slow. A total of 159 Slow cases were instead classified as Normal.

For KNN Tuned, 297 Fast cases were correctly classified, and 305 Normal cases were correctly classified. For the Slow category, KNN correctly identified 82 cases. This number was higher than that of SVM, which correctly identified only 74 cases. In addition, the number of Slow cases classified as Normal decreased from 159 with SVM to 135 with KNN. These findings indicate that the improvement in KNN performance was not only reflected in overall accuracy but also in several aspects of class-level classification. KNN increased the number of correct predictions in the Fast and Slow categories. However, both algorithms still exhibited the same weakness, namely a tendency to classify Slow cases as Normal.

Overall, the results of this study show that KNN Tuned achieved the highest overall performance among the models evaluated on the study dataset, with an accuracy of 55.88%, precision of 55.40%, recall of 52.39%, and F1-Score of 52.48%. Nevertheless, these results indicate that classifying case resolution duration remains a relatively complex task. The features used in this study were not yet fully capable of distinguishing cases with longer resolution durations.

The low recall for the Slow class is an important finding of this study. Most cases that were actually Slow were instead predicted as Normal. This indicates that case resolution duration may not be associated only with the registration year, month, registration day, case type, and attendance, but may also be influenced by other factors that were not included as features. Therefore, future research may consider adding features that more directly represent the complexity of the case resolution process.

Conclusion

This study compared the performance of Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms in classifying case resolution duration at Religious Courts into three categories: Fast, Normal, and Slow. Based on the evaluation results, KNN after hyperparameter tuning achieved an accuracy of 55.88%, precision of 55.40%, recall of 52.39%, and F1-Score of 52.48%, while SVM Tuned achieved an accuracy of 53.35%, precision of 58.16%, recall of 49.64%, and F1-Score of 50.16%.

Overall, KNN Tuned achieved higher performance in terms of accuracy, recall, and F1-Score, although SVM Tuned achieved higher precision. Both algorithms still experienced difficulties in identifying the Slow category, as indicated by recall values of 25.96% for SVM Tuned and 28.77% for KNN Tuned. These results indicate that KNN Tuned was more suitable for classifying case resolution duration on the evaluated dataset; however, further feature development and improvements to the classification methods are still needed to achieve better performance.

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