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Classification metrics for pet adoption prediction with machine learning

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ABSTRACT

Millions of pets are temporarily placed in shelters, making it challenging for shelters to ensure pets find permanent homes. High adoption rates are crucial for animal welfare and the sustainability of shelter operations. This study aims to identify key factors influencing pet adoption and create classification metrics using five machine learning (ML) classification model approaches to predict the likelihood of pet adoption, to find the best model performance for each analysis. The dataset was obtained from several features related to animal characteristics and adoption conditions. The results of the study present classification of metric models that indicate decision tree and random forest (RF) as the most effective models with superior performance in terms of accuracy and class separation ability. Further research provides initial exploration of ML models that are not only limited to classification models but also model integration into internet of things (IoT) systems for the implementation of a pet adoption prediction system based on ML inference. The implementation of ML classification models helps improve the efficiency of animal adoption programs and optimize shelter operations, ultimately increasing the chances of successful pet adoption. The results of the study provide insights into factors influencing pet adoption, minimizing the length of stay (LOS) in shelters, and contribute to practitioners/ researchers as a reference for exploring new related factors and exploring the performance of ML models, especially classification models.

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1. INTRODUCTION

Animal adoption is a procedure carried out by humans to keep animals, especially the most common ones such as cats and dogs, but currently many also keep other pets. One of the ways to control animals is by taking lost or abandoned animals and placing them in animal shelters [1]. Statistical information on pets in a study conducted by [2] provides information that each year, approximately 6.5 million pets end up in animal shelters. These animals are temporarily housed in various locations, such as animal shelters, rescue group shelters, or wildlife sanctuaries. The study also revealed that of the 6.5 million animals in shelters, only about 4 million are adopted in an average year, resulting in more animals in shelters. Liu and Meng [3] stated that the increasing number of abandoned animals not only affects animals in nature but also human life. Currently, animal rescue by the community is still in its early stages, there are a series of problems such as limited rescue locations, remote rescue locations, and high investment demand. Adopting animals has a more realistic and profound meaning when you have experienced life with pets. Adopting animals increases public awareness of caring for animals. Adopting pets can also help children develop awareness to protect animals, have a sense of compassion, and help to further appreciate the charm of nature and protect nature. Animal shelters face challenges in ensuring that pets find permanent and loving homes.

High adoption rates are critical not only for animal welfare but also for the sustainability of shelter operations. Understanding the factors that influence adoption likelihood can help shelters optimize shelter operations, target resources more effectively, and ultimately improve adoption outcomes. By predicting pet adoption likelihood and identifying key factors, shelters can better support and increase the chances of successful adoption.

Several studies have been conducted on observing and identifying characteristics that influence pet adoption prediction. Diesel *et al.* [4] revealed that the adoption rate of dogs in the UK can be predicted by the breed and size of the dog as well as several other factors and provides factors that influence the success of dog shelters in the UK. Another study by [5] showed that the cat's activity level was a key factor in adoption rates. A subsequent study was conducted by [6] who looked at two animal shelters in New York State and revealed that age, breed, and size had a significant effect on a dog's length of stay (LOS). A follow-up study was conducted by [7] who also looked at shelters in the Czech Republic and revealed that lower LOS was associated with small, young, and female dogs. An American study [8] showed that behavioral factors, such as friendliness toward adopters and a happy cat can make an animal desirable to adopt. The next study conducted by [9] showed factors that help minimize the length of time animals stay in shelters and found several pet characteristics such as age, color, and size that affect adoption rates. A recent study by [10], [11] revealed that not only do physical characteristics play an important role but the language used in pet adoption advertisements is also a factor in the LOS and adoption. Even a recent study by [1] developed a pet adoption system based on artificial intelligence (AI). A recent study by [12] developed a predictive model with textual gradient enhancement and applied data mining techniques to predict adoption rates. Although previous studies have made major contributions, each study focuses on certain factors, so further exploration of the factors that influence the likelihood of pet adoption is needed to explore more widely the model/method to predict the likelihood of pet adoption by utilizing machine learning (ML). ML itself has been proven useful in previous studies by [13] for predicting animal behavior.

In this regard, to fill the existing gap, this study aims to create a classification metric for predicting the likelihood of pet adoption based on the identification of potentially influential factors by utilizing ML. Classification metrics are carried out as an evaluation of the performance of the classification model in ML. ML consists of efficient model design and accurate prediction algorithms. More specifically, ML algorithms are used to detect classification and prediction patterns from big data and develop models to predict future outcomes [14]. The use of ML in this pet adoption prediction study is due to the involvement of many factors that influence pet adoption while ML can handle many variables and has high predictive capabilities which ultimately support strategic decision making in increasing pet adoption rates. Classification is one of the ML tasks to categorize input data into specific object classes. Some ML and data mining algorithms for classification and prediction include logistic regression (LR), decision trees (DT), random forest (RF), support vector machine (SVM)/support vector classifier (SVC), and naïve Bayes (NB).

Based on the existing explanation, this study evaluates the performance of the classification model in ML by creating a classification metric to predict the likelihood of pet adoption and identifying the main factors that influence pet adoption. This study contributes to providing insight into the factors that influence pet adoption and helps minimize the length of time animals stay in shelters and contributes to practitioners/researchers as a reference to explore new factors related to pet adoption and exploration of ML models for knowledge of ML model performance, especially classification models.

2. RESEARCH METHOD

The steps in this study can be seen in Figure 1, which begins with dataset collection and pre-processing, exploratory data analysis (EDA), feature engineering, ML models, evaluation, and visualization. Classification metric analysis uses 5 (five) classification models, namely LR, DT, RF, SVM, and NB to produce prediction output. The predictions result of the five models are validated and evaluated using measurement methods to measure the performance of the five classification models by displaying evaluation metrics of accuracy, precision, recall, F1-score, and confusion matrix as well as receiver operating characteristic (ROC) and area under the curve (AUC) for each model to evaluate the trade-off between positive and negative classes so that the significance of the five classification models can be concluded. This study uses observations at known animal shelters and utilizes the pet adoption dataset at https://www.kaggle.com, which provides comprehensive information about pets available for adoption and includes a variety of characteristics and attributes to build a predictive model of the likelihood of pet adoption. There are 11 (eleven) features used in the dataset.

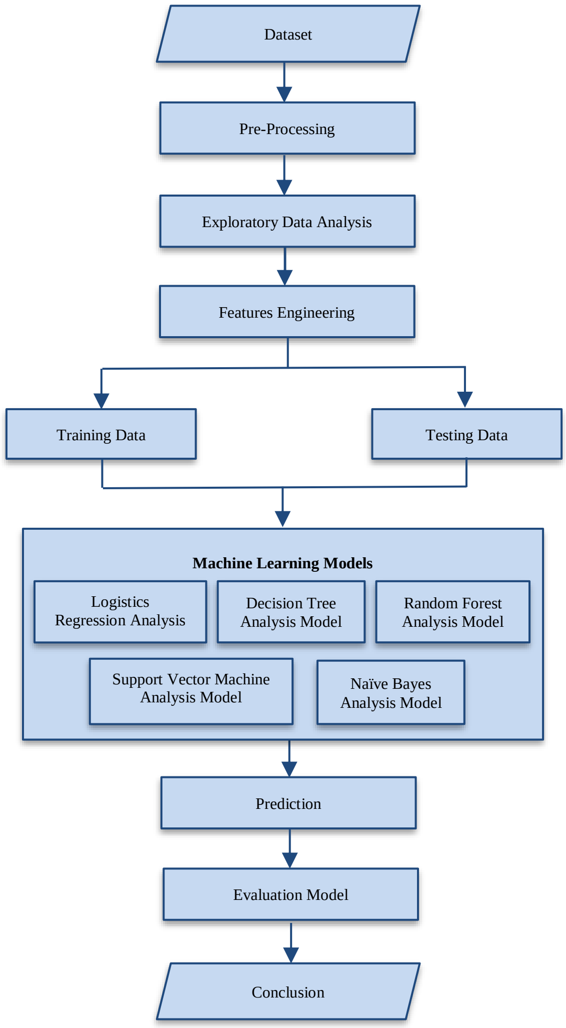

Figure 1. Research flowchart

2.1. Data loading and pre-processing

This stage involves loading the dataset and pre-processing the data as an initial step for further analysis. Dataset loading is done by importing the data into the program, while preprocessing is performed as a data cleaning step to investigate missing values in the dataset and handle them. Preprocessing is also performed to identify categorical data that needs to be converted into numeric form so it can be used and processed in a ML model.

2.2. Exploratory data analysis

This stage involves data exploration and visualization to understand the features and distribution of features in the dataset. EDA is used as an approach to analyze the dataset so that it is easy to understand the structure and pattern of the data before applying the ML model. Descriptive statistics of the features in the dataset are presented in Table 1, meanwhile Figure 2 presents the visualization of the distribution of the features.

Based on Table 1 descriptive statistics can be understood the distribution and central tendency of various attributes related to pets in shelters, for example, the AgeMonths feature produces an average value of 92.63 months (±7.7 years) with a standard deviation of 51.53 months (±4.3 years) ranging from 1 (min) to 179 (max) months (±15 years). The data quartiles show the first quartile/Q1 (25%) 49 months which means 25% of pets are less than or equal to 49 months old, the median or second quartile/Q2 (50%) 93 months which means 50% of pets are less than or equal to 93 months old, and the third quartile/Q3 (75%) 138 months which means 75% of pets are less than or equal to 138 months old. Likewise for the values in other features according to Table 1.

Table 1. Descriptive statistics of features in the dataset

	AgeMonths	WeightKg	Vaccinated	HealthCondition	TimeInShelterDays	AdoptionFee	PreviousOwner
Count	2007	2007	2007	2007	2007	2007	2007
Mean	92.63	15.7	0.71	0.2	44.82	251.69	0.31
Standard deviation	51.53	8.44	0.45	0.4	25.68	144.55	0.46
Min	1	1.04	0	0	1	0	0
25%	49	8.66	0	0	22	129.5	0
50%	93	15.75	1	0	45	250	0
75%	138	23.14	1	0	67	374	1
Max	179	29.99	1	1	89	499	1

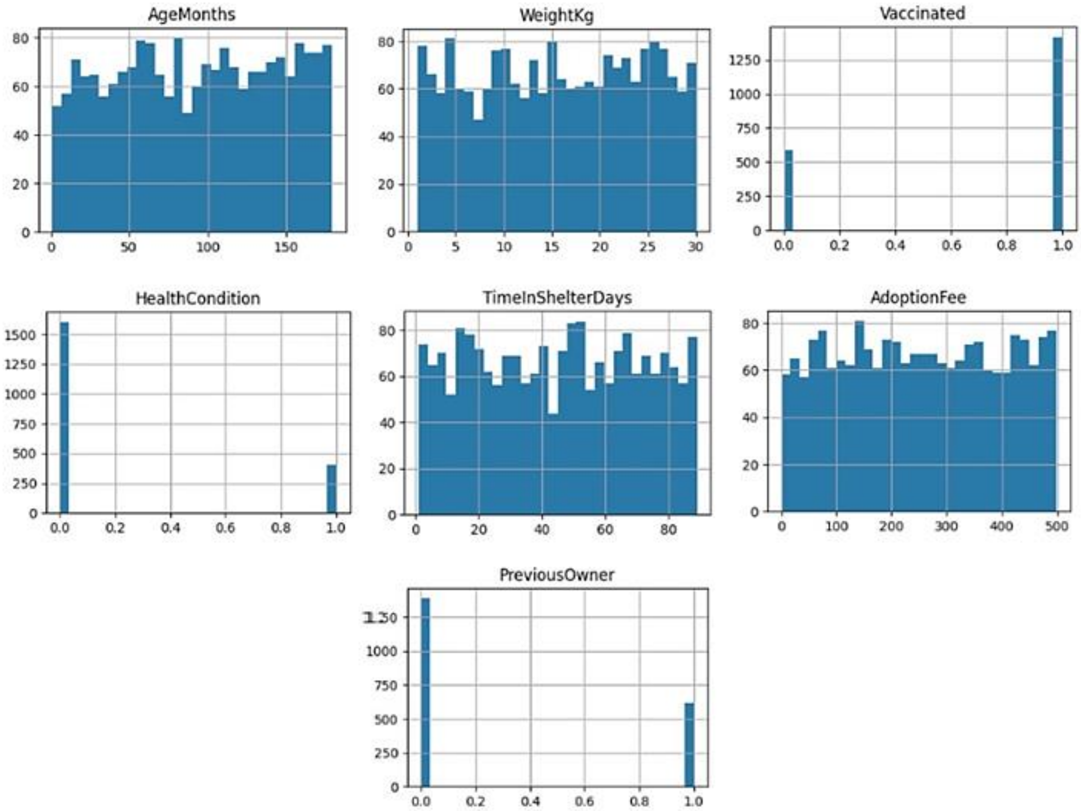

Figure 2. Distribution of features in the dataset

2.3. Feature engineering

This stage involves selecting and creating relevant features from the existing data to improve the performance of the ML model. This stage is done by separating the data into features (x) and targets (y) and dividing the data into a training set and a test set for model evaluation. Kurniasari *et al.* [15] revealed that the general data-sharing rate is 80% for training and 20% for testing and there is no definite rule regarding the optimal rational ratio for each dataset in data sharing. In some studies, some suggest a test set size between 25% and 50% [16], and some recommend a test set size of 50% [17]. However, extensive numerical studies show that the optimal test data ratio is about 30% [18]–[20]. The data distribution in the study was done by dividing it into 70% for training and 30% for testing. Training data is used to identify patterns and relationships between features and labels while test data is used to test the performance of the ML model after the training process.

2.4. Machine learning models

This stage involves selecting, training, and implementing a ML model to predict the likelihood of pet adoption based on identified features. This stage is carried out by initializing the model where in this study 5 (five) classification models are used, training the model with training data and making predictions using the trained model to make predictions on the test data. The five classification models used are LR, DT, RF, SVM, and NB.

2.5. Model evaluation

This stage involves evaluating model performance using evaluation metrics to determine the model's performance in predicting the likelihood of pet adoption. Classification model evaluation is a crucial stage in the ML model development and evaluation process. Model performance is measured through validation and evaluation processes. Validation and evaluation are used as measuring tools to determine how well the model performs in making predictions, thus revealing significant differences. Model performance is analyzed and evaluated through various measures generated from the confusion matrix. The confusion matrix results are obtained after the classification process is trained on the validation set to identify which classes are confusing the classification and then a more specific classification structure can be created [21]–[23]. As a representation of the results of the classification process, there are four values: true positive (TP), true negative (TN), false positive (FP), and false negative (FN) [24]. TP is the number of positive data correctly obtained, while the TN value is the number of negative data correctly collected. The model confusion matrix can be seen in Table 2 [25].

Table 2. Confusion matrix model

Class	Predicted as positive (+)	Predicted as negative (-)
Positive (+)	TP	FN
Negative (-)	FP	TN

Other evaluation metrics used for validation are accuracy, which describes how accurately the model makes correct predictions; precision, which describes how accurately the model identifies the positive class; recall, which describes how accurately the model identifies all TP classes; F1-score, which examines the balance between precision and recall; and ROC and AUC to measure the model's performance in classifying positive and negative classes. At this stage, the most influential features in the ML classification model are also identified. The formula for each evaluation metric used is represented in (1)-(4).

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

$$F1 - score = \frac{2\ x\ (Recall\ x\ Precision)}{Recall+Precision} \quad (4)$$

2.6. Model visualization

This stage involves visualizing the model results to understand and present the model performance intuitively.

3. RESULTS AND DISCUSSION

3.1. Analysis and results

Five classification models were used as an approach to determine the model that performed best in classifying the likelihood of pet adoption predictions. The five classification models used for comparison in this study were LR, DT, RF, SVM, and NB to produce prediction output. The five models were trained and tested based on the data division of 70% for training and 30% for testing. After training and testing data prediction, the decision tree model was considered more effective in determining classification with a higher accuracy value than the other 4 (four) classification models. Table 3 presents details of the performance results of the five ML classification models.

In general, the five ML classification models have achieved good accuracy results with scores above 80%. The decision tree and RF classification models have almost the same performance in achieving accuracy as the performance of algorithms that use a tree-based paradigm in building classification models. Figure 3 displays a visualization of feature importances that inform the factors that most influence animal adoption.

Table 3. Classification model performance results

Classification model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LR	90.5	94.5	76.5	84.6
DT	95.4	94	92.16	93.1
RF	95	95.8	89.2	92.4
SVM	90.5	95.1	76	84.5
NB	87.9	84.3	78.9	81.5

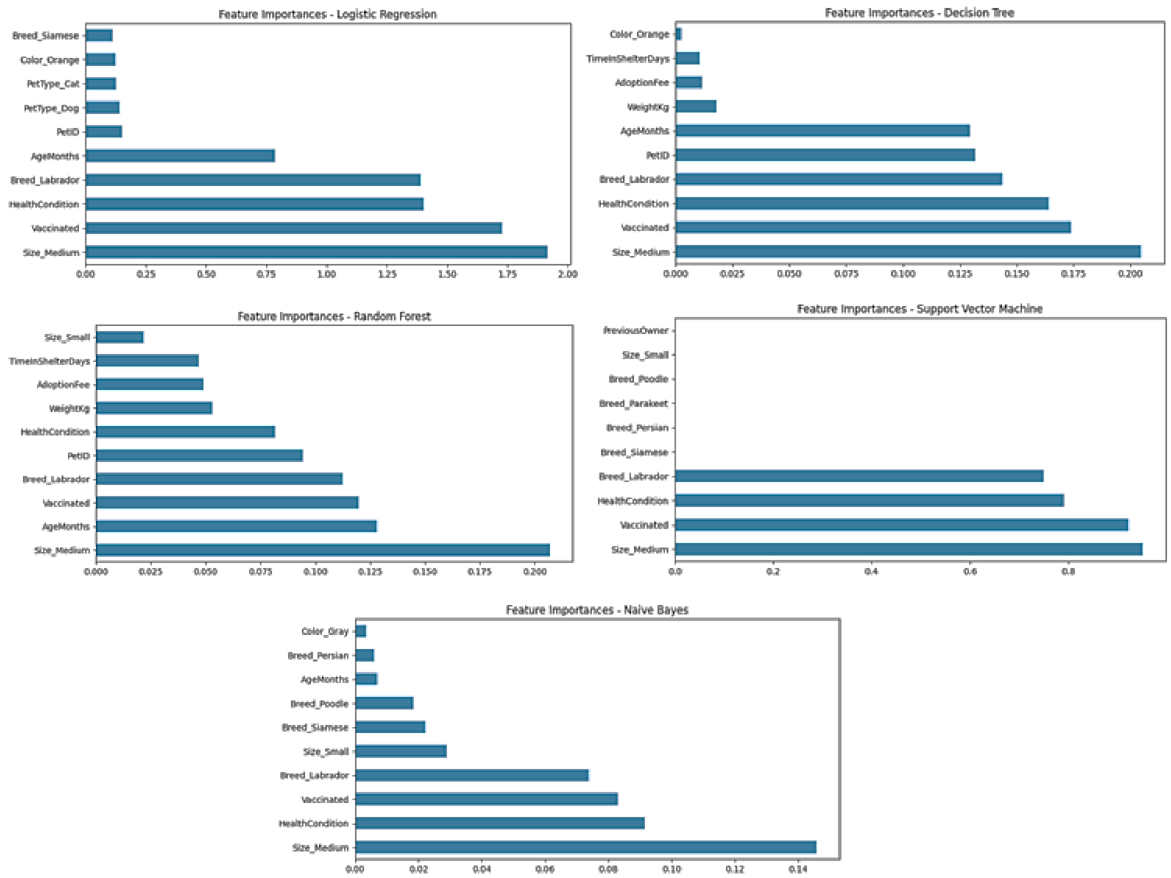

Figure 3. Feature importance of each classification model

From Figure 3, it can be understood which attributes are most influential in making predictions. The DT and RF models are models that directly support feature importances, while the LR, SVM, and NB models are models that do not directly support feature importances but use model coefficients as a proxy for feature importances. In the diagram in Figure 3, the y-axis shows the features, and the x-axis shows the relative importance of the features. The feature with the highest value in the diagram shows that the feature makes the greatest contribution and is considered more important in influencing predictions. Based on Figure 3, the AgeMonths, WeightKg, and TimeInShelterDays factors are the most important and influential features in predicting pet adoption in the DT and RF models as the models identified with the best model performance. From these results, areas of improvement can be identified to increase adoption rates, such as the need to focus on animal health conditions, completeness of animal vaccinations, and duration in shelters.

The confusion matrix for each pet adoption class is shown in Figure 4, which is generated from each machine-learning classification model. Figure 4 visualizes the results of the confusion matrix as an evaluation tool to determine the performance of the classification model. The confusion matrix provides information on the number of correct and incorrect predictions. When viewed in Figure 3, it provides an analysis that the DT and RF models provide the best performance in terms of accuracy and minimal number of errors, thus showing a strong ability to predict classes correctly. LR and SVM also have good performance but slightly more errors than the tree-based model. While NB has the lowest performance among all models with a higher number of errors.

The final evaluation metric used to validate the model performance was tested using ROC and AUC in classifying positive and negative classes. ROC AUC measures the performance of the model in classifying positive and negative classes. ROC AUC has a range of values between 0 and 1, with 1 indicating perfect performance. ROC AUC provides an overall performance of the classification model at various classification thresholds and has stability that is not too influenced by the distribution of classes in the data, making it a more stable measure than other metrics such as accuracy and facilitating comparison of the performance of various classification models. The visualization of the ROC AUC curve of the five classification models can be seen in Figure 5.

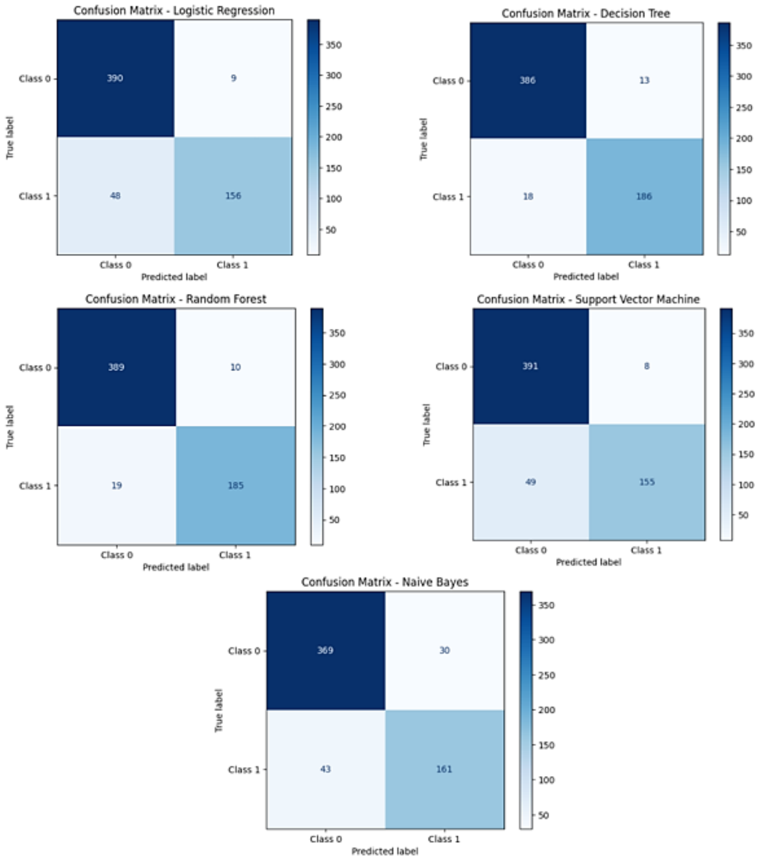

Figure 4. Confusion matrix of each classification model

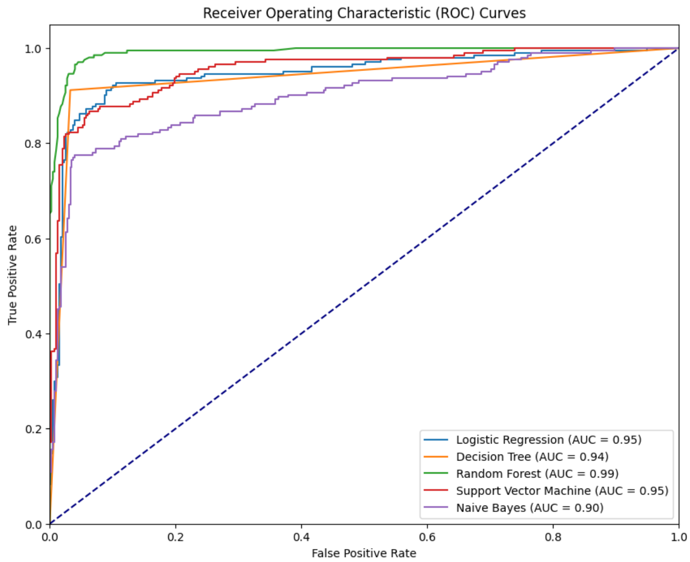

Figure 5. ROC AUC curve

The ROC curve in Figure 5 provides information that RF has an AUC value of 0.99 which is close to 1, thus indicating a very extraordinary performance and the best model in separating classes based on the ROC curve shown is almost close to a perfect model. LR and SVM have AUC values of 0.95 which indicate strong performance and are equivalent to high AUC and good and effective predictive ability in separating classes. DT also shows strong performance with an AUC value of 0.94 which is slightly lower than LR and SVM, but this difference is quite small, and the DT model still has good predictive ability, while NB has slightly lower performance than other models with a lower AUC value of 0.90. However, the NB model is still quite good at separating classes but is not as accurate as other models.

The conclusion that can be given in the research results is given in the visualization of the comparison results of the five classification models that have been tested and evaluated and shows the proportion of predictions which can be seen in Figure 6. Figure 6 provides a visualization of the accuracy results that have been presented in Table 3. This visualization also serves as an explanation of the prediction and evaluation results that have been carried out on the five ML classification models where in general the five ML classification models have achieved good accuracy results with scores above 80%, but the DT and RF models have performance that tends to be the same and is the best in achieving accuracy with the performance of the algorithm that uses the tree-based model in building the classification model compared to the other three models.

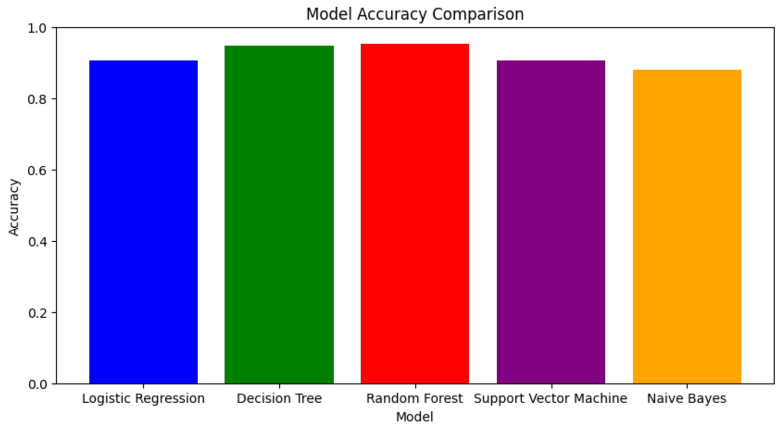

Figure 6. Model comparison

3.2. Discussion and future research

The previous stage has provided the results of the analysis of the five classification models that have been tested and evaluated to provide a proportion of pet adoption predictions. Of the five classification models, they provide good accuracy results with a score of more than 80%, although of course there is the best model with the highest accuracy performance. In order to improve the usefulness of the pet adoption prediction model, this system can be integrated into the internet of things (IoT) architecture. The IoT-based monitoring system allows the collection of animal behavior data in real time through various sensors, such as cameras, motion sensors, accelerometers, and temperature or heart rate sensors. The data is then sent via a wireless connection to a server or edge device to be analyzed using a ML classification model. This integration allows automatic detection of behavioral changes, analysis of adoption trends over time, and provides data-based insights to pet shelter managers. In implementing a pet adoption prediction system, two main approaches can be used to run ML model inference, namely cloud-based and edge-based, although both approaches have their own advantages and limitations. However, in the context of animal shelters, edge-based inference is more suitable for locations with limited internet connectivity and improves data security and system responsiveness. Figure 7 illustrates the flow diagram/architecture of IoT integration with ML inference for monitoring and predicting pet adoption with edge and cloud approaches.

Based on Figure 7, it can be illustrated that IoT integration with ML inference begins with data collection through various sensors which are then pre-processed, and initial ML inference is carried out on edge devices using field programmable gate array (FPGA). The results of the process are sent via the network and stored in cloud storage for the advanced ML model training process. The results of the analysis and prediction are sent back to the edge devices to update the ML model and improve accuracy.

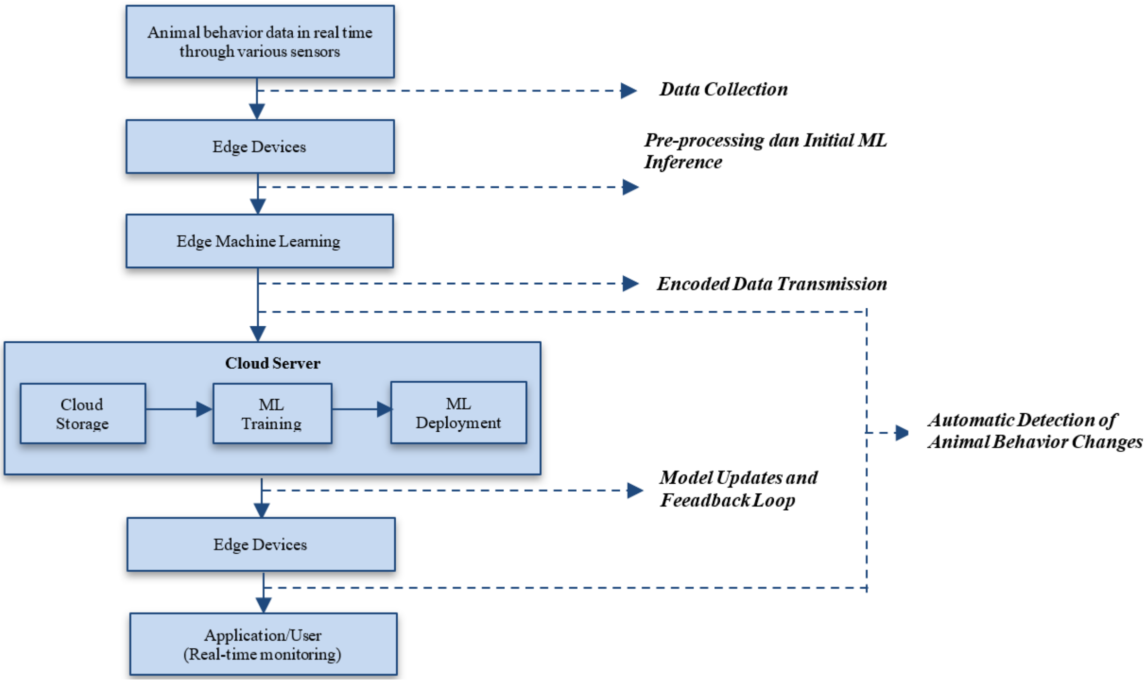

Figure 7. Architecture diagram of pet adoption prediction with IoT integration and ML inference

4. CONCLUSION

Based on a comprehensive evaluation of several classification models for pet adoption prediction, it can be concluded that the DT and RF models are the most effective models to use in this context. Both models not only show very high accuracy but also a good balance between precision and recall and a near-perfect AUC value. This shows that both models are more reliable in balancing the ability to recognize animals that are truly potentially adoptable while minimizing prediction errors. The LR and SVM models also provide adequate performance and can be considered reliable alternatives. However, the NB model, although simpler and faster, shows less optimal performance compared to other models in terms of accuracy, recall, and AUC. Considering the results of this analysis, the selection of the optimal model is highly dependent on the specific objectives and desired performance criteria. The resulting classification metrics can provide a comprehensive evaluation of model performance in predicting pet adoption and identify potential/main factors that influence predicting pet adoption with the use of ML. The practical implication is that the DT and RF models can be used by shelters or adoption organizations to prioritize animals with a low likelihood of immediate adoption, allowing them to receive specialized interventions such as more intensive promotion or behavioral training programs. Thus, implementing these models can help increase adoption success rates while optimizing shelter resources. Further research can be done by conducting a broader exploration of other ML models that are not limited to classification models as well as the integration of prediction models into IoT systems for pet adoption monitoring and the implementation of a pet adoption prediction system based on ML inference.

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