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Comparative Analysis of Tail Tip and Hip Based Features for Dog Tail Wag Classification with Depth Cameras and Support Vector Machines

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Abstract. Understanding dogs' emotional patterns through their tail movement is key to strengthening the human-canine bond and improving their well-being. This study presents an innovative approach to identify the direction of tail movement (either left or right), using the dog's hip as the primary reference point. Through a preprocessing and feature extraction process, a Support Vector Machine (SVM) classifier was trained with spatial data from the hip and compared to a classifier from a previous study. The results indicate that the classifier trained with hip data achieved a 99% score in accuracy, precision, and F1-score metrics. Additionally, the Friedman test was performed to verify whether there are statistically significant differences between the two classifiers.
Keywords: Tail Tip, Hip, Tail Wagging, Support Vector Machines

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1 Introduction

The relationship between dogs and humans is based on the interpretation of non-verbal signals, with tail movement being a crucial element for understanding emotions and intentions (Ferretti & Papaleo, 2019; Pike, 2018). The direction in which the tail moves can reflect different emotional states: movement to the right is generally associated with positive feelings, while movement to the left may suggest negative emotions (Leonetti et al., 2024). Accurately recognizing these signals is essential for promoting animal welfare and strengthening the bond between dogs and people.

Thanks to recent advances in artificial intelligence, particularly in the field of machine learning, it is now possible to identify and classify dog emotions by observing their body posture, including tail movement (Raman et al., 2022). Through machine learning algorithms, images or videos can be analyzed to detect tail movement patterns that relate to various emotional states (Ren et al., 2022; Hernández-Luquin et al., 2022). This technological approach provides a more objective and accurate interpretation of canine emotions, which is beneficial for pet owners, trainers, and animal care professionals. Furthermore, it allows for a deeper understanding of dogs' emotional needs and facilitates early interventions in cases of behavioral or welfare issues.

In a previous study, a classifier using Support Vector Machines (SVM) was developed to identify tail movements, using the tip of the tail as a reference point (Greene et al., in press; Muller, 2016). This new study proposes a different approach: processing spatial data from the dog's body, focusing on the hip, and comparing it with the tip-of-the-tail method. The goal is to develop machine learning models capable of more accurately detecting whether the tail is moving to the right or to the left.

This work is organized into sections: first, a theoretical framework on canine communication and artificial intelligence is presented; then, a review of the literature related to tail movement analysis using machine learning techniques is provided. The methodology section describes the data preprocessing steps, 3D-to-2D transformation, feature extraction, labeling, and the selection and configuration of classifiers. Next, the evaluation procedure is detailed, followed by the results obtained, the analysis and discussion of the findings, and finally, the conclusions on the effectiveness of the proposed approach.

2 Theoretical Framework

Canine communication is expressed through a variety of meaningful behaviors and gestures directed toward both other dogs and humans. These signals, which are usually physical, include postures, gazes, and specific movements that reflect the animal's emotional state (Ferretti & Papaleo, 2019).

Among these behaviors, tail movement stands out as one of the most representative elements of canine emotional expression. Its interpretation varies depending on the context and interaction, with the direction and angle of the movement being key factors in understanding its meaning. For instance, movement to the right is generally associated with positive emotions, while movement to the left may indicate negative responses such as anxiety or fear (Quaranta et al., 2007; Leonetti et al., 2024).

In this regard, artificial intelligence (AI) opens new possibilities for analyzing animal behavior. This field, which is part of computer science, focuses on developing systems capable of performing tasks that would normally require human intelligence (Bartneck et al., 2021). Within this domain, machine learning enables machines to carry out specific tasks by using algorithms and repeated exposure to examples, thereby improving their performance over time (Muller, 2016).

3 Previous Work

In recent years, behavioral analysis has emerged as a valuable tool for understanding dog emotions. This topic has been the subject of numerous studies focusing on how dogs behave during their interactions with humans and other dogs (Nagy & Korondi, 2022; Heath, 2027). Through these investigations, several emotional indicators have been identified, such as ear position, facial expressions, and, most notably, tail movement.

Multiple studies have shown that the direction in which the tail moves is closely linked to the dog's emotional state. For instance, one study found that rightward tail movement generally indicates positive emotions, such as joy when reuniting with the owner (Leonetti et al., 2024). In contrast, leftward movement is often associated with negative reactions, such as fear or aversion in response to unfamiliar or threatening situations (Ruge et al., 2018; Quaranta et al., 2007). These findings have led to the development of machine learning models aimed at classifying tail movements as indicators of emotional states.

One example is a study that proposed an intelligent system based on computer vision using a GoPro camera to record dog actions (Ehsani et al., 2018). Although the approach focused on visual input, inertial measurement units (IMUs) were also integrated to collect angular data from different parts of the body, facilitating the modeling of movements in specific time intervals.

Another study focused on tail movement during social interactions (Ren et al., 2022). The researchers developed a platform using deep learning-based motion tracking techniques to monitor the trajectory of the tail tip, hip, back, and neck. The results showed that rightward movements increased over several days of interaction, which was interpreted as a sign of growing social familiarity.

In a different line of research, 3D body reconstruction technology and deep learning-based point detection were used to investigate how caregiver separation affects dog behavior in unfamiliar environments (Völter et al., 2023). The study found that the presence of strangers reduced rightward tail movement, supporting the idea that both caregivers and unfamiliar individuals influence the dog's emotional response.

More recently, research has examined the use of the tail tip as a reference point to detect movement patterns (Greene et al., in press). In that study, various classifiers were tested, including SVM, CNN, K-NN, logistic regression, and random forests, with SVM achieving the best performance.

Despite significant progress, most existing studies depend on external or peripheral body points, which makes movement estimation sensitive to occlusions, perspective variations, and lighting conditions. To address this limitation, the present study introduces the hip as an internal spatial reference for analyzing tail movement direction. Unlike previous methods, this approach minimizes environmental dependence and leverages an anatomically stable point to achieve more robust and consistent classification of rightward and leftward tail motion. Moreover, this work aims to establish a methodology that is both computationally efficient and generalizable across different conditions.

4 Methodology

To develop a classifier capable of identifying tail movement using spatial data from the hip, we have designed a methodology inspired by our previous work. This approach focuses on the collection and analysis of spatial data from the hip, allowing us to accurately identify the type of movement performed by the dog. The methodology includes several activities, as illustrated in Figure 1.

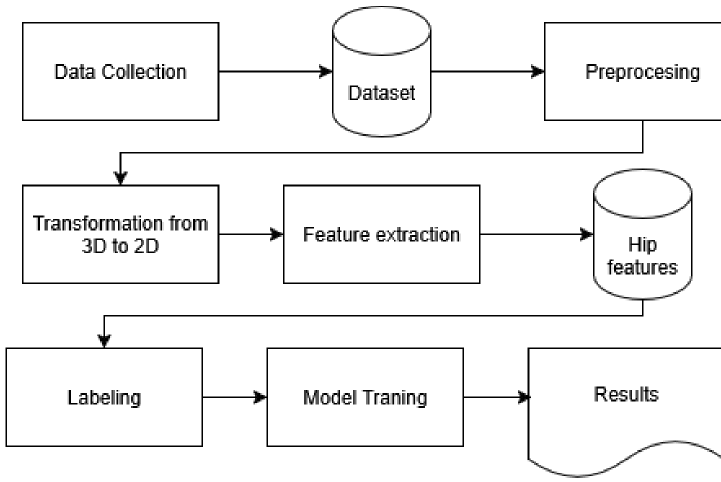

Figure 1. Flowchart of the methodology.

4.1 Data Collection

In the first activity, a review of previous studies on dog behavior in different contexts was conducted. These studies provided detailed spatial data obtained through three-dimensional markers placed on the nape, hip, and tip of the tail of the animals. The information was collected in controlled environments where the dogs interacted with humans, other dogs, or objects of interest. After the analysis, two datasets that met these criteria were identified and compiled: one from the work by Ren et al. and another from the study by Völter et al. (2023). The characteristics of both datasets are presented in Table 1.

Table 1. Markers from the Ren and Völter databases (Ren et al. 2022, Völter et al. 2023)

Databases	(Ren et al., 2022)	(Völter et al., 2023)
Markers	Tip of the tail Hips Back Neck	Tip of tail Base of tail Hip Neck Right ear Left ear Center of head Snout
Dog breed	Beagles	Various breeds
Number of dogs	10	37
Number of females	5	19
Number of males	5	18
Age of dogs	1 to 2 years	Approximately 75 months
Number of frames	1,340,754	352,531
Frames per second	150 frames/s	24 frames/s

4.2 Preprocessing

A preprocessing process was carried out on the two obtained datasets, which included the removal of incomplete, null, or outlier data. This was done to ensure the quality and reliability of the information to be used in the analysis. Then, the data was normalized to a scale of -1 to 1 (Equation 1), with the aim of unifying the range of features and preventing those with larger values from having a disproportionate impact on the machine learning models, which could lead to undesired biases (Patro & Sahu, 2015).

$$x_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

4.3 Transformation from 3D to 2D

A 3D-to-2D transformation was performed for each marker located on the selected areas of the dog's body (tail tip, hip, and nape), with the aim of obtaining a top-down (overhead) perspective. This projection facilitated the calculation of the angles formed at the hip in relation to the tail tip and the nape, which later enabled the extraction of relevant features.

To carry out this transformation, the OpenCV library was used (OpenCV, 2021), which includes a function based on the pinhole camera model (Stunm, 2024). Using this model, each three-dimensional position of the markers in the scene (P_w) was projected onto the image plane through a perspective transformation, resulting in the corresponding two-dimensional coordinates (p). Both P_w and p were represented in homogeneous coordinates, as 3D and 2D vectors, respectively. Equation 2 describes this transformation, where R and t represent rotation and translation, s is an arbitrary scaling factor, and A is the intrinsic matrix of the camera.

$$sp = A[R|t]P_w \tag{2}$$

4.4 Feature Extraction

The following section describes the complete feature extraction process used in this study. First, the data were segmented into 2-second time windows with an overlap of 0.3 seconds (Ren et al., 2022). This segmentation technique helps create more compact representations of the original data while preserving their most important discriminative characteristics.

For each of these time windows, several features were calculated for each marker and for each axis (x and y): the mean, standard deviation, maximum value, and the correlation between the two axes. The magnitude of the movement was also computed (Equation 3), defined as the distance from the marker to the origin in the plane (Freilich, 1997). From this magnitude, additional features were extracted, including the mean, standard deviation, the area under the curve (AUC), as shown in Equation 4, and the mean differences between consecutive values, as detailed in Equation 5 (García et al., 2018). Here, x_f and y_f represent the marker data at frame f, and F is the last frame of the window interval.

In addition, the distance traveled by each marker during the time window was computed, along with the mean, standard deviation, and maximum value of its velocity, which was calculated using the Savitzky-Golay filter (Sleap, 2021; Schafer, 2011).

Finally, the angles formed at the hip, in relation to the tip of the tail and the nape, were calculated, as illustrated in Figure 2. These angles were defined so that a positive value indicates a rightward movement, while a negative value indicates a leftward movement. Based on this information, angular features were extracted, such as the mean, standard deviation, minimum, and maximum angle, as well as the angular velocity and angular amplitude, which are described in Equations 6 and 7. These equations detail the dynamics of the tail's trajectory (Ren et al., 2022). Here, θ_i and θ_j represent consecutive angles, and t_i and t_j are the corresponding timestamps. This set of features allowed for a more precise capture of the dog's movements in each time segment, providing valuable information for the subsequent classification models.

$$Magitude(x, y, f) = \sqrt{x_f^2 + y_f^2} \tag{3}$$

$$AUC = \sum_{f=1}^{F} Magitude(x, y, f) \tag{4}$$

$$meandif = \frac{1}{F-1}\sum_{f=2}^{F} Magitude(x, y, f) - Magitude(x, y, f-1) \tag{5}$$

$$v = \frac{\theta_i - \theta_j}{t_i - t_j} \tag{6}$$

$$amplitude = |\theta_i - \theta_j| \tag{7}$$

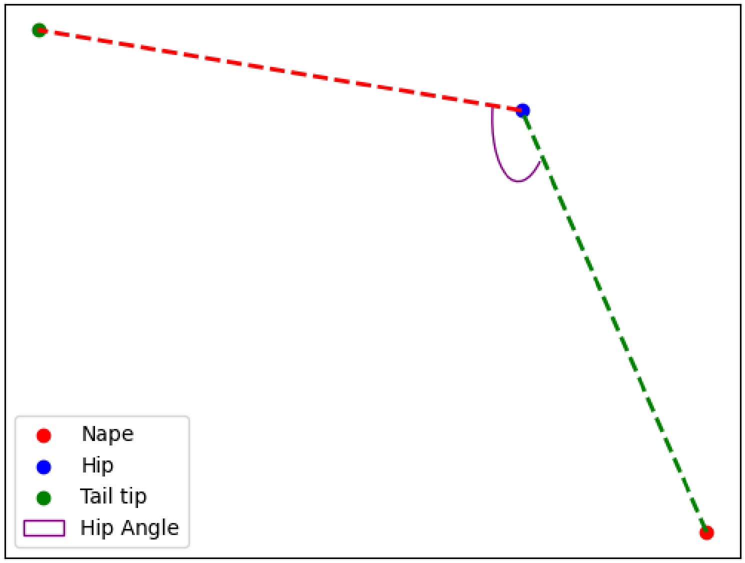

Figure 2. Tail tip, hip and neck markers with their respective angles.

4.5 Labeling

The feature extraction process allowed us to identify two clusters within the data, each associated with a specific type of movement. This can be clearly observed in Figures 3 and 4, through the use of Principal Component Analysis (PCA) applied to the features extracted from both datasets. Based on this analysis, we proceeded to the labeling phase. For this, we adopted an approach using the K-means algorithm on the extracted features to identify and classify tail movements to the left and to the right (Ehsani et al., 2018).

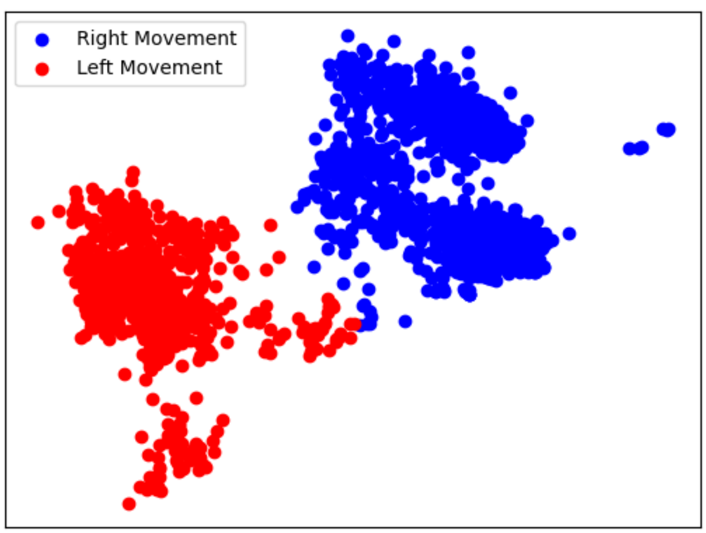

Figure 3. Characteristics of the Ren database (Ren et al., 2022) reduced in 2 dimensions using principal component analysis (PCA).

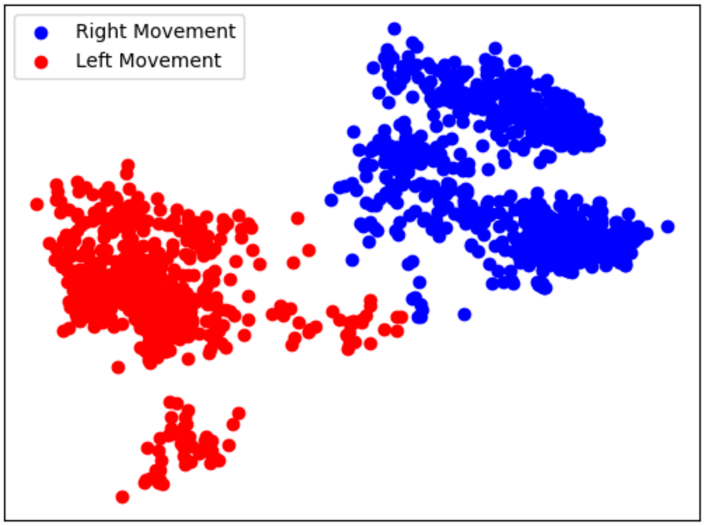

Figure 4. Characteristics of the Völter (Völter et al., 2023) database reduced in 2 dimensions using principal component analysis (PCA).

4.6 Classifier Training

To train a perceptron classifier using only the hip data, the process began with the application of an undersampling technique (Muller, 2016) to balance the number of samples per class and thus avoid potential bias during the learning phase.

Then, various classifier configurations were evaluated through cross-validation (Muller, 2016), which allowed for the identification of the most suitable parameters for the extracted feature set. The best results were achieved using L1 regularization and an α value of 0.001. Once these optimal parameters were defined, a model was trained using both available datasets.

At the same time, another classifier was built using only the tip of the tail data, replicating the approach of the previous study (Greene et al., in press). This procedure was repeated over 30 iterations to enable statistical testing and ensure the validity of the results.

5 Evaluation

To evaluate the two tail movement identification classifiers, a descriptive analysis and the Friedman test (Pereira et al., 2015) were applied to the data obtained from the 30 training and testing iterations.

5.1 Descriptive analysis

To evaluate the performance of each classifier, a set of metrics was used, including Accuracy, Precision, Recall, and F1-Score. The mathematical definitions of these metrics are presented in Equations 8, 9, 10, and 11, respectively. In these equations, TP represents true positives, TN true negatives, FP false positives, and FN false negatives. Accuracy measures the proportion of correct predictions relative to the total number of predictions made; Precision indicates the percentage of positive predictions that were actually correct; Recall shows how well the model identified the actual positive cases; and F1-Score is the harmonic mean between Precision and Recall (Igual & Seguí, 2017).

Subsequently, descriptive statistics such as the mean and standard deviation of the performance metrics obtained over 30 training and testing iterations were calculated. This allowed for the evaluation of both the average performance and the variability of the two classifiers. In addition, a boxplot was created using the Precision scores of both classifiers to provide a visual representation of the models' behavior across the different repetitions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

$$F1 - Score = \frac{Precision \cdot Recall}{Precision + Recall} \tag{11}$$

5.2 Friedman Test

The next step in the evaluation involves applying the Friedman test (Pereira et al., 2015), which is a non-parametric test designed to compare the performance of different treatments under similar conditions. In the context of this study, the treatments refer to the classifier trained with data from the dog's hip and the classifier trained with data from the tip of the tail. The objective is to determine which of these two models performs better in predicting tail movement. To identify whether one classifier significantly outperforms the other, the test establishes the following hypotheses:

- **Null Hypothesis (H_0):** There are no statistically significant differences in accuracy between the hip based classifier and the tip of the tail based classifier.
- **Alternative Hypothesis (H_a):** There are statistically significant differences in accuracy between the two classifiers.

This test yields ranks, which serve as relative performance indicators for each classifier in each test block. Each model is assigned a rank based on its accuracy across 30 iterations: the model with the lower accuracy in a given block receives rank 1, while the one with higher accuracy receives rank 2. The accuracy values obtained in each iteration are organized in a table, where the rows represent the iterations (blocks) and the columns represent the treatments (classifiers). Then, the rank sums for each classifier are calculated.

The Friedman test statistic is computed using Equation 12, where n is the number of blocks (iterations), k is the number of treatments (2 in this case), and R_j is the sum of ranks for classifier j. Finally, the value of the test statistic is compared to a *chi-square* distribution with $k - 1$ degrees of freedom to determine the *p-value*. If this value is less than the significance level (α = 0.05), it is concluded that there are statistically significant differences between the classifiers. This allows us to determine whether the hip based model outperforms the traditional tip of the tail based model.

$$Q = \left(\frac{12 \cdot n}{k \cdot (k+1)}\right) \cdot \left(\sum_{j=1}^{k} R_j^2\right) - 3 \cdot n \cdot (k+1) \tag{12}$$

6 Results

6.1 Descriptive analysis

The evaluation results are presented below. The average values of performance metrics such as accuracy, precision, recall, and F1-score obtained during the 30 training and testing iterations are shown in Tables 2 and 3. It can be observed that the classifier using hip data achieves higher average scores across all metrics (except for Recall in Table 2) compared to the classifier based on tail tip data. This suggests that the hip based model performs better in identifying the direction of tail movement.

Moreover, the classifier that uses hip data exhibits less variability than the model based on the tail tip, as shown in Tables 4 and 5. This indicates that using the hip as a reference produces more consistent and stable results across different training and testing repetitions.

Finally, Figures 4 and 5 display boxplots illustrating the accuracy scores of both classifiers over the 30 iterations. These visualizations show the dispersion of the results and reinforce the previous statistical findings: the hip based classifier not only has a higher average accuracy but also demonstrates lower variability in its predictions.

In summary, this descriptive analysis suggests that the classifier trained with hip data may have an advantage over the one based solely on tail tip data. However, to determine whether these differences are statistically significant, the next section presents the results of the Friedman test.

Table 2. Accuracy, Precision, Recall and F1-Score averages of the 30 iterations with the Ren database (Ren et al., 2022).

SVM model	Average Accuracy	Average Precision	Average Recall	Average F1-Score
SVM trained with hip	0.992391	0.99.7097	0.98.7681	0.99.2333
SVM trained with tip of the tail	0.98.2790	0.96.7831	0.99.9275	0.98.3185

Table 3. Accuracy, Precision, Recall and F1-Score averages of the 30 iterations with the Völter database (Völter et al., 2023).

SVM model	Average Accuracy	Average Precision	Average Recall	Average F1-Score
SVM trained with hip	0.998039	0.998163	0.997939	0.998042
SVM trained with tip of the tail	0.969453	0.973667	0.965151	0.969320

Table 4. Standard deviation of the accuracy of the 30 iterations with the Ren database (Ren et al., 2022)

SVM model	Accuracy standard deviation	Precision standard deviation	Recall standard deviation	F1-Score standard deviation
SVM trained with hip	0.005815	0.004896	0.010578	0.005880
SVM trained with tip of the tail	0.011336	0.021017	0.002758	0.010898

Table 5. Standard deviation of the accuracy of the 30 iterations with the Völter database (Völter et al., 2023)

SVM model	Accuracy standard deviation	Precision standard deviation	Recall standard deviation	F1-Score standard deviation
SVM trained with hip	0.002368	0.003643	0.004088	0.002366
SVM trained with tip of the tail	0.008556	0.009844	0.013937	0.008703

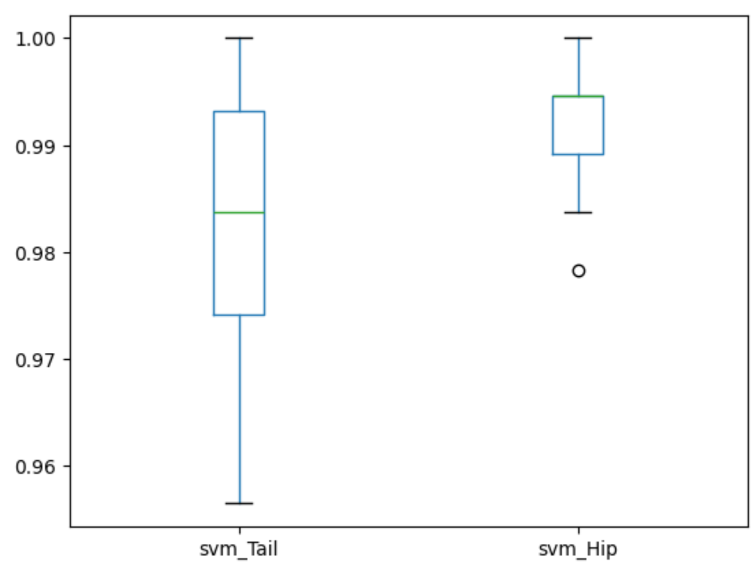

Figure 4. Boxplot of Accuracy score with Ren database (Ren et al. 2022).

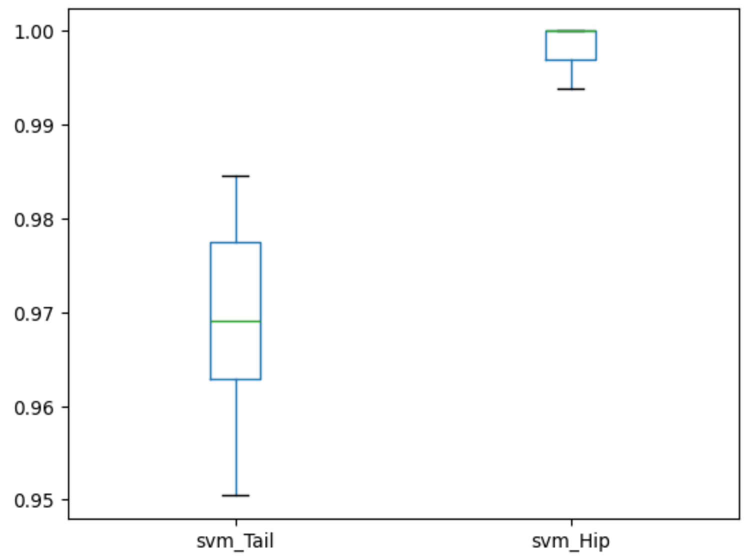

Figure 5. Boxplot of Accuracy score with Völter database (Völter et al. 2023).

6.2 Friedman Test

The Friedman test was conducted using the accuracy values obtained from both classifiers. The results, shown in Table 6, indicate that for both datasets, the *p-value* was below the statistical significance threshold (α = 0.05). This allows us to reject the null hypothesis (H_0), which states that there are no significant differences between the classifiers, and to accept the alternative hypothesis (H_a), which suggests that there are statistically significant differences in the performance of the two models.

Additionally, Table 7 presents the ranks assigned to each classifier in the test, where it can be seen that the SVM classifier trained with hip data achieved a higher rank than the classifier trained with tail tip data. These findings support the conclusion that the hip-based model not only achieves higher accuracy in identifying tail movements but also demonstrates statistically superior performance.

Table 6. *P-values of the Friedman test in the Ren and Völter databases (Ren et al. 2022; Völter et al., 2023).*

Database	P-value
(Ren et al., 2022)	7.237830e-08
(Völter et al., 2023)	4.320463e-08

Table 7. Friedman test ranges in Ren and Völter databases *(Ren et al. 2022; Völter et al., 2023)*.

SVM model	Ranks with Ren database (Ren et al., 2022)	Ranks with Völter database (Völter et al., 2023)
SVM trained with neck	5.568	5.477
SVM trained with multi-view	10.863	10.954

7 Discussions

This study has highlighted the effectiveness of the proposed preprocessing and feature extraction method for recognizing tail movements in dogs using the hip as a reference point. The results indicate that the classifier trained with hip data achieved remarkably high performance, outperforming the classifier based on the tail tip. Its performance reached up to 99% in metrics such as Precision, Accuracy, and F1-Score across both datasets. Moreover, it exhibited lower variability in its predictions, suggesting greater stability in its performance.

The hip-based model not only proved to be more effective than the one trained with tail tip data but also achieved statistically significant differences according to the Friedman test. This reinforces the idea that the hip can serve as a more robust and reliable reference point for identifying the direction of tail movement during social interactions.

However, it is important to note that a key limitation of the study was the use of only two datasets, which restricts the ability to generalize the results and claim that the hip-based model will always outperform the traditional approach. Although the findings are promising, further evaluation on additional datasets is necessary to confirm its effectiveness.

Lastly, the labeling method employed based on K-means may not be the most suitable for high-dimensional data, as Euclidean distance can lose effectiveness in such cases, and the resulting clusters may not accurately reflect the true structure of the data (Igual & Seguí, 2017). For future work, it is recommended to explore more robust labeling techniques and to expand the dataset by including dogs from different cultural contexts, such as Mexican dogs, as well as incorporating additional body parts to move toward the recognition of more specific emotions.

8 Conclusions

This study presents an innovative method for processing data, focusing on the recognition of tail movements in dogs using the hip as the main reference point. Through preprocessing and feature extraction, a Support Vector Machine (SVM)-based classifier was developed, capable of automatically identifying leftward and rightward tail movements with high precision.

The results showed that the classifier trained with spatial data from the hip not only achieved scores above 99% in metrics such as accuracy, precision, and F1-score, but also exhibited lower variability in its predictions compared to the classifier based on the tip of the tail. Moreover, the validity of the method was supported by statistical tests, such as the Friedman test, which confirmed that the hip-based model presents statistically significant differences compared to the tail-tip-based method. This suggests that the hip is a more stable and reliable reference point for analyzing tail movement direction, particularly in social interaction contexts.

In contrast to previous studies, such as those by Ehsani et al. (2018), which combined computer vision with inertial sensors to model movement, or Ren et al. (2022) and Völter et al. (2023), which relied on multiple body markers (e.g., tail tip, back, and neck) to reconstruct body trajectories, the present work demonstrates that focusing on a single spatial reference (the hip) can yield equally or even more robust results. Unlike Leonetti et al. (2024) and Quaranta et al. (2007), whose analyses were centered on behavioral interpretation of tail direction to infer emotional states, this study advances toward a computational perspective, proposing an efficient machine learning framework that reduces the dependency on complex or multi-sensor setups. Additionally, compared with our previous work, where the tail tip was used as the primary reference point, this study provides evidence that the hip yields superior performance in identifying movement direction, due to its lower variability.

One of the major advantages of this approach is that it eliminates the need for sensors such as gyroscopes or accelerometers, making it less invasive for the animals (Aich et al., 2019). This simplification not only reduces experimental complexity but also facilitates real-world deployment in behavioral studies.

This approach has several practical applications in the field of animal behavior. It can be used to train service dogs, evaluate their well-being, and conduct ethological studies that help us interpret non-verbal signals related to their emotions or moods. By implementing advanced machine learning techniques like SVM, the ability to objectively and automatically detect behavioral patterns through tail movement is enhanced. This not only strengthens the bond between humans and dogs but also allows for a better understanding of their behavior.

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