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Multi-view Learning with Perceptron for Dog Tail Displacement Identification

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Abstract. This paper presents a novel approach to enhancing human-canine communication through data fusion techniques that analyze tail displacement patterns in dogs. By integrating data from multiple viewpoints—specifically, the tail tip, hip, and neck—this study aims to improve the automatic interpretation of canine signals. Tail displacements to the right are generally associated with positive emotions, while leftward displacements suggest negative emotions. A Perceptron model was developed using this fused data and compared with a previous Perceptron model that used only tail-tip data. Various performance metrics, including accuracy, precision, recall, and F1-scores, and a statistical test was performed to identify which Perceptron model is the best at identifying these displacements.

Keywords. Dog, dog tail displacement, multi-view learning, perceptron.

1 Introduction

The interaction between dogs and humans is based on the interpretation of non-verbal signals, with tail displacement being a key element in identifying dog’s emotions and intentions [1-2].

Correctly recognizing these signals is important, as it promotes the well-being of dogs and strengthens their bond with humans [2].

It has been identified that the direction of tail displacement can reflect different emotional states: displacement to the right is generally associated with positive emotions, while displacement to the left may suggest negative emotions [3].

View fusion (or multi-view learning) is an approach that combines data from different reference points or views to improve the analysis and interpretation of patterns [4]. In the case of tail displacement, this technique allows integrating information from multiple body parts, offering a more comprehensive view of emotion-related displacements. Its application is crucial in this context, as the fusion of multiple reference points increases the accuracy of displacement recognition by capturing patterns more robustly and in greater detail, thereby reducing possible errors or limitations that may arise from relying on a single view [5].

In a previous study, a Perceptron classifier [6] was developed using only the information from the tip of the tail to identify displacement direction [7]. However, this approach may be limited due to the lack of additional spatial information.

Therefore, in this study, an improved method is proposed that utilizes a Perceptron classifier integrating multi-view from multiple body parts of the dog, specifically the tip of the tail, hip, and neck, and will be compared with a classifier that only used the tip of the tail. By combining these reference points, it is expected to increase the accuracy of tail displacement identification.

The structure of the article is organized as follows: first, in Section 2, a theoretical framework on canine communication and artificial intelligence is presented; then, related literature on tail displacement analysis using Machine Learning is reviewed in Section 3; subsequently, the methodology for data preprocessing, 3D-to-2D transformation, feature extraction, labeling, and classifier configuration is described (Section 4); the process of evaluating the new classifier against the previous study's classifier is outlined in Section 5; and finally, the results are presented, findings are discussed, and conclusions on the effectiveness of the proposed approach are provided.

2 Theoretical Framework

Communication in dogs encompasses a wide range of behaviors and signals they use to interact, in both dogs and humans. These signals are often physical, such as glances or postures, and are intended to express the dog's emotions or mood [2].

Tail displacements are one of the most prominent aspects of canine communication. Their meaning can vary depending on the situation or type of interaction.

The direction and angle of the displacement are key to interpreting it: generally, a displacement to the right is associated with positive emotions such as happiness, while a displacement to the left often indicates negative reactions, such as anxiety and fear [3, 8].

On the other hand, artificial intelligence (AI) is a field of computer science that develops systems capable of performing tasks that typically require human cognition [9].

Within AI, machine learning is a discipline based on creating algorithms so that machines can learn to perform tasks and improve with practice [6]. In this study, machine learning is used to analyze dogs' tail displacements and infer their emotional state.

Multi-view learning involves integrating information from various sources to achieve a more comprehensive and accurate understanding of a subject [4].

In animal behavior analysis, this technique allows the use of data collected from different body parts, such as the neck, hips, and tail, which is expected to enhance accuracy in identifying a specific target within a given segment.

3 Previous Work

Emotion recognition in dogs through behavioral analysis has been a subject of study for decades. These studies have focused on the direct observation of dogs and their interactions, either with humans or other dogs [10, 11]. These works have allowed the identification of canine behaviors related to different emotional states, such as ear position, facial expression, and tail displacement.

There are investigations analyzing the connection between tail displacement and canine emotions. Several studies have shown that dogs tend to wag their tails to the right in response to positive emotional stimuli and to the left when facing negative or threatening stimuli [3][8]. These findings have enabled the development of machine learning models that classify a dog's emotional state based on its tail displacement.

Aich developed a system that uses accelerometers and gyroscopes to detect dogs' activities and emotions in real-time [12], applying machine learning techniques such as artificial neural networks, random forests, perceptrons, K-NN, and naive Bayes classifiers [6]. Ren developed a platform to track tail displacement during dog-human interactions, finding that displacement to the right indicates social familiarity [13]. Völter employed 3D tracking to investigate the impact of caregiver separation on dog behavior, observing a decrease in rightward tail displacement in the presence of strangers [14].

Recently, the possibility of detecting tail displacements using the tip of the tail as a reference was explored [7]. Different classifiers were evaluated, including perceptron, convolutional neural networks (CNN), k-nearest neighbors (K-NN), logistic regression, and random forests [6]. Statistical tests indicated that the best-performing classifier for identifying these displacements was the perceptron. However, this methodology relies solely on the tip of the tail and does not consider multiple reference points, such as the hip and the nape. The inclusion of these additional points could significantly improve the accuracy of tail displacement identification and the recognition of dogs' emotional states.

These studies have established a solid foundation for canine emotion recognition through machine learning. However, the recognition of tail

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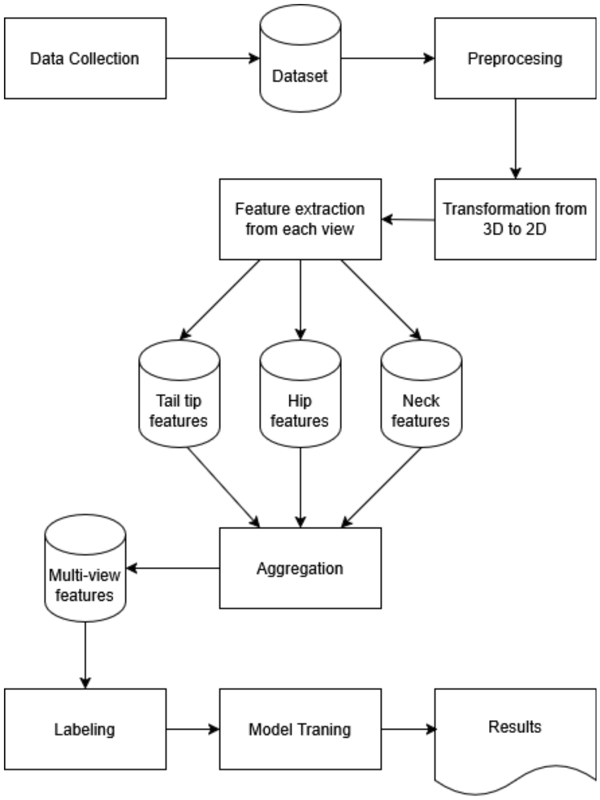

Fig. 1. Flowchart of the methodology of detecting the dog´s pose

Table 1. Databases information of the works of Ren and Völter

Databases	Ren´s database	Völter´s database
Markers	Tip of tail Hip Back Neck	Tip of tail Base of tail Hip Neck Right ear Left ear Center of head Snout
Characteristics of dogs	10 Beagles	37 dogs of various breeds
	5 males	18 males
	5 females	19 females,
	Ages 1 to 2 years	Minimum shoulder height of 45 cm
		Average age of 75 months.
Range	(-2.263478, 3.561027)	(-31.899638, 40.467200)
Amount of data	1340754	352531

displacement patterns in dogs using multi-view learning has not yet been sufficiently developed. Therefore, there is an opportunity to create new methodologies that leverage the combination of data from multiple views, which could significantly improve accuracy and generalization in tail displacement analysis.

4 Methodology

The purpose of the study is to create a perceptron classifier that analyzes tail displacement using data from the tip of the tail, hip, and neck views (multi-view classifier) to identify whether the dog experiences positive or negative emotions. To achieve this, a method was developed that employs data science and machine learning techniques based on previous work [7], as shown in Figure 1.

4.1 Data Collection

The first activity involved gathering previous research on dog behavior in various contexts, including databases with spatial information from 3D markers placed on the tip of the tail, hip, and neck of dogs. Two studies with these characteristics are specified in Table 1.

4.2 Preprocessing

Both databases underwent a cleaning process during the preprocessing activity, where null, outlier, or incomplete data were removed. Additionally, they were normalized to a scale of -1 to 1, as shown in Equation 1 [15], to prevent data with wider ranges from disproportionately influencing the classifier and causing undesired biases:

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

4.3 Transformation from 3D to 2D

The next activity involved transforming the 3D coordinates of each marker on the selected body parts into 2D coordinates, simulating a top-down view of the dog. This transformation facilitates the calculation of angles between the tip of the tail, the hip, and the neck, allowing for the extraction of relevant features.

The OpenCV library was used, which includes a pinhole camera model that enables this transformation [16]. Each 3D position of the markers in the scene P_w was projected onto the image plane through a perspective transformation, generating the corresponding pixel p (the 2D coordinates). Both p and P_w are represented in homogeneous coordinates, with P_w being a 3D homogeneous vector and p a 2D homogeneous vector. This transformation is illustrated in Equation 2 [16, 17]:

$$sp = A[R|t]P_w. \quad (2)$$

here, P_w represents the 3D coordinates of a marker, p corresponds to the 2D coordinates in the image plane, and s is the arbitrary scale factor of the transformation. The terms t and R represent the translation and rotation, respectively, which define the conversion from 3D to 2D coordinates. A is the intrinsic camera matrix, whose value is shown in Equation 3:

$$A = \begin{pmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{pmatrix}. \quad (3)$$

The parameters f_x and f_y define the focal distances, c_x and c_y the principal point is typically located near the center.

4.4 Feature Extraction

To carry out the feature extraction activity, the procedure of García was followed, but using the transformed data from the tip of the tail, hip, and neck views [5].

First, the data was segmented into 2-second time windows with an overlap of 0.3 seconds [13]. Then, for each marker, the mean, standard deviation, maximum values of the x and y axes were extracted, along with the measurement between the two axes of each marker. Additionally, the distance of each marker from the origin point within a defined plane was extracted as magnitude [18], along with the standard deviation of magnitude, the area under the magnitude curve (AUC), and the mean magnitude differences between consecutive readings [5]. The magnitude, AUC, and mean magnitude differences are represented in Equations 4, 5, and 6, respectively:

$$Magitude(x, y, t) = \sqrt{x_t^2 + y_t^2}\,, \quad (4)$$

$$AUC = \sum_{t=1}^{T} Magnitude(x, y, t)\,, \quad (5)$$

$$meandif = \frac{1}{T-1}\sum_{t=2}^{T} Magnitude(x, y, t) - Magnitude(x, y, t-1)\,. \quad (6)$$

Here x_t^2 and x_t^2 are the marker data at time t and T is the last time interval.

Additionally, the Savitzky-Golay filter [19, 20] was used to obtain the velocity of the markers. This allowed for the extraction of the distance traveled by each marker, as well as the mean, standard deviation, and maximum velocity value of each marker within its time window.

Finally, the angles formed between the tip of the tail, hip, and neck were calculated, as shown in Figure 2. This enabled the extraction of the mean angle, standard deviation of angles, minimum angle, and maximum angle value to describe the tail trajectory. Additionally, angular velocity and angular amplitude [13] were also extracted, as stated in Equations 7 and 8:

$$v = \frac{\theta_i - \theta_j}{t_i - t_j}\,, \quad (7)$$

$$amplitude = |\theta_i - \theta_j|\,. \quad (8)$$

Where θ_i and θ_j are the adjacent movement angles; t_i and t_j are the timestamps of the movement angle of the tip of the tail θ_i and θ_j respectively.

Subsequently, the features extracted from the different views were merged using the aggregation method based on vector concatenation. In this approach, the feature vectors from each of the views (tip of the tail, hip and neck) were sequentially combined to create a single longer vector for each sample. This technique preserves the specific information from each view in the final dataset, maintaining the temporal correspondence among the different sources and creating a representative and multidimensional dataset [21].

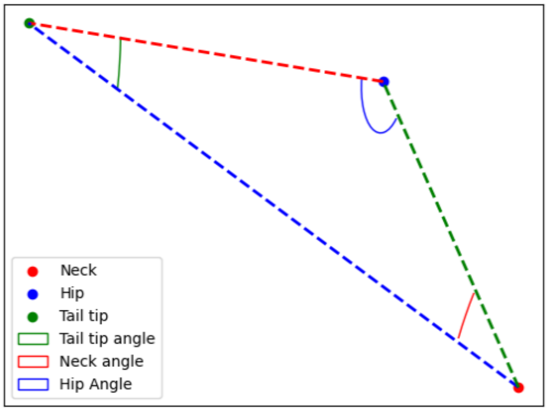

Fig. 2. Tail tip, hip and neck markers with their respective angles

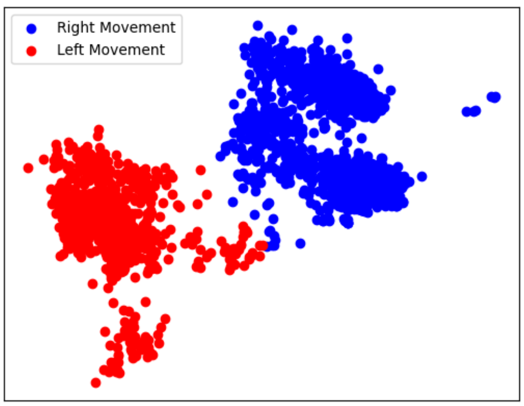

Fig. 3. Characteristics of the Ren´s database reduced in 2 dimensions using PCA

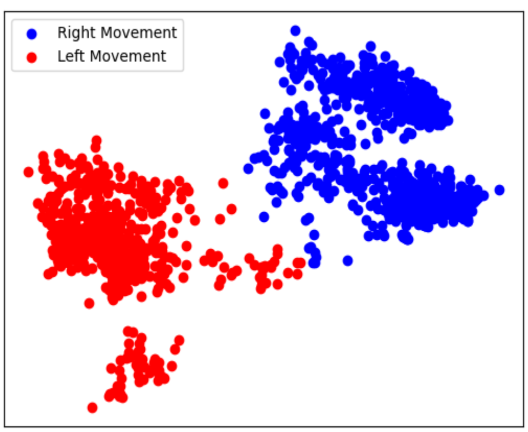

Fig. 4. Characteristics of the Völter´s database reduced in 2 dimensions using PCA

4.5 Labeling

After feature extraction, two clusters related to tail movements (left and right) were identified in both datasets. These clusters can be observed in Tables 3 and 4, by applying Principal Component Analysis (PCA) [6] to the features of both datasets. Therefore, to perform the labeling activity, a method proposed by Ehsani was used, which applied the K-means algorithm to the IMU sensor readings to identify animal actions [22]. However, in this study, we used feature information from the three views (tip of the tail, hip, and neck).

4.6 Classifier Training

Finally, a multi-view perceptron classifier was trained. Before this, the features were balanced using undersampling to ensure that the classes were balanced [6].

Subsequently, multiple perceptron classifiers were created to obtain the optimal parameters for predicting multi-view data features. For this task, the cross-validation technique was applied [6]. The results indicated that L1 regularization and α=0.001 were the most effective parameters.

A perceptron classifier was trained using both datasets; and, another perceptron classifier was trained using only the tip of the tail data according to the previous study [7]. This training and testing process was repeated 30 times to allow for subsequent statistical testing.

5 Evaluation

After the 30 iterations of training and testing of the two classifiers, a descriptive analysis and a statistical test were applied to identify which classifier is better at recognizing tail displacement. This section details how these classifiers were evaluated.

5.1 Descriptive Analysis

To evaluate the performance of the two classifiers in each iteration, several metrics were used: Accuracy (Equation 9), which measures the proportion of correct predictions relative to the total number of predictions; Precision (Equation 10),

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which indicates the fraction of positive predictions that are actually correct; Recall (Equation 11), which shows the percentage of actual positive cases correctly identified by the classifier; and F1-Score (Equation 9), which is the harmonic mean of Precision and Recall [6]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{9}$$

$$Precision = \frac{TP}{TP + FP}, \tag{10}$$

$$Recall = \frac{TP}{TP + FN}, \tag{11}$$

$$F1 - Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}. \tag{12}$$

In these metrics, TP refers to true positives, TN to true negatives, FP to false positives, and FN to false negatives.

Additionally, the mean and standard deviation of these metrics were calculated based on the 30 iterations of training and testing. To enhance this analysis, a boxplot of the Accuracy score was generated to provides a visual representation of the classifiers' performance across iterations.

5.2 Friedman Test

Additionally, a statistical test was conducted to determine which of the two classifiers performs better in detecting tail movement. Therefore, the Friedman test [23] was chosen to evaluate Accuracy. The Friedman test is a non-parametric test used to compare classifiers. It formulates the following hypotheses:

- Null Hypothesis (H0): There are no statistically significant differences between the classifiers.
- Alternative Hypothesis (Ha): There are statistically significant differences between two or more classifiers.

This test provides ranking values assigned to each classifier to indicate their relative position compared to the others, helping to identify which classifier has the highest rank.

The test is performed by organizing the Accuracy scores of both classifiers into a table, where columns represent a classifier, rows correspond to blocks, and each cell contains an Accuracy observation. Within each block, classifier values are sorted in ascending order and assigned ranks, with the lowest value receiving a rank of 1, the next lowest receiving a rank of 2, and so on. The ranks are then summed for each classifier across all blocks. The next step involves applying the Friedman statistic, as illustrated in Equation 13:

$$Q = \left(\frac{12 \times n}{k \times (k+1)}\right)\left(\sum_{j=1}^{k} R_j^2\right) - 3 \times n \times (k+1)\,. \tag{13}$$

Where n is the number of blocks, k is the number of treatments, and R_j is the sum of ranks for the treatment.

Finally, the obtained Q value is compared with the chi-square distribution with K-1 degrees of freedom, allowing the calculation of the p-value. This value is used to determine whether there are statistically significant differences between two or more treatments. If the p-value is less than α=0.05, the null hypothesis is rejected, and the alternative hypothesis is accepted. Otherwise, the null hypothesis is accepted, and the alternative hypothesis is rejected.

6 Results

This section presents the results obtained from the 30 iterations of training and testing for both perceptron classifiers, along with the descriptive analysis and Friedman test data, in order to determine which classifier is more effective in detecting the dog's tail movement.

6.1 Descriptive Analysis

The Tables 2 and 3 show the average values of the four performance metrics (Accuracy, Precision, Recall, and F1-Score) over the 30 iterations for both datasets. It can be observed that the classifier trained with the multi-view approach (tail tip, hip, and neck) achieves higher average scores across all four metrics compared to the classifier trained using only the tail tip view.

Tables 4 and 5 show the standard deviation of Accuracy, Precision, Recall, and F1-Score across the 30 iterations for both classifiers using the two datasets. The results indicate that the multi-view classifier (tail tip, hip, and neck) exhibits a lower

Table 2. Accuracy, Precision, Recall and F1-Score averages of the 30 iterations using the Ren's database

Perceptron classifier	Perceptron trained with tail tip view	Perceptron trained with multi-view
Accuracy	0.968333	0.991296
Presicion	0.966088	0.992514
Recall	0.971852	0.990370
F1-Score	0.967483	0.991302

Table 3. Accuracy, Precision, Recall and F1-Score averages of the 30 iterations using the Völter's database

Perceptron classifier	Perceptron trained with tail tip view	Perceptron trained with multi-view
Accuracy	0.939259	0.994444
Presicion	0.944943	0.993943
Recall	0.934815	0.995185
F1-Score	0.938095	0.994492

Table 4. Standard deviation of the accuracy precision, recall and F1-score of the 30 iterations using the Ren et al. database

Perceptron classifier	Perceptron trained with tail tip view	Perceptron trained with multi-view
Accuracy	0.027726	0.009419
Presicion	0.020983	0.015604
Recall	0.062428	0.014215
F1-Score	0.031637	0.009329

Table 5. Standard deviation of the accuracy precision, recall and F1-score of the 30 iterations using the Völter et al. database

Perceptron classifier	Perceptron trained with tail tip view	Perceptron trained with multi-view
Accuracy	0.036061	0.007295
Presicion	0.038006	0.014117
Recall	0.066330	0.006315
F1-Score	0.040374	0.007064

standard deviation compared to the classifier trained solely on tail tip data.

This suggests that the multi-view classifier provides more consistent results with less variability in detecting tail displacement.

To complement this analysis, Figures 5 and 6 present the boxplots corresponding to the Accuracy of both classifiers in the two datasets. These plots allow visualization of the distribution of accuracy values obtained across the 30 iterations. It can be observed that the multi-view perceptron (tail tip, hip, and neck) not only achieves a higher average, indicating better overall performance, but also shows less dispersion compared to the classifier trained solely with data from the tail tip view.

This descriptive analysis suggests that the perceptron trained with multi-view data performs better compared to the perceptron that only uses the tail tip view. However, to validate that this multi-view classifier truly outperforms the tail tip classifier, the results obtained through the Friedman test will be presented in the following subsection.

6.2 Friedman Test

The results of the Friedman test applied to Accuracy reveal that there are statistically significant differences between the two classifiers. As shown in Table 6, the *p-value* is lower than $\propto = 0.05$ in both datasets; therefore, we reject the null hypothesis and accept the alternative hypothesis.

On the other hand, as shown in Table 7, the ranks from this test reveal that the perceptron trained with multi-view data ranks higher than the perceptron trained with the tail tip view.

The descriptive analysis and the applied Friedman test demonstrated that the best classifier for identifying tail movement is the perceptron trained with multi-view data, as it is not only more accurate but also statistically superior to the classifier trained with the tail tip view.

7 Discussions

This study has demonstrated that the multi-view approach (tail tip, hip, and neck) outperforms the single tail tip view for identifying tail displacement in dogs. The multi-view perceptron achieved higher averages in metrics such as precision, accuracy, recall, and F1-score, while also obtaining a lower standard deviation, indicating less variability and greater consistency in tail movement identification.

Furthermore, the Friedman test revealed statistically significant differences between both perceptrons, with a higher rank for the multi-view

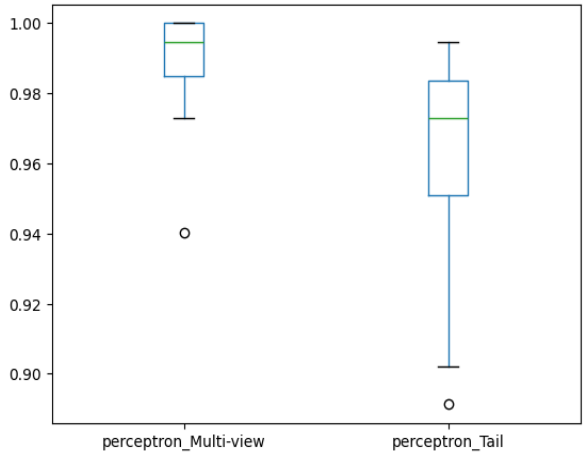

Fig. 5. Boxplot of Accuracy score of Ren et al. database

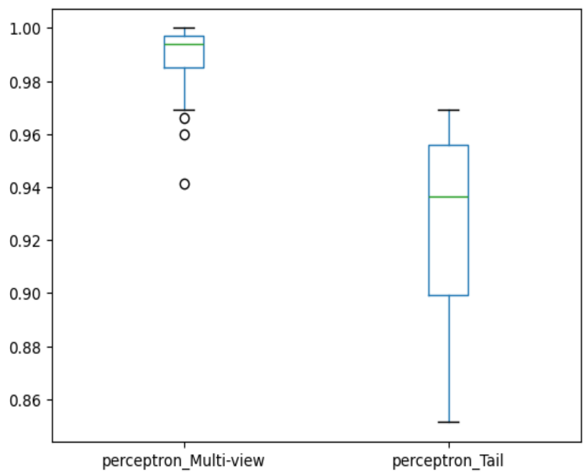

Fig. 6. Boxplot of Accuracy score of Völter et al. database

Table 6. *P-values* of the Friedman test

Database	***P-value***
Ren´s database	0.000019
Völter's database	0.000002

Table 7. Friedman test ranks

Database	**Perceptron trained with tail tip view**	**Perceptron trained with multi-view**
Ren´s database	6.11623	10.31544
Völter's database	5.84237	10.58930

classifier, reinforcing the importance of considering multiple reference points to improve accuracy in detecting tail movements in dogs.

However, it is important to note some limitations of the study. Only two datasets were used, which may not be sufficient to confirm that the multi-view perceptron is always the best classifier for this problem, even though this study suggests otherwise. Additionally, analyzing only two types of tail movements limits the ability to identify more specific emotions, such as anger, curiosity, anxiety, or fear, as these movements primarily reflect the dog's general emotional state (positive or negative) [13].

Therefore, future work aims to expand the dataset to include dogs in the Mexican context, allowing for a better understanding of these behavioral patterns in a specific cultural environment. Moreover, the analysis of tail displacement will be enriched with additional information, such as other types of tail movements, the sounds produced by the dog, body posture, or other body parts, with the goal of identifying more specific emotions.

8 Conclusions

In this study, we present a multi-view approach that combines data from the tail tip, hip, and neck to recognize tail movement patterns in dogs. The results of the descriptive and statistical analysis show that the perceptron trained with multi-view data outperforms the perceptron trained solely with tail tip data. This improvement is attributed to the integration of multiple reference points, providing a richer source of information and enabling a more accurate interpretation of tail movements.

The classifier based on a multi-view perceptron achieved an average accuracy of 99% on both datasets, which is considered an acceptable and efficient result within the context of tail movement recognition. This indicates that the model is capable of correctly distinguishing the main tail movements in most cases, validating the usefulness of the multi-view fusion approach for animal behavior analysis tasks. Additionally, greater stability in the predictions and a reduction in ambiguity were observed compared to the single-view approach.

Although using tail displacement to the right and left as an indicator has limitations for interpreting canine emotions, this work highlights the importance of multi-view learning for analyzing animal behavior.

Finally, this multi-view approach has various applications. For example, it could optimize service dog training by helping trainers better understand the dog's emotional responses and adapt training strategies based on tail movements. Additionally, this methodology could be useful for monitoring canine health and quality of life, as subtle changes in tail movement patterns could be related to physical or emotional issues, allowing for earlier and more effective interventions.

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