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Mariia Slobodian

Vasyl Stefanyk Precarpathian National University,

Ivano-Frankivsk, Ukraine

mariia.slobodian.17@pnu.edu.ua

ANALYSIS OF METHODS OF RECOGNIZING THE EMOTIONAL STATE OF DOGS, WHICH PROVIDE PHYSICAL PROTECTION AND SAFETY OF CRITICAL INFRASTRUCTURE OBJECTS

This paper presents a general overview of the methods for automated recognition of dogs' emotional states using acoustic features.

Keywords: barks classification, acoustic communication, dog vocalizations analysis, EDS, MFCC.

Artificial intelligence algorithms can now automatically classify animal sounds. The researchers discovered a number of sound patterns at the relationship between the regular and irregular components of the vocal signals. In this study, we examined the relationship between the emotional state of dogs that conduct physical protection and training models for bark classification.

Despite the importance of the problem, it should be highlighted that there is no theory that explains how the emotions of the dog relate to the features of the auditory signals. Reviewing existing algorithms and putting up suggestions for improving them are so necessary.

The capacity to recognize emotions is a critical attribute of social animals [1]. There hasn't been much scientific interest in using affective computing techniques to identify emotions in animals outside humans. Human emotional states have been studied using behavioral factors, just like other mammals. On the other hand, vocalizations can be utilized to assess emotional state [2, 3]. The acoustics, physiology, and cognitive control of human vocalizations share many characteristics with animals [4]. Furthermore, the majority of animals respond neurophysiologically in a similar way to emotional cues, modifying their pulse or cerebral activity, for example. [4] Therefore, modifications in an animal's emotional state ought to affect the muscular systems that control its vocal apparatus, altering the acoustic properties of vocal transmission especially when the animal conducts safety protection. [4]

Emotional speech signal can be utilized to identify emotions, according to research on human voice [5]. Dog barks are the most well-known animal voices to humans and have acoustic properties including frequency, pitch, loudness, and tempo. All barks that are associated with exact circumstances and can be recognized. [6, 7, 8] Similar studies found that children connected sympathetic body language to barking. [9]

In a study [10] employing over 6,000 samples of dog barks, a Bayesian classifier was developed to achieve two objectives. [10] The algorithm properly classified barks with a 43% accuracy rate. This model was honed for specific canines, and accuracy was 52%. In the research [11], a few learning algorithms for the classifiers of age, context, sex, and canine identification were evaluated. They attempted to use two models, one for the entire group of dogs and the other for each dog independently. Described an experimental procedure generates a number of dog vocalizations using a bi-dimensional model. [12] The analysis also made use of the studies [13, 14, 15].

The experiments have demonstrated the potential of using machine models to distinguish between various bark properties. However, it seemed that the level of precision attained was insufficient for usage in practical contexts. Additional training and improvement are needed to achieve greater results.

We discovered two key methodologies with shared data-processing procedures: EDS and MFCC. An audio signal processing system called EDS generates descriptors that are appropriate for a specific audio categorization issue. [10] It produces a lot of descriptors that are appropriate for a certain categorization problem. Following are the processes MFCC that is used to determine an animal's emotion [16]. So, after recording the audio of the animal sounds and mapping them to the MFCC, we could visualize it and gather photos for each audio file. And only after that we are allowed to create the deep learning model.

It requires effort on each part to analyze the dynamic movement of the vocal folds. So, to make things easier, the following voice indicators might be used: spectral composition, amplitude, intensity, loudness.

We assessed two approaches that have been used to categorize the emotions of animals, one for all species [16] and the other for dogs particularly [17]. The first model is based on image classification, with pictures produced from visualizations of MFCC signals. The second model employs polynomial SVM to forecast the emotional scale from 1 to 5 as a regression issue. It is based on numerous statistical traits of audio recordings of dog noises. Then, we made number of suggestions for cutting-edge techniques and their combinations that could be useful for the task of classifying the emotions of dogs.

Acoustic signals' statistical characteristic as time series. The proposed solution in [17] includes aggregating different acoustic features (frame energy, frame intensity, perceptual linear predictors, etc.) using average, max, and min functions, which may compress significant temporal dependencies between these features while reducing the dimensionality of the training dataset.

Transfer learning for dog's emotions specifically. The lack of the datasets for dogs sounds and emotions specifically makes it hard to train large complex models. On the other hand, datasets on human emotions in acoustic sounds as well as other animals could benefit to train the initial model. Just like famous VGG and ResNet neural networks are used as initial features for image classification.

Transformer-like architectures of neural networks. Transformer models are well recognized for being a very effective technique for time-series data regression and classification. These models might be useful for classifying the emotions of dogs if acoustic characteristics are converted into a time-series format.

Combination of acoustic features and their images. The concept set forward in [16], where they fed the CNN model with sound feature visualizations, may be expanded to include even more integrated input, such as audio sound features and their visuals simultaneously. The tabular format of the first kind of input, which may be aggregated as in [17], will be used for visualizations, which will use images to represent continuous time-series data. These two inputs will thus cover the dogs' noises from various angles and improve the model in various ways.

We investigated the feasibility of employing auditory feature sets and affective computing to categorize dog barks based on context, perceived emotion, and intensity. Our results show that speech recognition can be accurately classified by acoustic feature sets that are meant to represent human emotions. Each of the outcomes demonstrates that traits derived from people are suitable for classifying dog barks. This observation is consistent with the notion that emotional states in animals are followed by vocalization patterns and emotional responses that are comparable to those in humans. All mammals are also affected by these consequences. In addition, we offered recommendations for how to enhance the examined techniques for classifying emotions.

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