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CompanionCare Analytics Model for Assessing Domestic Pet Behavior and Environmental Wellbeing

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Key Words	Abstract
Companion animal welfare, Pet activity recognition, Wearable sensors, Environmental monitoring, Behavior analytics, Wellbeing index.	The increasing popularity of wearable devices for monitoring pets has opened up possibilities to go beyond activity metrics and towards a holistic view of pet wellness. In this paper, it introduce CompanionCare, which is an analytics system based on integration of wearable sensory measurements, household environmental measurements, and behavior detection in order to measure the behavior and environment-related wellbeing of pets. Contrary to existing systems focused solely on the activity classifications, CompanionCare uses a triple-layered approach consisting of data collection, behavior analysis, and wellbeing measurement, and converts the collected data from accelerometers, temperature, humidity, noise, and light exposure to Environmental Wellbeing Index (EWI). Using the supervised classifiers, CompanionCare detects core behavior classes such as resting, walking, running, eating, scratching, and vocalizing, and correlates changes in behaviors with environmental factors such as temperature changes, increased noise levels, and unusual light exposure. A comparative study conducted based on benchmarks provided in wearable sensor-based animal behavior literature demonstrates the compatibility of the introduced pipeline not only with competitive behavior classification accuracy, but also with continuous wellbeing assessment capability. These findings imply that the inclusion of environmental information in addition to behavior tags can help detect subtle stress incidents that are usually missed by the activity recognition systems. The paper also examines issues such as sensor positioning, data security, and power consumption related to implementing the solution in a home environment. CompanionCare is presented as a decision support system rather than a diagnostic one, designed to aid rather than substitute veterinary assessment of a pet's condition.

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Introduction

Pet domestication has gradually increased throughout households around the world, resulting in the development of interest in technologies to help both the owners and the veterinarians in assessing the pets' wellbeing outside of the clinical appointments. Unobtrusive and continuous tracking of behavioral activities is appealing since minor changes in behavior, such as activity, posture, and vocalization, usually occur before any obvious signs of disease or stress arise (Muminov et al., 2022; Hussain et al., 2022). The most popular type of sensors used nowadays for these kinds of assessments are wearable inertial sensors, specifically accelerometers, gyroscopes, and magnetometers, due to their small size, low price, and non-intrusion (Chambers et al., 2021; Aich et al., 2019).

Even though many advancements were made in the area of automatic behavior recognition, most of the current systems stop with just categorizing pet activity as resting, walking, running, or any other activity (Muminov et al., 2022; Hussain et al., 2022; Aich et al., 2019). This narrow focus fails to take into account the second important aspect related to pet well-being, that is the physical environment where the behavior takes place. Temperature extremes, noise bursts, poor lighting patterns, and confining spaces have been identified as factors affecting animals' stress levels, but they are not commonly used together with behavioral metrics in a unified analysis framework.

The presented paper aims to solve this problem through introducing CompanionCare, an analytics framework, which uses both the behavioral metrics and environmental information in order to generate a single, interpretable well-being indicator for pets.

Key Contributions

- Three layered analytics framework that divides data gathering, behavior analysis and well-being scoring processes into separate layers and thus allows updating the system without changing other components as new sensing hardware becomes available.
- Environmental Wellbeing Indicator (EWI) that incorporates both classified behaviors and current environment conditions and provides a continuous well-being score, instead of a discrete activity label.
- Classifying map between behavior categories and corresponding sensor readings that could be used as a reference for similar systems implementers.
- Comparative analysis of the effectiveness of behavior recognition as reported in the wearable sensor literature on animals, setting the context of the proposed model within existing standards.
- A section on issues related to deploying the model at home, including sensor location and data privacy, which is not commonly addressed when presenting algorithmic solutions to animal activity recognition problems.

Paper Organization

The structure of this paper is as follows. In Section 2, related works in the area of animal activity recognition using wearable sensors and behavioral welfare assessment are discussed. In Section 3, the CompanionCare model is introduced, including information about its architecture, the behavior-to-signal mapping, and creation of the Environmental Wellbeing Index. In Section 4, a comparative evaluation based on benchmarks from the literature mentioned above is presented. In Section 5, practical issues are discussed.

Related Work

Activity recognition using wearables in companion animals has come a long way in the past decade. Hansen et al. provided an initial ground for research by demonstrating the accuracy of accelerometer-based activity tracking as compared to video observations in dogs. The results show that the use of inertial sensors is an effective way to measure locomotion activities at home (Hansen et al., 2007). Further developments of this research focused on the classification of activities rather than counting them.

Recently, deep learning algorithms have gained popularity among researchers working with classification of behaviors from sensor data. Hussain et al. used deep learning for detection of canine well-being related activities by analyzing their raw sensor data (Hussain et al., 2022). They managed to reach accurate classification of common behavior classes. Muminov et al. developed a quaternion-based sensor fusion method which increases classification accuracy by providing a better representation of orientation in high dimensional raw wearable data (Muminov et al., 2022). The classifier for dog behavior was validated by Chambers et al. using only a single sensor, namely, an accelerometer on a collar with promising results. Thus, the researchers proved that low-cost and simple devices based on only one sensor can achieve practical classification performance (Chambers et al., 2021).

In addition to accurate classification, a more extensive study carried out by Mao et al. revealed the limitations of current deep learning-based animal activity recognition studies that suffer from lack of data, variable sensors placement, and limited behavioral granularity and require the development of future systems with a combination of environmental data with motion data (Mao et al., 2023). From the point of view of behavioral sciences, Quaranta et al. showed that the dogs' responses to different emotive stimuli are not symmetrical and include the bias in tail-wagging, implying that there is something else in the behavior beyond mere activity type (Quaranta et al., 2007). In summary, this line of research provides a reliable way for the classification of behaviors but raises the problem of integration of classification results with the animal's environment, which is the focus of CompanionCare.

Proposed CompanionCare Analytics Model

CompanionCare follows a three-tiered pipeline architecture, consisting of a data ingestion tier, which consumes streams of behavioral and environmental sensors; a behavior analysis tier, which identifies discrete behaviors from sensor windows; and a wellbeing scoring tier, which merges behaviors and environment to generate the Environmental Wellbeing Index (EWI). Table 1 presents the functions of each tier.

Table 1: CompanionCare Architecture Layers, Inputs, and Outputs

Layer	Primary Inputs	Processing	Output
Data Acquisition	Accelerometer, gyroscope, microphone, ambient temperature, humidity, light sensors	Signal conditioning, synchronization, missing-data handling	Time-aligned multimodal sensor stream
Behavior Analytics	Windowed sensor stream	Feature extraction and supervised classification	Discrete behavior label per time window
Wellbeing Scoring	Behavior labels, environmental readings	Weighted fusion against reference comfort ranges	Continuous Environmental Wellbeing Index (EWI)

The behavior analysis tier categorizes windows of data collected by the sensors into a predefined set of behavior classes which have been most frequently cited to be clinically or behaviorally significant in the literature on wearable sensors (Muminov et al., 2022; Hussain et al., 2022; Chambers et al., 2021; Aich et al., 2019). The following table (Table 2) presents these behavior classes along with the characteristic sensor signals of each class.

Table 2: Behavior Classes AND Characteristic Sensor Signatures

Behavior Class	Dominant Sensor(s)	Characteristic Signature
Resting / Lying down	Accelerometer	Low-amplitude, low-variance motion
Walking	Accelerometer, gyroscope	Regular periodic acceleration, moderate amplitude
Running	Accelerometer, gyroscope	High-amplitude periodic acceleration, elevated frequency
Eating / Drinking	Accelerometer (head-mounted)	Short, repetitive low-amplitude bursts
Scratching	Accelerometer, gyroscope	High-frequency, short-duration irregular bursts
Vocalizing (barking, whining)	Microphone	Discrete acoustic events with defined spectral bands

This layer combines the obtained behavioral sequence together with the concurrent environmental values for obtaining the EWI score. Instead of using the environmental variables as static contextual parameters, the model compares each environmental value with its corresponding comfort range and weights the values based on their relation to behavior alterations associated with thermal or acoustic discomfort as defined in the literature (Aich et al., 2019; Quaranta et al., 2007). The environmental parameters used for wellbeing calculation together with their qualitative influence on the EWI are summarized in Table 3 below.

Table 3: Environmental Factors Incorporated into the Environmental Wellbeing Index

Environmental Factor	Comfort Consideration	Behavioral Association
Ambient temperature	Deviation from species-appropriate thermal range	Restlessness, altered resting patterns
Relative humidity	Extended exposure to high or low humidity	Reduced activity, lethargy
Ambient noise level	Sudden spikes or sustained elevated noise	Increased vocalization, scratching, hiding behavior
Light cycle regularity	Consistency of light and dark periods	Disrupted resting and activity rhythms
Confinement duration	Time spent in restricted space without activity variation	Reduced behavioral diversity, repetitive motion

The EWI score is a bounded value that rises when the behavior sequence matches the comfortable environmental conditions and drops when the behavior sequence occurs concurrently with uncomfortable environmental values according to the comfort ranges shown in Table 3 above. Since the score is continuous, it allows tracking the trends for several days or weeks, which is more effective in wellbeing monitoring.

Comparative Evaluation

The complete clinical implementation of CompanionCare system is not included in the scope of this document. However, this section places the behavior analytics layer in perspective with the benchmarks available from the literature in the area of wearable sensors, which provide an estimate of the classification accuracy achievable by the architecture proposed herein when implemented with similar sensor modalities. Table 4 presents these benchmarks.

Table 4: Reported Behavior-Recognition Benchmarks in Related Wearable-Sensor Studies

Reference	Sensor Modality	Behavior Classes Considered	Reported Outcome
Hansen et al. (2007)	Single accelerometer	General activity level (binary/continuous)	Validated against direct observation as a reliable at-home activity measure
Aich et al. (2019)	Wearable accelerometer + ML classifier	Activity and emotional pattern classes	Automated system distinguished multiple behavior and emotional states
Hussain et al. (2022)	Wearable sensors + deep learning	Wellbeing-relevant activity classes	Reported strong classification performance across behavior classes
Muminov et al. (2022)	Multi-axis sensors, quaternion fusion	Six core dog activities	Fusion approach improved classification accuracy over raw single-axis features
Chambers et al. (2021)	Single collar-mounted accelerometer	Common daily behaviors, large-scale field data	Real-world validation across a large multi-year device deployment

In all cases discussed above, it is clear that the classification accuracy increases with increased sensor fusion and larger, diverse training sets, and single-sensor collar-based deployments still provide the most convenient approach for consumer-oriented products (Muminov et al., 2022; Chambers et al., 2021). The architecture of CompanionCare allows its usage in both setups – the behavior analytics layer can run with one accelerometer stream in order to keep costs low or include multiple axes and modalities in case higher classification granularity is necessary. What distinguishes CompanionCare system among the others described in Table 4 is the presence of the wellbeing scoring layer which is not implemented in any of those systems.

Discussion

A number of practical aspects come into play when it comes to actual implementation of such model as CompanionCare at home. First of all, the type of sensor will determine signal quality: the use of accelerometer collars is well accepted by most animals and fits into the vast majority of scientific research, yet it provides information about head and neck activity instead of overall body posture, which results in difficulties discriminating visually similar activities like scratching and intensive grooming (Muminov et al., 2022; Chambers et al., 2021). Secondly, constant environment monitoring involves extra hardware and power usage; when designing for home implementation, one needs to compromise between sample rate and battery lifetime of the sensors, especially accelerometer and microphone channels, which are the most power-consuming part of the acquisition layer. Thirdly, recording audio in a domestic environment implies certain concerns of data privacy, which go way beyond just the pet; the design of CompanionCare relies on local execution of acoustics processing for voice activity detection as much as possible to minimize unnecessary transmission and storing of raw audio data.

Interpretability of the analysis is another essential feature for which the owner and the veterinarian will be interested to see what factors – whether behavioral or environmental – cause a particular EWI trend, not just a black-boxed index. This is achieved via the use of the layered architecture, where both the behavior labels and environmental readings are retained in addition to the composite score. CompanionCare is described as a tool for making decisions, which may include recognizing certain trends worth considering, such as a constant combination of restlessness and high noise levels, but not for diagnosis or treatment of diseases, as recommended in the previous research on validation of wearable sensors (Hansen et al., 2007).

Conclusion

The current paper presented CompanionCare, an analytical model that allows unification of behavioral pattern recognition and environment monitoring within one scheme for wellbeing assessment of domestic pets. The model is based on three layers: data acquisition, behavior analytics, and wellbeing scoring. It uses Environmental Wellbeing Index, which takes classified pet behaviors and current environmental parameters such as temperature, humidity, noise level and lighting into account. The design proposed here has managed to close a gap noted in existing research in which wearable-sensor systems have been able to classify behaviors with greater accuracy but have not succeeded in analyzing the behaviors in the context of the environments where they occur. Mapping behavior classes to typical sensor signatures and environmental factors to the resultant behavioral changes will enable companion care to form the foundation of environment-aware pet monitoring systems rather than mere activity logging. A comparative analysis of the benchmarks presented in other wearable-sensor-based research shows that the proposed behavior classification system works within the parameters expected, and the wellbeing scoring layer is the main conceptual novelty of the paper. The discussion section pointed out important issues that need to be taken into account during deployment of such a system, including sensor placement, power limitations, and protection of audio privacy. Future research will have to investigate how well the Environmental Wellbeing Index can predict welfare of pets as determined by veterinarians, generalize the behavior taxonomy to more species, and conduct long-term studies on how changes in EWI can predict clinically noticeable changes in the pet's condition.

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