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Development of a Program to Predict Canine Diseases through Changes in Canine Behavior Patterns and Health Monitoring Questionnaires: A Pilot Study

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Abstract: *Although canine and humans have interacted for centuries, human understanding of canine health remains limited. Several canine -health-monitoring systems have been developed in recent times. However, several factors, such as the canine breed, age, size, and weight, make data estimation challenging. In this study, activity sensors were installed on the necks of 30 canines of six breeds, ages, and weights, and a novel disease-inference program was developed to track changes in their scratching, licking, swallowing, and sleeping behaviors. Further, health questionnaires were created for similar diseases based on the observed abnormal canine behavior. In addition, a software program was developed and verified to predict canine diseases based on these data and recommend check-ups accordingly. The sensitivity and specificity of decision-making were verified by comparing the data on behavioral pattern changes and disease predictions collected via questionnaires with the results of veterinarian diagnoses. The average sensitivity and specificity of disease predictions (digestive and skin), estimated by the changes in behavioral patterns and the owner questionnaire, were 82% and 81%, respectively. Cohen's kappa coefficient was 0.79 in the diagnostic area, demonstrating diagnosis consistency. Therefore, the results show that canine's' abnormal scratching, licking, swallowing, and sleeping patterns can be used for health monitoring. This study contributes to the development of canine health status monitoring systems.*

Keywords: Accelerometer; Canine; Abnormal Behavior; Prediction of Companion Diseases; Gyro Sensor

1. Introduction

Approximately 50% of the American and 25% of the European households own one or more canines [1]. Furthermore, the number of people living with canines at home is increasing. Therefore, the health status of canines has attracted considerable attention [1]. Canines and humans have been interacting for centuries, and canines are known to express various emotions through facial expressions and gestures [2]. Canines exhibit certain behaviors to communicate and convey emotions to their owners. However, although canines can indicate their health conditions through specific behaviors, canine owners do not always understand these indications, leading to early diagnosis failures and increased treatment time [3, 4]. Therefore, analyzing abnormal behaviors related to canine health is essential for narrowing the communication gap between canines and their owners [5].

Thus, developing health-monitoring technology that can accurately analyze the health of companion animals through biological research and behavioral observation is critical. From a veterinary perspective, abnormal and repetitive scratching, licking, sleeping, and swallowing are common indicators of canine ill health patterns [6]. Thus, sensing technology that can accurately extract and distinguish these repetitive behaviors is essential. Canine disease prediction was previously studied based on a combination of behavioral findings and conditions because diseases in canines are affected by various factors. However, owing to the limited environmental conditions and a normal range of activities, observing abnormal behaviors and collecting data to predict diseases for canines living in households is possible. Therefore, this study assumed that the health status of canines could be assessed through daily-life monitoring based on the behavioral change data.

Representative diseases affecting canines can be categorized into digestive disorders, skin diseases, ear inflammation, periodontitis, and eye diseases. Canine owners take their pets to veterinary clinics to treat dermatitis, eczema, diarrhea, and vomiting [7, 8]. Notably, digestive disorders are more common at an early age. Maltese canines and Poodles are prone to otitis externa, and Shih Tzu and Yorkshire terriers are prone to dermatitis and eczema [9]. Moreover, numerous eye diseases have been reported in the Shih Tzu breed. These observations suggest that individual breeds can exhibit distinct disease symptoms [10]. Therefore, this study was conducted to monitor the health status of canines based on behavioral patterns (scratching, licking, sleeping, and swallowing) and behavioral change data.

Predicting human diseases involves applying medical knowledge and acquired data while considering individual characteristics [11]. Because canine breeds are more diverse than humans, extracting abnormal signs for each breed based on characteristics such as size and weight is challenging, even if based on basic medical treatment or treatment data. According to the International Canine Federation (Federation Cynologique Internationale), more than 350 canine breeds are currently registered, and generating standard data based on simple behavioral differences is difficult [12]. Consequently, setting the standard for abnormal behavior is also difficult. Most studies have presented algorithms developed using conditional research based on a designated canine breed, size, and weight [13]. Therefore, unconditional data-based accessibility can broaden the margin of error.

Additionally, unlike humans, canines cannot manage their health. Therefore, owners must periodically check their canines' health status, and systematic canine health management must be accomplished through a health checkup program [14]. However, by using an information-technology-based behavior-extraction device to observe and evaluate canine behavior with an artificial intelligence solution based on veterinary big data, canine owners may identify underlying health conditions without a veterinary diagnosis. Thus, this study aims to increase the enhance the understanding of owners on the health status of their pet canines by developing a platform that predicts canine diseases and recommends the necessary diagnostic tests.

A study was previously conducted in Korea and investigated the correlation between specific behaviors and the amount of physical activity in companion canines and cats. The study results revealed that determining diseases through behavioral analysis is critical and strongly dependent on highly accurate measurement tools [15]. A subjective analysis of companion-canine behavioral data was developed to obtain accurate data [16, 17]. Only the disease prediction results of companion canines can be trusted because the general public does not have veterinary knowledge. Therefore, the results in this study were differentiated and improved by adding the results of a canine questionnaire developed in cooperation with a veterinarian to increase data reliability for both the veterinarian and canine owner. Furthermore, to obtain high reliability, the user perspective was considered only when it increased the accuracy of the measured data values.

This study collected data on changes in behavioral patterns in everyday environments from 30 randomly selected companion canines. The canines were categorized by breed, age, and weight to analyze abnormal behavioral patterns. Based on this analysis, a data-driven program was implemented to differentiate between normal and abnormal behavioral patterns, enabling quantification. Additionally, the study incorporated health monitoring questionnaires completed by the canine owners and used the data-driven system to predict potential diseases. To enhance the reliability of the results, the program's specificity and sensitivity were cross-verified with veterinary opinions, thereby validating its effectiveness.

Through this study, we aim to validate a system that predicts the health status of companion canines based on data extracted from their daily behaviors at home. This system is intended to assist in predicting diseases and supporting timely veterinary visits.

2. Materials and Methods

2.1 Data collection

In this study, 30 companion canines of varying sizes, breeds, weights, and ages were randomly selected and observed at a canine playground center in Gyeonggi Province. The selection criteria for the study participants were based on the veterinarian's diagnosis, indicating that the canines had no issues with physical activity, could eat well, and were estimated to be under 10 years old based on the combined opinions of the canine's owner and the veterinarian. The research was conducted with the consent of the pet owners. The study period was from December 2021 to July 2022, spanning 8 months. It was a principle to observe the canines in different living environments, without providing a uniform living situation.

The activity data extraction sensor used in the experiment was designed and manufactured in-house to collect data. The sensor is still in the development and verification stage, and while no serious side effects are expected during the experiment, a written consent form was provided to the pet owners to account for any minor side effects that may occur due to the involvement of companion canines. The sensor was developed to record the behavioral patterns of the participating pet canines. In the future, through further development of the sensor, its capabilities will be confirmed in large-scale experiments. The sensor could measure up to 2 G of the device and comprised a built-in 2000 °/s acceleration sensor and a 50-Hz resolution gyro sensor. The sensor size was 33 × 38 × 18.3 mm and weighed 15 g. The sensor was attached to the neck of the canines on a light collar to avoid interference with their activities. Six-axis acceleration measurement data were acquired whenever the sensor detected a critical movement, and the collected data were stored on a server.

2.2 Data preparation

For unit-by-unit experimental verification, the activity data provided by the sensor were analyzed and synchronized. This approach was used to establish a technique for distinguishing between normal and abnormal behavior and to validate further the data within the normal range. Canine behavior can be categorized into dynamic and static behavior. Dynamic behavior includes swallowing, shaking, scratching, and sniffing, whereas static behavior includes lying, sitting, and standing. In this experiment, no distinct movements or actions were identified for static behaviors. Therefore, we analyzed the range of activities detected by the sensor during dynamic behaviors. As depicted in Figure 1, canine activities were monitored by observing their daily lives using a sensor placed on their necks. This direct observation method increased the accuracy of canine behavior analysis. Furthermore, a filtering algorithm was introduced to improve its accuracy. The approach involved the integration of actual activities with filtered data and the modification of sensor measurements by comparing them with actual behaviors.

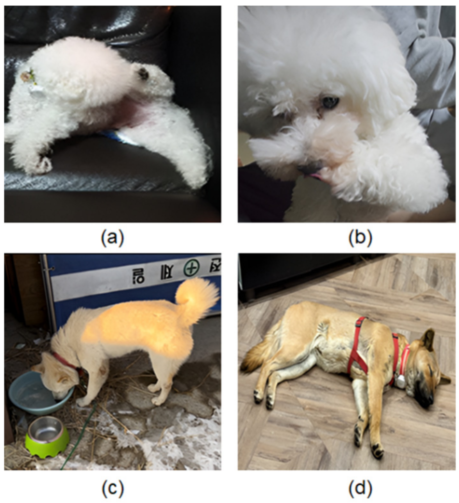

Figure 1. Four recorded canine behaviors: (a) scratching, (b) licking, (c) swallowing, and (d) sleeping

2.3 Data recording algorithms

The attached sensors recorded behavior patterns, such as the number of scratching, repetition cycles, intensity, repetition pattern of the number of licks, sleep time and cycle, and water and food consumption; these are typical behaviors observed in the daily lives of canines.

It was assumed that by checking changes in the frequency and count of behavioral patterns from a canine's daily data and comparing them with their baseline healthy data, potential diseases could be suspected. For example, in cases of suspected skin infections or otitis externa, the frequency and count would increase, so by comparing these changes with the normal range of the individual's baseline, the system was designed to estimate possible similar diseases when abnormal findings persist. Therefore, after confirming the canine's health status, the system collected about three months of daily behavioral patterns to establish the normal range, taking into account the individual characteristics of each canine.

Some behaviors of the canines can be correlated as shown in Figure 2. Figure 2 compares the behaviors of the canines as represented by the sensor data. Minor differences were noted in the sensor's range pertaining to the detection of activities, such as shaking, walking, and running, making it challenging to establish criteria for abnormal findings based on these differences. Therefore, it is preferable to use individual canine data from daily life as reference. Additionally, as the data obtained included many repetitive patterns, similar data were excluded to focus solely on the analysis of changes in patterns by performing filtering.

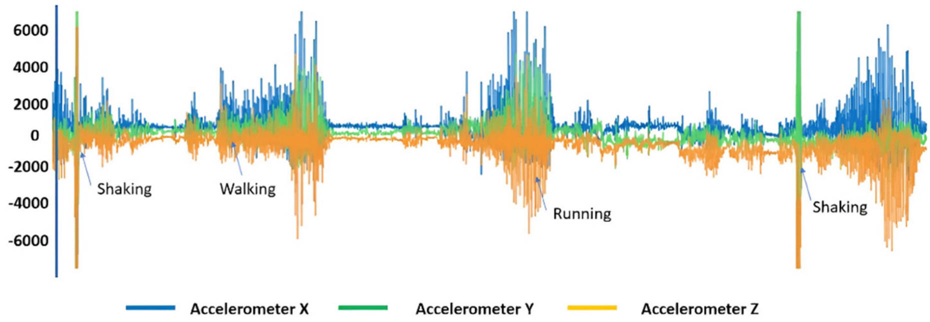

Figure 2. Sensor analysis of the behavioral patterns of a canine

2.4 Disease prediction method

The various activities can be identified by attaching a microphone to the neck sensor; for example, drinking water can be distinguished from eating food. If the canine drinks more water than the set standard, diseases, such as chronic kidney failure and diabetes, can be suspected. Digestive problems can be estimated from the consumption of diminished quantities of food. In the related data analysis, the data were classified and filtered based on veterinary advice [18]. On average, canines sleep between 7.7 and 16.0 h per day [19]. Thus, dementia or dermatitis, which interfere with continuous sleep patterns, and representative diseases, such as digestive system disorders and lethargy, can be inferred through a data analysis of sleep patterns (i.e., waking frequency and excessive sleeping) [20]. Therefore, an algorithm was developed for a decision-making system that establishes the complex relationships between abnormal behavior and the associated diseases by analyzing the sensor data extracted from the canine rather than from a single correlation. This experiment limited the verified target diseases to skin and digestive diseases to indicate the changes in data values for the canines. Furthermore, the scratching, licking, swallowing, and sleeping data extracted from the sensor were visually confirmed through an application. Activity data were collected by simultaneously recording the behavior of participating canines using a sensor and smartphone camera. Subsequently, the data were filtered through a comparative analysis process to verify the accuracy of the data obtained from the initially worn sensor. Figure 3 displays the canine movement data observed with respect to time. The figure depicts a filtering method that distinguishes meaningful behavioral patterns from actual images. The real-time data obtained was interpreted by specifying a usable range, and filtering was performed by designating regions to remember and match the same pattern forms. This preprocessing step was added to filter the observational data. This process reduced the volume of real-time data and improved the data quality by incorporating additional preprocessing steps.

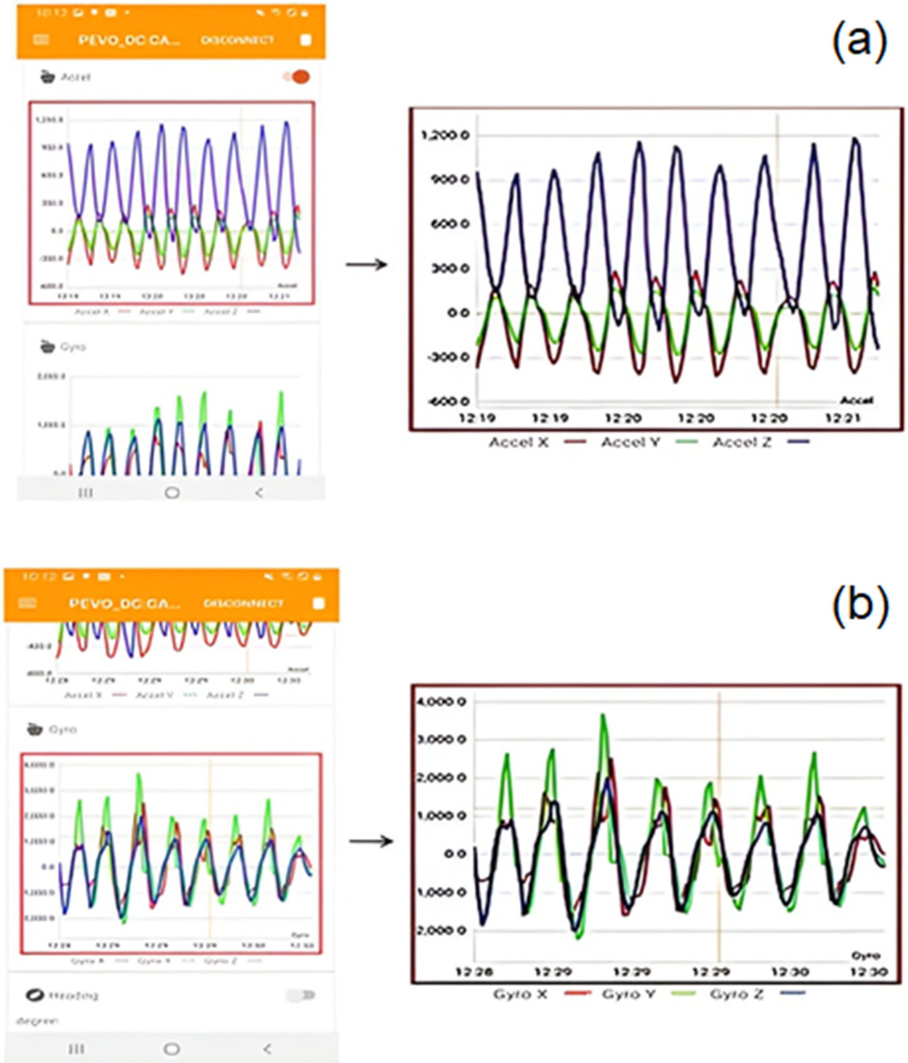

Figure 3. Filtering scope using data collection and analysis. (a) Case in which the minimum value is low and the behavioral pattern is inconsistent with the actual image; (b) case in which the behavioral pattern matches the video and time (24-h basis)

The extracted data comprised four areas corresponding to the scratching, licking, swallowing, and sleeping behaviors. A method was applied where data deviating from typical patterns, rather than regular daily data, was stored and analyzed. The canine disease estimation algorithm was developed using a neural network approach based on fuzzy associative memory. By organizing a range of disease symptoms assessed by veterinarians, the relationship between the symptoms and diseases submitted in the health questionnaire was inferred. The algorithm was trained using over 800 cases of four types of data obtained from dogs of the same breed with skin and digestive diseases at animal hospitals. It started with matching similar data and was compared and analyzed with the extracted data. However, discrepancies were noted in the primary data on age and weight with the canine breeds used in the experiment; therefore, a fuzzy associative memory technique was applied to each breed based on the data [21]. This technique considered the initial, changed, and diagnostic results as one component. To enhance the accuracy of veterinary symptoms, we developed and added a symptom questionnaire for similar diseases in canines, as shown in Table 1. This questionnaire was created with the consultation of emergency medicine veterinarians and veterinary radiologists. It included detailed weightings of all the items related to the risk of gastrointestinal and dermatological conditions that were used to implement the algorithm [22-24].

Table 1. Questionnaire reviewed by all the canine owners to assess the conditions of their canines

Canine Questionnaire: Skin and Digestive Diseases					
Licking (Skin Disease)	**State**		**Sleep and Swallowing (Digestive Disorders)**	**State**	
	O	X		O	X
Swollen skin			Frequent vomiting		
Significant bleeding from the skin			Not eating food		
Canine loses hair and shows signs of hair loss			Licking lips continuously		
Canine looks helpless			Drooling excessively		
Frequent skin licking			Licking things over and over		
Blisters appear on the abdomen			Sounds in the stomach		
Oily skin			Sensitive to touch on the stomach		
Visible dandruff			Diarrhea observed		
Visible tumors on the skin			Does not drink water well		
Body stinks			Burps often		
Red spots observed			Broken wind smells bad		
Pus on the skin			Looks restless		
Frequent skin scratching			Has bloody stools		
Has your canine taken a walk to a grassy place or been on grass recently?			Looks helpless		

2.5 Data implementation method

The learning model of the result-value weight of the questionnaire, standard data, and disease symptom data was implemented, as presented in Equation (1) [25].

$$x = \sum_{i=0}^{\infty} x_i \ \ \textbf{in case of}$$

$$\sum_{i=0}^{n-1} (n_i - a_i)^2 = NET_p, \tag{1}$$

$$W = \sum_{n=0}^{n+m} \{a(n-1)(m-1)\}_p^2 = f\left(\sum_{n=0}^{n+m} a_n \times a_m\right) = f\big(NET_p\big), \tag{2}$$

Where i refers to the data from the sensor as an input window, n denotes the abnormal behavior data, and m denotes the weighting data obtained from the questionnaire. The weighting of the health questionnaire is set when the abnormal data detected in the canine matches the symptoms provided by the owner. The basic data obtained from the sensor for each breed are regarded as a, and p denotes the output window. Therefore, the data from the questionnaire completed by the canine owner denote a standard for discriminating between basic and abnormal data, and the final symptom data were learned repeatedly. Inter-relationships between data were defined in advance to prevent data conflicts. Abnormal data were used as learning data to identify symptoms by applying associative memory to infer learning data for existing diagnosed diseases and inputting the results into the decision-making system. As presented in Equation (1), the weights of the data can be implemented through repeated learning because the decision value can vary depending on the definition of ideal data acquired from companion canines. Therefore, the canine disease estimation program in this study used the data extracted from the sensor and the questionnaire prepared by the canine owner observations to increase the decision-making accuracy. Figure 4 displays the configuration sequence of the final canine health diagnosis algorithm.

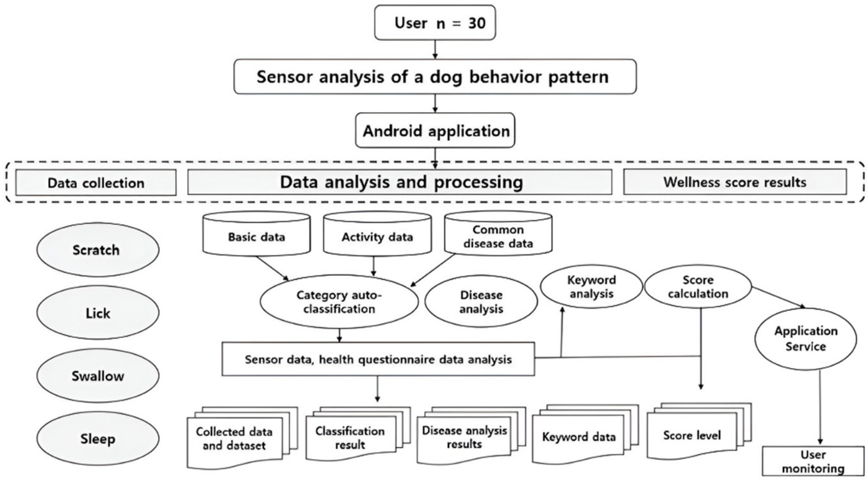

Figure 4. Proposed canine health-check configuration diagram

2.6 Data analysis method

Furthermore, a canine-health monitoring mobile application (app) was developed. The app included information on abnormal behaviors identified based on the collected data and developed and presented content recommending test items based on disease prediction. The validity of the contents was verified by analyzing the disease prediction results produced by the app and by comparing them with the diagnoses of three veterinarians. The veterinarians evaluated the sensitivity and specificity of the digestive and skin disease predictions by comparing the estimated disease symptom index and diagnostic results [26]. Furthermore, Cohen's kappa coefficients were used to verify the accuracy of veterinarian diagnosis and disease prediction indicated by sensors because Cohen's kappa enables continuous and easy evaluation of the inter-rater reliability for the effectiveness program [27].

SPSS (version 13.0 K, IBM, USA) was used for statistical analysis, and the canines corresponding to outliers in the extracted data were evaluated for disease.

3. Results

Table 2 lists the characteristics of the canines that participated in the study. The average canine age was in the range of 3–7 years, 13 of the 30 canines were male, and the average body weight was in the range of 4–29 kg. Pomeranians and poodles accounted for most of the target canines, and the rest were mixed breeds.

Table 2. Canine information considered in the study

Division	Canine Breed (Number)	Average Age (Years)	Gender (Male/Female)	Average Weight (kg)
Participating canine breeds	Retriever (3)	5.5	1/2	28.5±0.02
	Korean Jindo dog (3)	4	2/1	23.2±0.02
	Pomeranian (7)	4.5	2/5	4.0±0.12
	Poodle (8)	3	3/5	7.5±0.12
	Bichon frisé (5)	3	3/2	7.4±0.10
	Mixed breed dogs (4)	7	2/2	6.3±0.02

3.1 Observation of Daily Behavioral Patterns in Canines

The target canines had sensors attached to them, and 100 d of daily activity data were processed based on veterinarian diagnoses. Table 3 lists the average result values detected by the sensors for all four behaviors based on the breed. Initially, baseline data were established for each canine, and abnormal data were obtained and compared with the baseline data. Consistent with the initial research hypothesis, the results revealed that when setting the behavior decision data, the standard data must be set differently for each canine breed. The retriever breeds averaged 342 scratching and 17 (the highest) licking counts. Jindo dogs had 17 (highest) swallowing counts. The Pomeranian scratching count was 420, and the sleep time was 8.7 h. The Bichon scratch count was 445 (highest); the poodle and mixed breeds did not exhibit any specific high or low levels when compared with the other breeds.

Table 3. Canine behavioral patterns detected by the sensor designed in the study (24-h basis)

Measured Behavioral Items	Sensor Detection Coefficient According to Canine Breed (Average)					
	Retriever	Korean Jindo dog	Pomeranian	Poodle	Bichon Frisé	Mixed Breed Dogs
Number of scratches	342	221	420	195	445	205
Number of lickings	17	6	4	3	10	5
Number of swallowings	65	17	58	72	62	66
Sleep time (h)	14	12.5	8.7	13	9.2	14.2

This study identified anomalies by tracking basic data changes. The sensitivity and specificity of predicting digestive and skin diseases were evaluated by comparing a) the disease prediction results based on changes in canine behavioral patterns and b) the medical diagnoses of canines with abnormal behaviors. Therefore, the program predicted the disease after analyzing the four types of data extracted from the canine (scratching, licking, swallowing, and sleeping), questionnaire results completed by the canine owner, and the canine the veterinarian presented using the app, yielding abnormal findings and normal data. The results obtained after diagnosis are listed in Table 4. The results revealed that the abnormal findings in the retrievers were skin diseases, and the veterinarian concurred. The program suggested skin diseases for the poodles, and the questionnaire yielded a similar response from the canine owners; however, the veterinarian's opinion was that the findings were normal and unrelated to skin diseases. For the other mixed breeds, medical diagnosis revealed suspected periodontitis rather than digestive disease.

Table 4. Application-based prediction of canine diseases and veterinarian diagnosis

Division	Situation	Presence or Absence of Disease	Retriever (3)	Korean Jindo dog (3)	Pomeranian (7)	Poodle (8)	Bichon Frisé (5)	Mixed Breed Dogs (4)
App	Normal	Asymptomatic	2	3	5	4	4	2
	Abnormal	Skin disease	1		1	2	1	1
		Digestive disease			1	2		1
Veterinarian	Normal	Asymptomatic	2	3	6	5	4	2
	Abnormal	Skin disease	1			1	1	1
		Digestive disease				2		
		Other symptoms			1			1

The lists of the application predictions and veterinarian diagnoses for the 30 canines participating in the study are shown in Table 5. The sensitivity to skin diseases based on behavioral patterns such as licking was 100%, and the specificity was 90.9%. The larger the canine, the higher the accuracy. The no-disease prediction was also accurate. Table 6 shows that the abnormal activity algorithm is excellent for comparison with the diagnosis, and the combination of the questionnaire and the abnormal behavioral patterns is essential in disease prediction. Cohen's kappa coefficients for both analyses were 0.790 and 0.842, respectively, indicating a high degree of agreement between the evaluations.

Table 5. Comparison between veterinarian diagnoses of canine disease and application diagnoses

		Veterinarian									
		No Disease		Skin Diseases		Gastrointestinal Diseases		Others		Total	
App	No disease	20	90.9%	0	0.0%	0	0.0%	0	0.0%	20	66.7%
	Disease suspicion	1	4.5%	4	100.0%	0	0.0%	1	50.0%	6	20.0%
	Gastrointestinal diseases	1	4.5%	0	0.0%	2	100.0%	0	0.0%	3	10.0%
	Others	0	0.0%	0	0.0%	0	0.0%	1	50.0%	1	3.3%
Total		22	100.0%	4	100.0%	2	100.0%	2	100.0%	30	100.0%

Kappa coefficient κ = 0.790.

Table 6. Sensitivity and specificity of canine disease prediction application

		Veterinarian					
		No Disease		Disease Suspicion		Total	
App	No disease	20	90.9%	0	0.0%	20	66.7%
	Disease suspicion	2	9.1%	8	100.0%	10	33.3%
Total		22	100.0%	8	100.0%	30	100.0%

Kappa coefficient κ = 0.842.

Implementation of a mobile app comprised a presentation screen for abnormal behavioral patterns, a questionnaire filled by the canine owner after confirming the abnormal behavior, a health rating based on the probability of the final disease, and examination items based on the estimated disease, as shown in Figure 5.

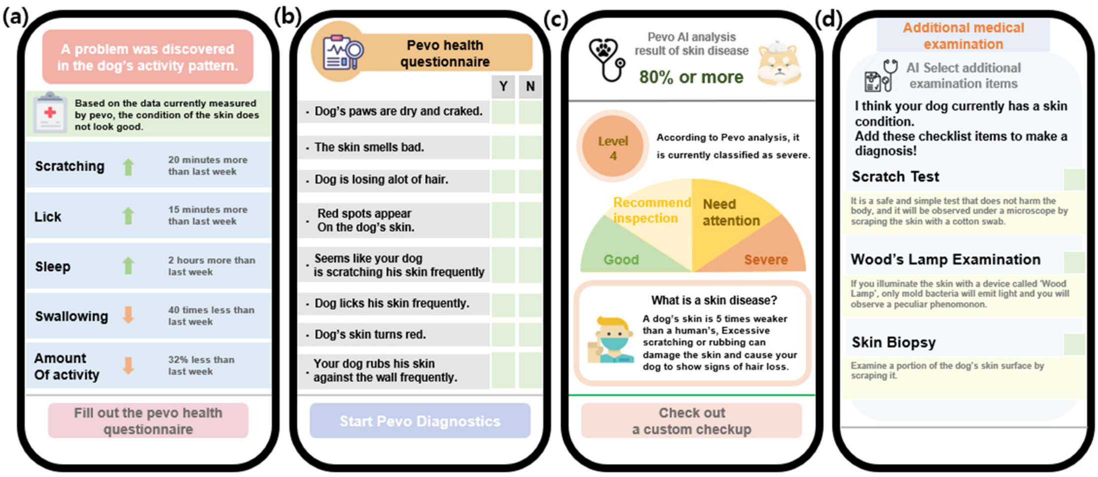

Figure 5. Final implemented canine health management application screen. (a) Changes in five behaviors—scratching, licking, sleeping, swallowing, and activity level—are presented with visual symbols and explanations. (b) Screen where the canine's health status is entered directly by the owner (observer). (c) This screen shows the potential diseases that can be inferred by combining the results of the questionnaire and the sensor data. (d) Presentation of information about the inferred diseases

4. Discussion

In this study, we aimed to assist in the diagnosis of canine health conditions by attaching sensors to the necks of the canines to determine the healthy baseline data ranges followed by the detection of abnormal behavioral patterns outside the normal ranges. These patterns were used as data for disease inferences. Therefore, we anticipate that a large amount of training data will be needed to narrow the gap between baseline and decision data.

Recent approaches to predicting companion canine diseases involve using genetic data to predict diseases quantitatively or analyzing behavioral videos obtained from CCTV through AI to detect diseases [28, 29]. However, while no published algorithms currently exist, these methods are centered around the lifestyle of companion canines. This study introduces a novel approach that analyzes behavior patterns using sensors to reduce individual differences in the daily life of companion canines.

Unlike traditional research methods that match similar behaviors and diseases, this study presents a model that extracts abnormal patterns based on data collected from daily life and predicts disease likelihood quantitatively through a disease-specific symptom questionnaire completed by the owner. Although the implemented algorithm connects symptoms and diseases using a single neural network structure, it can enhance accuracy in the future by applying fuzzy associative memory techniques to track data through learning [30]. The algorithm's results were similar to those of veterinarians for some breeds. Particularly, the health diagnoses in the absence of disease were accurate. However, determining diseases early within a short period is difficult owing to the small abnormal pattern-recognition range for heavyweight or large breeds. Nevertheless, the algorithm presented in this study could be used to predict canine diseases in its early stages, and the sensitivity and specificity of the diagnostic results were excellent.

This study proposed a novel method for inferring diseases by analyzing the abnormal canine activity observed using sensors installed on their collars. Furthermore, a questionnaire was developed for canine owners to share reliable data with veterinarians regarding the behavioral changes of their canines to increase the accuracy of disease estimation. Learning data linking the symptoms and results of canine diseases were prepared based on 800 cases of the same canine breeds as those participating in this experiment. However, this study has a few limitations. First, this study is limited to skin and digestive diseases. Therefore, in the future, the program must be expanded to include various other illnesses. Second, 800 basic veterinary diagnosis learning data samples are insufficient for the analysis and decision-making system. Third, only three veterinarians participated in the feasibility study. Fourth, as the subjects in this study were randomly selected from companion canines active in daily life at a canine playground center, this small-scale observational study was conducted using only six species, including mixed breeds. Diversifying analysis data using large-scale data for verification and accuracy is necessary in the future.

The mobile app created based on veterinary knowledge regarding canine diseases will facilitate preliminary home diagnoses and become a medium for interaction with veterinary hospitals. Additionally, these results are valid in existing canine-specific disease research cases [31]. The results of this study can prove useful in improving communication between companion canines and humans by analyzing behavioral patterns according to companion canine activity patterns and emotions. Predicting health is a cautious and challenging task even for humans. In the case of canines, where communication is not possible, this becomes even more critical. The technology embedded in wearable devices aims to connect deviations from standardized personal activity patterns with health, serving as a means of communication with the canine. This approach carefully proposes a new channel for communication. However, according to existing research, such wearable sensors can disrupt the natural activities of pets, making it difficult to obtain normal data from the pet [32].

The canine health monitoring market is expected to expand, evolving from a focus on food quantity and questionnaire-based disease information programs to intelligent health management systems [33]. APP programs like the results of this study will offer various accessibility options and also play a role in reducing veterinary costs in the canine health market.

The sensor-based technology used in this study is believed to have minimal limitations for specific environments and can enhance the accuracy of data collection. This sensor technology is expected to contribute to the future development of a high-level platform for in-depth monitoring of canine health.

5. Conclusions

This study determined the health status of canines by analyzing their abnormal behavioral patterns using a device with a built-in gyroscope and accelerometer. Scratching, licking, swallowing, and sleep behavioral data were used for estimation. The target diseases included digestive and skin diseases. Comparing the diagnostic results of the veterinarian with those of the developed program for the same canines revealed that the skin disease specificity was higher when the canine size and weight were lower, and the sensitivity to digestive diseases was higher when the size and weight were larger. The average sensitivity and specificity of both disease predictions, estimated by the changes in behavioral patterns and the owner questionnaire, were 82 and 81%, respectively, indicating the potential of the proposed model for monitoring the health status of canines. This study can contribute to the future development of health status monitoring systems for canines. Future studies should expand the program to include various other illnesses. Diversifying analysis data using large-scale data for verification and accuracy is also necessary.

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References

[1] L. J. Wallis, D. Szabó, B. Erdélyi-Belle, and E. Kubinyi, “Demographic change across the lifespan of pet dogs and their impact on health status,” Front. Vet. Sci., vol. 5, no. 200, p. 20, Aug. 2018, doi: https://doi.org/10.3389/fvets.2018.00200.

[2] G. Ford, K. Guo, and D. Mills, “Human facial expression affects a dog’s response to conflicting directional gestural cues,” Behav. Processes, vol. 159, pp. 80-85, Feb. 2019, doi: https://doi.org/10.1016/j.beproc.2018.12.022.

[3] N. Albuquerque, K. Guo, A. Wilkinson, B. Resende, and D. S. Mills, “Mouth-licking by dogs as a response to emotional stimuli,” Behav. Processes, vol. 146, pp. 42-45, Feb. 2018, doi: https://doi.org/10.1016/j.beproc.2017.11.006.

[4] J. Reid, A. M. Nolan, and E. M. Scott, “Measuring pain in dogs and cats using structured behavioural observation,” Vet. J., vol. 236, pp. 72-79, Jun. 2018, doi: https://doi.org/10.1016/j.tvjl.2018.04.013.

[5] P. A. M. Overgaauw, C. M. Vinke, M. A. E. van Hagen, and L. J. A. Lipman, “A one health perspective on the human–companion animal relationship with emphasis on zoonotic aspects,” Int. J. Environ. Res. Public Health, vol. 17, no. 11, p. 3789, May. 2020, doi: https://doi.org/10.3390/ijerph17113789.

[6] R. D. Chambers, N. C. Yoder, A. B. Carson, C. Junge, D. E. Allen, L. M. Prescott, S. Bradley, G. Wymore, K. Lloyd, and S. Lyle, “Deep learning classification of canine behavior using a single collar-mounted accelerometer: Real-world validation,” Animals, vol. 11, no. 6, p. 1549, May. 2021, doi: https://doi.org/10.3390/ani11061549.

[7] J. W. Stull, “Companion animal zoonoses in immunocompromised and other high-risk human populations,” In Greene's Infectious Diseases of the Dog and Cat, 5th ed., pp. 218-237, Mar. 2023, doi: https://doi.org/10.1016/B978-0-323-50934-3.00019-7.

[8] K. M. Weishaar, Z. M. Wright, M. P. Rosenberg, G. S. Post, J. A. McDaniel, C. A. Clifford, B. S. Phillips, P. J. Bergman, E. K. Randall, A. C. Avery, D. H. Thamm, A. A. C. Hull, C. M. Gust, and A. R. Donoghue, “Multicenter, randomized, double-blinded, placebo-controlled study of rabacfosadine in dogs with lymphoma,” J. Vet. Intern. Med., vol. 36, no. 1, pp. 215-226, Dec. 2022, doi: https://doi.org/10.1111/jvim.16341.

[9] E. Kim, C. Choe, J. G. Yoo, S. I. Oh, Y. Jung, A. Cho, S. Kim, and Y. J. Do, “Major medical causes by breed and life stage for dogs presented at veterinary clinics in the Republic of Korea: A survey of electronic medical records,” PeerJ, vol. 6, pp. e5161, Jul. 2018, doi: https://doi.org/10.7717/peerj.5161.

[10] R. M. A. Packer, D. G. O’Neill, F. Fletcher, and M. J. Farnworth, “Great expectations, inconvenient truths, and the paradoxes of the dog-owner relationship for owners of brachycephalic dogs,” PLOS ONE, vol. 14, pp. e0219918, Jul. 2019, doi: https://doi.org/10.1371/journal.pone.0219918.

[11] M. Zitnik, F. Nguyen, B. Wang, J. Leskovec, A. Goldenberg, and M. M. Hoffman, “Machine learning for integrating data in biology and medicine: Principles, practice, and opportunities,” Inf. Fusion, vol. 50, pp. 71-91, Oct. 2019, doi: https://doi.org/10.1016/j.inffus.2018.09.012.

[12] M. B. Ali, J. M. Evans, H. G. Parker, J. Kim, S. Pearce-Kelling, D. T. Whitaker, J. Plassais, Q. M. Khan, and E. A. Ostrander, “Genetic analysis of the modern Australian Labradoodle dog breed reveals an excess of the poodle genome,” PLOS Genet. vol. 16, pp. e1008956, Sep. 2020, doi: https://doi.org/10.1371/journal.pgen.1008956.

[13] M. Foster, R. Brugarolas, and K. Walker et al., “Preliminary evaluation of a wearable sensor system for heart rate assessment in guide dog puppies,” IEEE Sens. J, vol. 20, no. 16, pp. 9449-9459, Aug. 2020, doi: https://doi.org/10.1109/JSEN.2020.2986159.

[14] R. Garcia, “Preventive healthcare plans under animal activity licences,” Vet. Rec, vol. 184, no. 16, pp. 506-507, Apr. 2019, doi: https://doi.org/10.1136/vr.l1797.

[15] Y. Choi, H. Chae and J. Lee et al., “Cat monitoring and disease diagnosis system based on deep learning,” J. Korea Multimed. Soc. vol. 24, no. 2, pp. 233-244, Feb. 2021, doi: https://doi.org/10.9717/kmms.2020.24.2.233.

[16] Z. Cleghern, M. Foster and S. Mealin et al., “A cloud data collection platform for canine behavioural prediction using objective sensor data,” Int. J. Cloud Comput, vol. 10, no. 3, pp. 247-264, 2021, doi:

https://doi.org/10.1504/IJCC.2021.118012.
[17] A. N. Paynter, M. D. Dunbar and K. E. Creevy et al., "Veterinary big data: When data goes to the dogs," Animals(Basel), vol. 11, no. 1872, pp. 1-10, Jun. 2021, doi: https://doi.org/10.3390/ani11071872.
[18] Y. McGrotty and S. Randell, "Diagnostic approach to polyuria and polydipsia in dogs," InPract, vol. 41, pp. 249-258, Aug. 2019, doi: https://doi.org/10.1136/inp.l4418.
[19] R. Bódizs, A. Kis, and J. Topál, "Sleep in the dog: Comparative, behavioral and translational relevance," Curr. Opin. Behav. Sci., vol. 33, pp. 25-33, Dec. 2019, doi: https://doi.org/10.1016/j.cobeha.2019.12.006.
[20] S. Barrah, H. Jebali, and R. Kheder, et al., "Pellagra disease in a hemodialysis patient," Saudi J. Kidney Dis. Transpl., vol. 31, no. 4, pp. 874-876, Jul-Aug. 2020, doi: https://doi.org/10.4103/1319-2442.292325.
[21] G. Arji, H. Ahmadi, M. Nilashi, and T. A Rashid, et al., "Fuzzy logic approach for infectious disease diagnosis: A methodical evaluation, literature and classification," Biocybern. Biomed. Eng., vol. 39, pp. 937-955, Sep. 2019, doi: https://doi.org/10.1016/j.bbe.2019.09.004.
[22] M. Diez, P. Picavet, R. Ricci, and M. Dequenne, et al., "Health screening to identify opportunities to improve preventive medicine in cats and dogs." J. Small Anim. Pract., vol. 56, pp. 463-469, May. 2015, doi: https://doi.org/10.1111/jsap.12365.
[23] S. Lynch, K. Savary-Bataille, and B. Leeuw, et al., "Development of a questionnaire assessing health-related quality-of-life in dogs and cats with cancer." Vet. Comp. Oncol., vol. 9, pp. 172-182, Sep. 2011, doi: https://doi.org/10.1111/j.1476-5829.2010.00244.x.
[24] J. P. Scott and J. L. fuller, "Genetics and the Social Behavior of the Dog," University of Chicago Press, Chicago, United States, pp. 44-91, 2012.
[25] G. Lippi and L. M. Heaney, "The "olfactory fingerprint": Can diagnostics be improved by combining canine and digital noses?," Clin. Chem. Lab. Med., vol. 58, pp. 958-967, Jan. 2020, doi: https://doi.org/10.1515/cclm-2019-1269.
[26] R. G. Hamilton, Assessment of human allergic diseases, Elsevier Press, Netherlands, 2019.
[27] P. Theerthagiri, I. J. Jacob, A. U. Ruby, and Y. Vamsidhar, "Prediction of COVID-19 possibilities using KNN classification algorithm," pp. 2-14, Jan. 2020, doi: https://doi.org/10.21203/rs.3.rs-70985/v2.
[28] A. Flory, K. M. Kruglyak, and J. A. Tynan et al., "Clinical validation of a next-generation sequencing-based multi-cancer early detection "liquid biopsy" blood test in over 1,000 dogs using an independent testing set: The CANcer Detection in Dogs (CANDiD) study," Plos one, vol. 17, no. 4, e0266623, Apr. 2022, doi: https://doi.org/10.1371/journal.pone.0266623.
[29] A. I. Pereira, P. Franco-Gonçalo, and P. Leite et al, "Alves-Pimenta, M. S., Colaço, B., ... & Ginja, M. (2023). Artificial intelligence in veterinary imaging: an overview," Veterinary Sciences, vol. 10, no. 15, 320, Apr. 2023, doi: https://doi.org/10.3390/vetsci10050320.
[30] V. Maheshwari, M. R. Mahmood, and S. Sravanthi, et al., "V.P. Nanotechnology-based sensitive biosensors for COVID-19 prediction using fuzzy logic control," J. Nanomater., 3383146, Nov. 2021, doi: https://doi.org/10.1155/2021/3383146.
[31] M. Layan, S. Dellicour, and G. Baele et al., "Mathematical modelling and phylodynamics for the study of dog rabies dynamics and control: A scoping review." PLOS Negl. Trop. Dis., vol. 15, e0009449, May. 2021, doi: https://doi.org/10.1371/journal.pntd.0009449.
[32] H. Wang, O. Atif, J. Tian, Y. Chung, et al., "Multi-level hierarchical complex behavior monitoring system for dog psychological separation anxiety symptoms." Sensors (Basel), vol, 22, no. 4, 1556, Feb. 2022, doi: https://doi.org/10.3390/s22041556.
[33] G. S. Karthick, M. Sridhar, and P. B. Pankajavalli, "Internet of things in animal healthcare (IoTAH): Review of recent advancements in architecture, sensing technologies and real-time monitoring," SN Comput. Sci., vol. 1, pp. 1-16, Sep. 2020, doi: https://doi.org/10.1007/s42979-020-00310-z.