Journal of information and communication convergence engineering
http://jicce.org

J. Inf. Commun. Converg. Eng. 19(1): 29-35, Mar. 2021 Regular paper

CareMyDog: Pet Dog Disease Information System with PFCM Inference for Pre-diagnosis by Caregiver

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Abstract

While the population of pet dogs and pet-related markets are increasing, there is no convenient and reliable tool for pet health monitoring for pet owners/caregivers. In this paper, we propose a mobile platform–based pre-diagnosis system that pet owners can use for pre-diagnosis and obtaining information on coping strategies based on their observations of the pet dog's abnormal behavior. The proposed system constructs symptom-disease association databases for 100 frequently observed diseases under veterinarian guidance. Then, we apply the possibilistic fuzzy C-means algorithm to form the "probable disease" set and the "doubtable disease" set from the database. In the experiment, we found that the proposed system found almost all diseases correctly, with an average of 4.5 input symptoms and outputs 1.5 probable and one doubtable disease on average. The utility of this system is to alert the owner's attention to the pet dog's abnormal behavior and obtain an appropriate coping strategy before consult a veterinarian.

Index Terms: Pet dog, Pre-diagnosis, PFCM, Symptom database, Regularization

I. INTRODUCTION

The population of pets and related markets are continuously growing worldwide. According to a recent United States survey, two-thirds of American households own at least one pet, and 46% of them are dogs [1]. Similar statistics are provided by Italian researchers, in that 43% of Italian families own dogs or cats [2]. In Korea, it has been reported that the number of pets exceeds 10 million, and according to a recent survey, 6 million of them are dogs [3]. In light of these facts, the number of pet shops and veterinary clinics have exponentially increased in big cities, and in 2017 the pet-related market was estimated to be as large as $20 billion in Korea [4] and $95.7 billion in the United States [1].

With such an increase in the number of pets, interest in pets' healthcare is also increasing, as the publication of many related books in Korea indicates. However, there is no easy guidance on the appropriate coping strategy when a pet dog gives signs to its owner by expressing unusual behavior or a certain symptom [5]. Not knowing the appropriate treatment approach may mean that owners have to wait for a veterinarian consultation, which may delay providing treatment to the dog, or owners may try to treat their dogs based on their own limited knowledge, only to worsen the dog's condition. Thus, it is necessary for pet owners to have an easy guidance tool that explains common dog diseases and appropriate treatment approaches when the pet behaves abnormally [6].

If we are going to monitor a single disease like canine cat-

Received 29 January 2021, **Revised** 05 March 2021, **Accepted** 08 March 2021
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Open Access https://doi.org/10.6109/jicce.2021.19.1.29 print ISSN: 2234-8255 online ISSN: 2234-8883

aract, specific intelligent image-processing techniques can help owners to make a first-hand observation [7]. However, there are many other diseases worth monitoring, and gathering unbiased information on diseases and their corresponding treatments to develop an effective canine health surveillance system for experts poses multiple challenges [8, 9]. Although several computer-aided systems are available for dog health monitoring in the form of expert systems [6, 10, 11], their data collection methods are usually primary in nature and can only handle less than 10 related diseases based on traditional certainty factor [10] or fuzzy logic [11]. Thus, the utility of such a system is very limited, and possibly unreliable or subjective.What casual pet owners need is a first-hand abnormality monitoring tool that deals with a wide range of diseases and coping strategies without requiring deep knowledge of the diseases. Such information systems should accept observed symptoms as inputs and produce a list of probable diseases and possible treatments as outputs. The role of such a pre-diagnosis system is not to replace veterinarians but to alert the caregiver and detect possible disease as early as possible.

In this paper, we propose a first-hand pre-diagnosis system for general pet owners. Because the general pet owner is the main user of this system, the system is designed on the mobile platform using a machine learning technique called Possibilistic Fuzzy C-means (PFCM) clustering algorithm as the main association method between observed symptoms and a collected symptom-disease database [12]. The structure of the proposed system can be divided into database construction and fuzzy logic–based diagnostic algorithm. This very structure was effective in building a mobile Korean traditional medicine self-pre-diagnosis system [13]. In database construction, we created a symptom-disease association database based on the encyclopedia-style textbooks [14-17] and selected the 100 most frequent observable diseases under a veterinarian's guidance.

With such a database, the pet owner may give a set of symptoms he/she observes from the dog's behavior or the dog's body part abnormality. However, the symptoms from pet owners' observations are not based on clinical tests; thus, the association between input symptoms and probable diseases has a fuzzy relationship. The proposed system uses a PFCM-based algorithm to find a significantly probable (or doubtable) set of diseases that the dog might have based on the owner's observations. As PFCM is an unsupervised learning algorithm, there is no need to rely on a small number of experts' opinions for primary data collection. PFCM is an extension of popular fuzzy C-means (FCM) method [18, 19] as introducing the typicality concept and relaxing the sum-to-one restriction from FCM to make the cluster less sensitive to outliers [20]. PFCM has a rich theoretical background [12] and has been employed in many successful applications in engineering [21, 22] and medical domain [20, 23, 24], and the original model could be extended with respect to the applications [25-27]. We also extended the PFCM model by applying regularization [28] to investigate the regularization effect in this medical fuzzy reasoning task. The overall structure of the proposed system is similar to that of our previous prototype system [29], but there are many extensions such as database upgrade, PFCM-regularization algorithm, and the algorithm for deciding a probable set of diseases.

II. SYSTEM COMPONENTS

A. System Structure and Database

The overall system structure is shown in Fig. 1. When the pet owner observes the pet's abnormal behavior/symptoms, he/she classifies the symptoms/abnormal behaviors in four categories such as body, face, leg, and internal symptoms, as input. Then, the PFCM algorithm determines two sets of possible diseases based on the membership association value. The system outputs a Probable-Set, which contains diseases with most significant membership association values, and a Doubtable-Set, which includes diseases with non-negligible membership association values. Because this system is not an expert system but a pre-diagnosis system to alert general pet owners, the system output includes a wider range of possibilities than an exact identification of the disease.

The pet dog disease-symptom database has grown from 50 diseases with 92 symptoms [5] to 100 diseases with 413 symptoms [29] based on two older books [14, 15]. In this paper, we add two more recent books [16, 17] and re-evaluate the symptom-disease association and eliminate skin-related diseases and less frequent diseases under a veterinarian's guidance. After filtering, we identified 100 diseases and 217 frequently observed symptoms and included them in the database.

Our database consists of the following three main tables:

• Disease (ID, DiseaseCode, SymptomCode, Description)

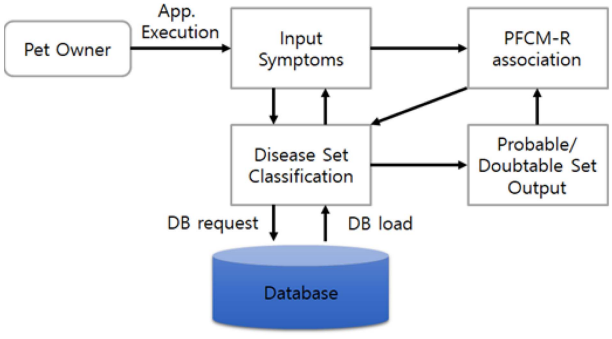

Fig. 1. Structure of the proposed system.

- Symptom (SymptomID, BodyPart, Description)
- LearnedResult (ClusterID, InputNeuron, Strength)

The SymptomCode of the Disease table contains multiple SymptomID of the Symptom table as a disease usually has more than one symptom. The LearnedResulttable stores the connection strength between the disease and the symptoms after learning.

B. PFCM for Diagnosis

In the next step, an unsupervised learning method is used to compute the degree of association between the disease and symptoms. We use two PFCM families to this end: one with regularization (PFCM-R) and the other without regularization (PFCM).

As the FCM is sensitive to noise, Krishnapuram and Keller introduced Possibilistic C-means (PCM) to the FCM method, which uses the degree of "typicality" between the data and clusters based on the relaxation of the probabilistic constraint [30]. However, the PCM algorithm is highly sensitive to initializations and, as a result, often generates coincident clusters. Furthermore, the typicality is influenced by the choice of the additional parameters [12]. PFCM, therefore, is designed to compensate for the drawbacks of FCM and PCM by combining the objective functions of these two algorithms.

Let Up = (u_{ij}) be a possibilistic cluster partition of X if

$$\sum_{j=1}^{n} u_{ij} > 0 \,, \forall i \in \{1, \dots, c\} \tag{1}$$

The element $u_{ij} \in [0, 1]$ is interpreted as the degree of typicality of datum x_j to cluster i, and u_{ij} for x_j resembles the possibility of being a member of the corresponding cluster.

The objective function in PFCM clustering can be calculated using (2).

$$J_{PFCM} = \sum_{k=1}^{n}\sum_{i=1}^{c}\left(au_{ik}^{m} + bt_{ik}^{\eta}\right) D_{ik}^{2} + \sum_{i=1}^{c}\gamma_i \sum_{k=1}^{n}(1 - t_{ik})^{\eta} \tag{2}$$

where D_{ik} denotes the distance between the k-th data x_k and u_{ik} denotes the membership value of x_k to the i-th cluster. In addition, there are c disease clusters and n symptoms. The term t_{ik} denotes the typicality of x_k belonging to the i-th cluster, m is the fuzzification degree of the membership value, η is the fuzzification degree of the typicality value, γ_i denotes the volume of the cluster, and a and b are the empirical weight constants, which were set to 1 in this study.

PFCM updates the center of clusters, membership degree, and typicality, as shown in (3)-(5).

$$v_i = \frac{\sum_{k=1}^{n}\left(au_{ik}^{m} + bt_{ik}^{\eta}\right) x_k}{\sum_{k=1}^{n}\left(au_{ik}^{m} + bt_{ik}^{\eta}\right)} \tag{3}$$

$$u_{ik} = \left(\sum_{j=1}^{c}\left(\frac{D_{ik}}{D_{jk}}\right)^{\frac{2}{m-1}}\right)^{-1} \tag{4}$$

$$t_{ik} = \frac{1}{1 + \left(\frac{b}{\eta_i} D_{ik}^{2}\right)^{\frac{1}{\eta-1}}} \tag{5}$$

This process continues until the update rule changes the typicality and membership degree to no more than the predefined threshold.

The PFCM algorithm showed better results than other FCM-based methods, but as the objective function becomes complex, more data are required to obtain a stable solution. Furthermore, there is a problem of generating multiple local optimal solutions in the solution space. The regularization of PFCM (PFCM-R), which was introduced in [27], flattens the solution space to obtain a similar solution that is relatively noise-insensitive and applicable with a small data size. The objective function of PFCM-R is given by (6) with the following constraints.

$$\begin{aligned} J_{PFCM-R} &= \sum_{k=1}^{n}\sum_{i=1}^{c}\left(u_{ik}^{m} + t_{ik}^{\eta}\right) D_{ik}^{2} + \sum_{i=1}^{c}\gamma_i \sum_{k=1}^{n}(1 - t_{ik})^{\eta} \\ &\quad + \beta \sum_{k=1}^{n}\sum_{i=1}^{c} u_{ik}^{m} \\ 0 \le u_{ik} \le 1, &\quad \sum_{i=1}^{c} u_{ik} = 1, \sum_{k=1}^{n} u_{ik} > 0 \\ 0 \le t_{ik} \le 1, &\quad \sum_{k=1}^{n} t_{ik} > 0 \\ \mathrm{m}, \eta > 1, &\quad \beta > 0 \end{aligned} \tag{6}$$

The advantage of using PFCM-R is that if we define the variable as (7), only the cluster center update rule is changed, as shown in equation (8) and the update rules of membership and typicality remain the same as (3) and (5), where β denotes the regularization constant and $D_{ik}'^2$ limits the minimum distance D_{ik} with constant β. As a result, we can prevent the membership degree from reaching an extreme value of 0 or 1.

$$D_{ik}'^2 = D_{ik}^2 + \beta \tag{7}$$

$$u_{ik} = \left(\sum_{j=1}^{c}\frac{\left(D_{ik}'^2\right)^{\frac{1}{m-1}}}{\left(D_{jk}'^2\right)^{\frac{1}{m-1}}}\right)^{-1} \tag{8}$$

III. EXPERIMENT

The proposed method is implemented in Android Studio

Version 5.0.0 and JDK 12.0.2, with an Intel(R) Dual Core(TM) i5-87005U CPU @ 3.3 GHz and 16 GB RAM PC. The symptom disease database contained 100 different diseases with 217 observable symptoms. The typical input and output are shown in Figs. 2 and 3, respectively.

To test the performance of our PFCM families in terms of their diagnostic power, we tested all 100 diseases by inserting a sufficient number of symptoms that are common to at least two out of the four resource books we used to build our database. In this experiment, the average number of input symptoms was 4.56, and at least two and at most nine symptoms were used to validate the performance of the proposed system. Table 1 shows the distribution of input symptoms and cases, showing that 80% of diseases need at most five symptoms to obtain reliable results. However, some diseases such as adrenocortical hypofunction need nine input symptoms to be recognized with high PFCM value as these diseases have many symptoms common with other diseases; hence, in the case of adrenocortical hypofunction, a veterinarian's expertise is a "must".

Fig. 2. User interface selecting body part and symptoms of the pet.

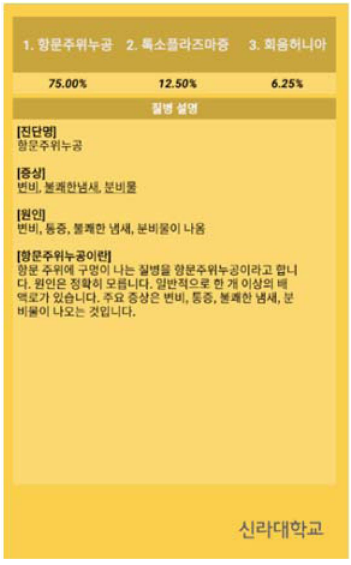

Fig. 3. Typical system output for the pet owner.

Reliable performance by PFCM is defined as designating the right diseases with the highest PFCM value among candidate diseases. In previous studies [5, 29], we generated the five diseases with the highest membership value with respect to the disease cluster; however, in this study, we provided two sets of possible diseases related to the input symptoms. First, we extract not more than 10 non-zero PFCM-valued candidate diseases and sort them in descending order, which means the first candidate has the highest PFCM value. We name this candidate set as L.

If enough observations are provided as input, in most cases, the proposed PFCM families are good enough to find no more than three dominating candidate diseases. Thus, we form two sets of diseases, P (meaning "Probable") and D (meaning "Doubtable"), that the system outputs for the user. If there is one dominating disease candidate, set P contains only that candidate. This situation usually occurs when the highest candidate has 2.5 times higher PFCM value than the second one. Otherwise, we add the next candidate until two ordered sets P and (L-P) have the highest margin of difference where L contains candidate diseases in descending order of non-zero PFCM values of the disease.

If the set P has enough normalized coverage (more than 60% of L) in terms of the PFCM value, all we need is set P. However, when there are no dominating disease candidates, the normalized coverage of set P is less than 60%. In such cases, we add the next disease candidate to the set D until the cumulated normalized PFCM values exceed 60%. PFCM relaxes the sum to one constraint in computing membership and typicality value; thus, it should be normalized to compare candidates relatively. This procedure can be written as follows:

1. $L = \{A_i | PFCM(A_i) \geqq PFCM(A_i + 1),\ 1 \leqq i \leqq 10\}$ is an ordered set of candidate diseases in descending order of non-zero PFCM values of such diseases. P, D = Null set.
2. Set P denotes "Probable" disease candidates and Set D

Table 1. Number of symptoms that gives reliable PFCM Performance

Symptoms	Cases	Cumulated
2	1	1
3	24	24
4	33	58
5	22	80
6	7	87
7	9	96
8	1	97
9	3	100

denotes “Doubtable” disease candidates.

3. If $A_1 > 2.5 * A_2$, $P = \{A_1\}$
4. Else Find P that maximizes the margin of average PFCM(A_i) A_i in P from PFCM(A_{ij}) A_i in L – P, where A_{j-1} is in C. $i \geq 2$.
5. Compute the normalized coverage of m(P), where $P = \{A_i | 1 \leqq i \leqq k\}$, where Cover(P) = sum(PFCM(A_i)) from 1 to k / sum(PFCM(A_i)) from 1 to 10.
6. If Cover (P) >= 0.6 then stop
7. Otherwise, Add A_{k+1} to D and compute Cover ($P \cup D$), all tied disease candidates are also included in D.
8. Go to 4.

We tested our database twice. First, PFCM and then PFCM-R are applied to the same condition to determine whether the regularization effect in this domain is meaningful.

IV. RESULT AND ANALYSIS

When our PFCM and PFCM-R generated the non-zero probability set L, we sent the input and the candidate diseases set L to the veterinarian and asked them to see if the target diseases in L could happen under a given input through a yes/no decision. Thus, if the veterinarian checks “yes”, it means that there is at least a non-zero probability to infer that disease under the given input. For all 100 target diseases, our PFCM generated 808 candidates, and 605 cases were checked as “yes” by veterinarians. That means, on average, PFCM generates 8.08 diseases as candidates but only 6.05 of them are “possible”; thus, the average correctness of candidate generation is 74.9%.

The typical results of our experiments are shown in Table 2.

In this example case, both PFCM and PFCM-R generate 10 candidates to set L, but one of them was regarded as inaccurate by the veterinarian (checked “X” in the last column). The order of the PFCM values in set L is slightly different. PFCM includes two diseases in set P, whereas PFCM-R includes three. However, the normalized coverage of the set P is less than 60 (38.4% for PFCM and 47.8% for PFCM-R) thus, the second set D contains long-shot disease candidates until the normalized coverage exceeds 60%. As a result, both algorithms add two more doubtable diseases each to set D. Thus, in this case, the pet owner will receive four outputs by PFCM (two probable two doubtable) and five (three probable two doubtable) by the PFCM-R algorithm. The ground truth used in the experiment is pneumonia, which is picked as the number one candidate by both algorithms. We can conclude that the regularization of PFCM is positively applied in that it provides more meaningful information than PFCM without regularization.

However, as can be seen in Table 3, the overall accuracy (picking meaningful diseases filtered by veterinarians as set P or set D) is similar, and the difference is statistically insignificant.

Still, we can say that if a disease is informed to the pet owner as a probable disease, the accuracy of picking up a meaningful disease with respect to the reported input is statistically significantly higher compared with the baseline (74.9%) of the database.

The number of meaningful candidate diseases selected by the two PFCM families is summarized in Table 4. As is clear from the table, PFCM-R statistically selected more diseases than did PFCM. This can be regarded as the “regularization effect”.

Overall, the top candidate of the 100-disease set with respect to the guided input symptoms was correctly picked in 99% by PFCM and 100% by PFCM-R.

Table 3. Accuracy of PFCM and PFCM-R.

	Coverage	Accuracy		
		Set P	Set D	Total
PFCM	59.1	98.6	85.3	93.4
PFCM-R	54.8	97.4	85.6	92.1
Dataset		74.9		

Table 2. PFCM reasoning example (Input symptoms: Cough, dyspnea, fever, enervation, ascites).

Candidate	PFCM	Candidate	PFCM-R	Doctor
Pneumonia	74.1	Pneumonia	80	O
Hematosepsis/peritonitis	34.3	Parainfluenza	36	O
Parainfluenza	30.1	Hematosepsis/peritonitis	36	O
Kennel Cough	26.67	Canine Distamper	30	O
Canine Distamper	25.8	Kennel Cough	26.67	O
Heart Disease	23.27	Heart Disease	26.67	O
Lung Tumor	19.8	Lung Tumor	22.5	X
Filariasis	17.9	Filariasis	20	O
Cushing's Syndrome	15.9	Cushing's Syndrome	20	O
Left-sided heart failure	14.8	Left-sided heart failure	20	O
P-Coverage	38.4	P-Coverage	47.8	

Table 4. Average number of selected diseases by PFCM and PFCM-R.

	Set P	Set D	Total
PFCM	1.47	0.95	2.42
PFCM-R	1.54	1.25	2.79
Dataset	8.08	6.05	

V. CONCLUSIONS

In this paper, we propose a mobile pre-diagnosis system for pet dog owners/caregivers under PFCM clustering. While the pet market and the interest in pet healthcare are rapidly increasing worldwide, there is no reliable and convenient tool for pet dog owners to monitor their pet's health status and perform a quick pre-diagnosis using coping tips before they go to the veterinarian.

The proposed system consists of a database collected from multiple textbooks with veterinarian filtering and an unsupervised learner called PFCM that forms several disease clusters associated with various related symptoms with respect to the body parts of the pet and the degree of typicality and membership value. The implemented software takes observed abnormal symptom from the owner as input and the PFCM learner explores the symptom-disease associations and outputs 1.5 "probable" diseases and 0.95 ~ 1.25 more 'doubtable' diseases that cover at least 60% of normalized association values defined by the PFCM objective function.

We tested two algorithms (PFCM and PFCM-R), but the effect of regularization was very limited in our experiment. However, we could verify that our system can accurately identify the disease as the most probable one, with an average of 4.5, symptoms as input (80% of diseases need no more than five input symptoms). Thus, we may conclude that the proposed system is a convenient tool for pet owners to monitor their pet's health. However, the role of this system is not to replace veterinarians' diagnosis but to stimulate the owner's attention to pet dog's abnormality and get appropriate information about the disease and coping strategy before consulting a veterinarian.

The main contribution of this research is to develop a first-hand pre-diagnosis system for pet owners with much wider coverage of dog-related diseases than the existing expert system style systems that cover fewer than 10 diseases. In addition, the proposed system is more flexible and reliable than previously developed self-diagnosis systems that only work for a fixed number of diseases regardless of the statistical significance among related diseases.

However, the limitation of this research is that the fuzzy inference system is tested only for database validation (providing significantly higher accuracy than the database collection itself) but not tested with real dog patient data. In order to validate the clinical effectiveness of the system, we need more extensive dog patients' clinical data, which requires veterinarian hospital participation.

ACKNOWLEDGMENTS

This research is a partial result of the "Leaders in INdustry-university Cooperation +" Project, supported by the Ministry of Education and National Research Foundation of Korea.

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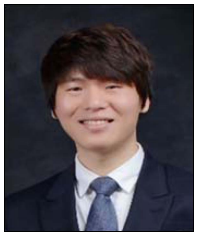

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