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

J. Inf. Commun. Converg. Eng. 19(4): 234-240, Dec. 2021

Regular paper

Hybrid Fuzzy Association Structure for Robust Pet Dog Disease Information System

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Abstract

As the number of pet dog-related businesses is rising rapidly, there is an increasing need for reliable pet dog health information systems for casual pet owners, especially those caring for older dogs. Our goal is to implement a mobile pre-diagnosis system that can provide a first-hand pre-diagnosis and an appropriate coping strategy when the pet owner observes abnormal symptoms. Our previous attempt, which is based on the fuzzy C-means family in inference, performs well when only relevant symptoms are provided for the query, but this assumption is not realistic. Thus, in this paper, we propose a hybrid inference structure that combines fuzzy association memory and a double-layered fuzzy C-means algorithm to infer the probable disease with robustness, even when noisy symptoms are present in the query provided by the user. In the experiment, it is verified that our proposed system is more robust when noisy (irrelevant) input symptoms are provided and the inferred results (probable diseases) are more cohesive than those generated by the single-phase fuzzy C-means inference engine.

Index Terms: Fuzzy associative memory, Hybrid inference, Pet dog, Pre-diagnosis, Robust inference

I. INTRODUCTION

The number of pet dog owners and related markets is rapidly growing worldwide [1-3]. According to a recent report [4], the number of companion animals in Korea is continuously increasing, with over 6 million families raising at least one companion animal. Most of these companion animals are pet dogs, with 80% of such families owning 1.2 dogs on average according to the same report, resulting in approximately 6 million pet dogs living with people in Korea. The owners spent a yearly average of $400 to care for their dogs, with those raising older dogs (over 10 years of age) paying $900 per year [4]. The three most common types of disease that occur in old dogs are eye-related, skin-related, and oral health-related diseases; pet owners rely on regular checkups and consultation with veterinarians to detect and manage these conditions. Other than costly and time-consuming visits to animal hospitals, pet owners have no clear guidance on abnormal pet behavior and appropriate coping strategies [5].

As argued in [6], computer-aided dog health monitoring software in the form of an expert system developed for veterinarians [7, 8] is ineffective because of the difficulty of primary data collection methods and the narrow range of diseases that such software can cover. Rather, a mobile information system that can provide first-hand abnormal behavior monitoring and appropriate coping strategies without requiring deep knowledge of the diseases is more relevant for the growing number of pet owners who take care of older dogs [9]. Such software may handle one specific disease, such as canine cataracts [10], or cover many diseases by providing

Received 29 September 2021, **Revised** 12 October 2021, **Accepted** 12 October 2021
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Open Access https://doi.org/10.6109/jicce.2021.19.4.234 print ISSN: 2234-8255 online ISSN: 2234-8883

rough pre-diagnosis based on owner-observed symptoms [6]. The role of this pre-diagnosis information system is not to replace veterinarian-like expert systems but to alert the caregiver with limited knowledge when their pet exhibits abnormal behavior indicative of disease, allowing the abnormalities to be addressed as early as possible.

Recently, a mobile pet disease information system was proposed for casual pet owners, providing a rough pre-diagnosis based on fuzzy query processing of observed abnormal symptoms by owners [6]. The major function of this software is the fuzzy inference system based on a machine learning algorithm called possibilistic fuzzy C-means with regularization (PFCM-R) [11, 12] which associates observed symptoms with a collected symptom-disease database. A set of symptom-disease database is constructed based on several dog disease textbooks under the guidance of veterinarians, covering 100 frequently observed diseases in pet dogs; the power of the inference system under controlled queries showed statistically significant results during simulation [6], the structure of which is shown in Fig. 1.

This structure is similar to the Korean Traditional Medicine self-pre-diagnosis system, whose database is based on the Korean Standard Causes of Death Disease Classification Index developed by the Korean government [13]. However, there is no reliable data source for animal diseases; thus, we developed our database based on several encyclopedias relating to animal diseases. Furthermore, the database query is entirely dependent on the set of symptoms observed by pet dog owners (no clinical test involved); thus, the association between input symptoms and probable diseases should have a fuzzy relationship. Thus, PFCM-R works well for reasonably formed queries consisting of observed symptoms, as shown in the simulated experiment in [6]. The system generates 2-5 strongly connected diseases based on input symptoms using PFCM-R inference. Since the observations of the pet owners are not professional, it is better for the system to provide multiple probable diseases to account for possibly insufficient or incorrect information. This reinforces the main role of such software: to alert casual owners to the abnormality of their pets' conditions; the system suggests further consultation with veterinarians in the case that a serious condition is detected.

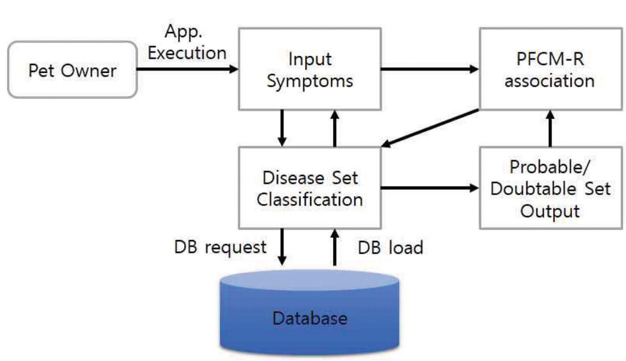

Fig. 1. The system structure of CareMyDog Information System [6].

However, in a real-world situation, casual owners may make incorrect observations, causing the database query to consist of unrelated symptoms. Alternatively, the pet dog may be affected by a compounded disease, causing the casual owner to misunderstand and believe that all observed symptoms relate to a single disease, again forming a query including irrelevant symptoms. Since casual pet owners' observations are not based on any clinical data, these less controlled queries may harm the robustness of the inference system. That is, if a pet caregiver observes five abnormal symptoms, but one of those five input symptoms is unrelated to the others, the inference system may report several unrelated or less related diseases as possible diagnoses, negatively influencing the strength of inference due to such outlier symptoms in the input. This situation is likely to arise because the customers of this software are casual pet owners rather than well-trained veterinarians, with insufficient understanding to filter unrelated features to infer the target disease effectively.

Thus, we propose in this paper a hybrid inference based on fuzzy association memory (FAM) and double-layered fuzzy C-means (FCM) instead of the previously proposed PFCM-R inference to filter or mitigate the negative influence of unrelated symptoms during the query forming process in the system structure of [6], as shown in Fig. 1.

Associative memory is a well-known and efficient human characteristic of learning. When storing and recalling associations among patterns, FAM [14] is a theoretically sound noise tolerant, fast convergence structure that captures the content of each pattern and the association between them [15, 16]. Some FAM models have demonstrated their utility in several engineering problems [17-19], and fuzzy expert systems have been implemented for limited medical domains [20-22]. The original FAM model was designed as a single-phase learning structure. However, pure FAM does not handle unrelated input noise well, which saturates the associative memory and negatively affects classification performance [22].

Thus, we need a mechanism to filter unrelated input attributes during the candidate disease generation process (classification phase). To accomplish this goal, we adopt a two-phase FCM learning structure, including an auto-encoder structure from [23], to reduce the input dimensionality.

In this paper, we propose a hybrid inference structure that accommodates single-phase FAM and a double-layered FCM structure, where the first layer of FCM is used to filter input symptoms unrelated to others. By using this hybrid structure for the disease inference (classification) phases, we expect our proposed method to be more robust than the previous PFCM-R-based classification owing to stronger cohesion between the resultant set of diseases leading to more reliable inference.

II. HYBRID INFERENCE BASED ON FUZZY ASSOCIATION MEMORY

The basic associative memory model allows for the storage of pattern associations and retrieval of the desired output pattern upon receiving a possibly noisy or incomplete version of an input pattern [24], as shown in Fig. 2.

The FAM can be described in terms of the following relationship between an input pattern $x \in [0, 1]^n$ and the corresponding output pattern $y \in [0, 1]^m$, as shown in the following equation:

$$\mathrm{Y} = (\mathrm{W} \circ_T X) \circ \theta, \tag{1}$$

where Y denotes the output and W denotes the connection strength matrix with threshold θ, which is defined as follows:

$$\theta = \wedge_{k=1}^{p} y^k, \quad (0 \leq \theta \leq 1), \tag{2}$$

where y^k denotes the output of the k^{th} learned pattern (of maximum p patterns available).

As mentioned in the previous section, this single-phase learning structure may have a negative influence on the input symptoms that are relatively unrelated to other input symptoms. Such input sources may hinder the identification of similar diseases under a given input so that only 1-2 diseases are focused upon, leaving other possibilities insufficiently explored.

Thus, our goal is to exclude several symptoms from the input that are not related to other symptoms or goal diseases. To accomplish this, we utilize a double-layered structure, as shown in Fig. 3.

User input symptoms form the input layer, but the first association learning serves to exclude or mitigate the effect of inputs unrelated to the goal disease based on FCM. The second layer, which consists of relatively high scores of first layer learning, acts as the input of the second FCM structure to relate the goal disease. As in [6], the proposed inference algorithm generates the 10 most probable diseases with respect to user input symptoms.

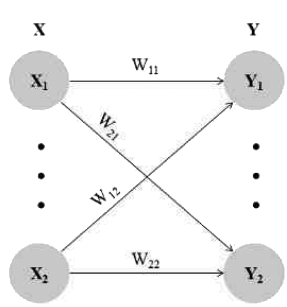

Fig. 2. Basic Fuzzy Associative Memory structure [19].

The middle layer represents the body parts of the pets relevant to the input symptoms. If some of the input symptoms are not related to the same parts other symptoms are related to, the connected strength of this input is penalized; thus, the resultant diseases in the output layer are less influenced by such outlier input symptoms. In our proposed system, the middle layer consists of 12 parts/behaviors, including the full body, skin, mouth, eye, tail, head, breast, legs, back spine, hip, behavior (vomit), and feces.

However, the hard exclusion of such seemingly unrelated input symptoms may cause saturation of the exploring disease space to occur too early. To counteract this, we adopt a hybrid approach that includes single-phase FAM and double-layered FCM inference, as shown in Fig. 4.

The three associative relationships are shown in Fig. 4. Throughout this paper, w_1, w_2, and w_3 refer to the weight matrices of the relationship between the input and middle layers, middle and output layers, and the direct association of the input and output layers, respectively.

The matrix w_1 is computed using the equation (3)-(6) as follows:

$$d_{1j} = \sqrt{\left(pm\dot{i}n_i - P_{ij}\right)^2}, \tag{3}$$

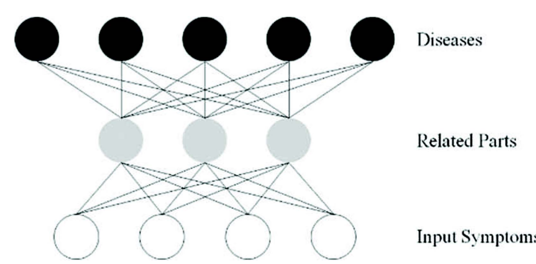

Fig. 3. Double-layered Fuzzy Association with FCM.

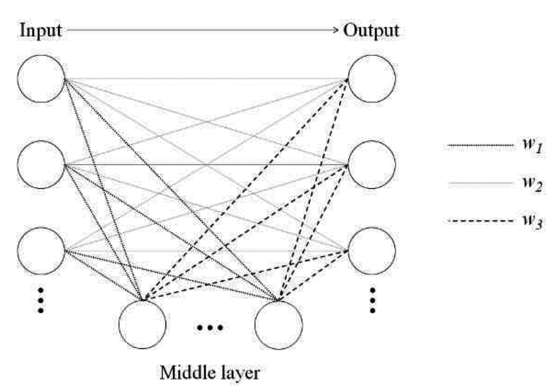

Fig. 4. Hybrid Fuzzy Association structure.

$$d_{2j} = \sqrt{\left(pmax_i - P_{ij}\right)^2}, \tag{4}$$

$$\mu_{ij} = \left(\sum_{k=1}^{c}\left(\frac{d_{1j}}{d_{2j}}\right)^{m}\right)^{-1}, \tag{5}$$

and

$$w_1 = \mu_{ij} \,. \tag{6}$$

Here, P_{ij} denotes the number of diseases that contain the i-th symptom on the j-th part (middle layer), and the variables $pmax_i$ and $pmin_i$ denote the maximum/minimum number of diseases that contain *the* i-th symptom over all parts, respectively. Then, the fuzzy membership degree w_1 is computed based on the normalized distance for FCM. Because the distance within a cluster is defined as the normalized number of related diseases, outlier symptoms in the input will be penalized according to the FCM principle; thus, its negative influence will be mitigated. The meaning of the membership degree with respect to w_1 is represented by Fig. 5.

Likewise, w_2 is computed using equations (7)-(12) as follows:

$$d_1 = \sqrt{\left(dmin_i - D_{ij}\right)^2}, \tag{7}$$

$$d_2 = \sqrt{\left(dv_i - D_{ij}\right)^2}, \tag{8}$$

$$d_3 = \sqrt{\left(dmax_i - D_{ij}\right)^2}, \tag{9}$$

$$dv_i = \frac{\sum_{k=1}^{i}(\mu_{2k})^m d_k}{\sum_{k=1}^{i}(\mu_{2k})^m}, \tag{10}$$

$$\mu_{ij} = \left(\sum_{k=1}^{c}\left(\frac{d_{1j}}{d_{2j}}\right)^{m}\right)^{-1}, \tag{11}$$

and

$$w_2 = \mu_{ij} \,. \tag{12}$$

Here, D_{ij} denotes the number of symptoms that the j-th disease has, including the i-th symptom. Variables $dmax_i$ and dmn_i denote the maximum and minimum number of symptoms of such diseases, respectively. The variable dv_i denotes the centroid point, which indicates the relative relevance of the i-th symptom and disease in the output phase. Thus, the closer dv_i and $dmin_i$ are, the less diseases are expected to be output in the resultant diagnosis.

Then, the fuzzy membership degree w_2 is computed based on the normalized distance of the FCM. The meaning of the membership degree with respect to w_2 is shown by Fig. 6.

The direct association between user-provided symptoms and disease is represented by w_3, and the computation is shown in equation (13):

$$w_3 = \frac{1}{N} \times \frac{1}{j} \times \sum_{k=1}^{N}\left(\sqrt{\sum_{i=1}^{i}(X_{ki} - D_{ki})^2}\right), \tag{13}$$

where X_{ki} denotes the number of symptoms given by the user on the i-th part for the k-th disease and D_{ki} is the number of symptoms given in the database on the i-th part for the k-th disease; there are a total of j parts (j = 12 in this study) and N diseases (N = 50 in this paper).

Thus, there are three outputs in this learning structure.

During the first FCM learning phase, user-provided symptoms are related to the middle layer (body parts) and y_1 is computed using equation (14):

$$y_1 = \frac{1}{j}\sum_{n=1}^{j}(\min(w_1, x_n)), \tag{14}$$

where x_n is the ratio of the number of users provided symptoms divided by the possible number of symptoms in the database for the body part n, and y_1 is the average of the minimum of w_1 and x_n; thus, any irrelevant user input is penalized.

$$y_2 = \frac{1}{j}\sum_{n=1}^{j}(\min(w_2, x_n)). \tag{15}$$

The output of the above upper-layer FCM learning (y_2) is computed using equation (15) in a similar fashion to y_1, except that this layer exhibits iterative FCM learning with respect to the centroid movement rule specified in equations (7)-(12).

The output of the direct association between symptoms and diseases is by definition the same as that of w_3. Thus, the final output of this hybrid learning is the minimum of y_2 and w_3. Similar to the standard FCM algorithm, our proposed hybrid learning is continued until the final output exhibits stable positioning of the cluster centroid over iterations.

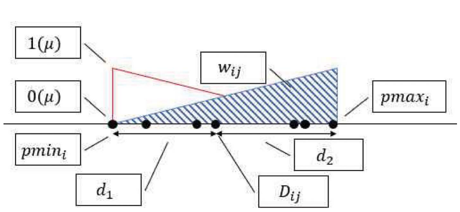

Fig. 5. Graphical Representation of the distribution of w_1.

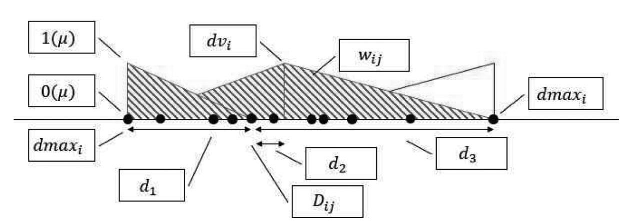

Fig. 6. Graphical Representation of w2 distribution.

After the learning phase, the proposed system provides the top 10 probable diseases based on the user-provided symptoms in order of final output (strength of inference).

III. EXPERIMENT

Our proposed method is implemented on the Google Pixel 4 virtual machine using Android Studio Version 5.0.0 and JDK 12.0.2 on a PC with an AMD(R) Ryzen(TM) 5 3600X 6-core CPU @ 3.3 GHz and 16 GB RAM. The symptom disease database contained 50 different diseases with 217 observable symptoms, all of which were verified by multiple veterinarians.

To test the robustness of our proposed system, we generated one query consisting of five related symptoms for each disease under the guidance of veterinarians. Because these 50 queries do not have any unrelated symptoms, we denote it as the pure set. Then, we add up to three random noise (unrelated to the target disease) attributes to the pure set, referred to as Noise1, Noise2, and Noise3. If an inference system used in classification is robust, the resultant class (diseases) should not be drastically changed when adding one, two, or three irrelevant attributes. The proposed system is compared with single-phase FCM-based diagnosis in terms of diagnostic accuracy over four sets (Pure, Noise1, Noise2, Noise3), as shown in Table 1.

The inference is correct if the target disease is selected as the first probable disease with respect to the query consisting of five relevant symptoms and k irrelevant symptoms ($0 \leq k \leq 3$).

When the user gives only five relevant symptoms (pure set), FCM inference may perform better; however, when two or more irrelevant attributes are added to the query, the accuracy of FCM is drastically reduced. However, our proposed hybrid inference structure is no worse than FCM if there exists any irrelevant feature in the query (a likely case because the user is not a professional) and maintains its robustness even when two or more irrelevant features are added.

To see the difference in classification robustness, we demonstrate typical examples of the top five diseases inferred by the proposed system and the FCM method over four sets (Pure, Noise1, Noise2, Noise3), as shown in Tables 2 and 3, respectively.

From Tables 2 and 3 it is apparent the two algorithms are successful in inferring the target disease when the query is formed as a pure set without any irrelevant symptoms. However, as the number of noise attributes increases, the FCM method quickly loses its inference power. Moreover, the order of the top five probable diseases is quite unstable as the number of noise symptoms increases when FCM is applied. On the other hand, the order of the top five probable diseases generated by the proposed system shows much less variation than the FCM inference. Thus, we can conclude that the proposed inference structure is more robust for noisy inputs. This robustness is critical for demonstrating the system's reliability for field experts (veterinarians) and casual pet owners.

Table 1. Accuracy of target disease inference (%)

Set	Proposed	FCM
Pure	86	92
Noise1	80	80
Noise2	76	54
Noise3	50	22

Table 2. Robustness of proposed inference (Target: periodontal disease)

Rank	Set			
	Pure	Noise1	Noise2	Noise3
1	periodontal disease	periodontal disease	periodontal disease	oral tumor (fibrosarcoma)
2	oral tumor (carcinoma)	oral tumor (carcinoma)	oral tumor (carcinoma)	oral tumor (carcinoma)
3	stomatitis	stomatitis	stomatitis	periodontal disease
4	root abscess	root abscess	root abscess	root abscess
5	root tumor	root tumor	root tumor	root tumor

Table 3. Robustness of FCM inference (Target: urolithiasis)

Rank	Set			
	Pure	Noise1	Noise2	Noise3
1	urolithiasis	urolithiasis	gastric ulcer	skin tumor (basal cell)
2	uterine sinusitis (occlusive)	gastric ulcer	peritonitis	urolithiasis
3	gastric ulcer	peritonitis	uterine sinusitis (occlusive)	uterine sinusitis (open)
4	peritonitis	uterine sinusitis (open)	ileus	uterine sinusitis (occlusive)
5	uterine sinusitis (open)	ileus	skin tumor (basal cell)	ileus

IV. CONCLUSIONS

In this paper, we propose a hybrid inference algorithm for a robust pre-diagnosis system for pet dog caregivers under fuzzy associations between symptoms and diseases. The goal of our proposed method is to increase inference robustness for noisy inputs. Because the mobile pre-diagnosis system is not an expert system for veterinarians but for casual pet dog owners without deep knowledge of various pet diseases, it is expected that the input query (set of observed symptoms) may not be sound or well formed.

We propose that the inference system incorporates FAM and double-layered FCM as opposed to single-phase FCM, which we used in our previous system. The lower level of the proposed double-layered FCM is designed to mitigate the negative influence of noise symptoms in the input query, and its output serves as the input to the higher layer of FCM learning. The FAM is a direct association between symptoms and diseases, and can preserve basic inference power regardless of the relevance of input symptoms to the target diseases. By combining these two fuzzy associative inference algorithms, the proposed method is expected to be more robust than single-phase FCM for noisy inputs.

In our experiment, the proposed inference method was more noise-tolerant and provided more cohesive output (probable diseases) than single-phase FCM inference, as shown in Tables 1, 2, and 3. Since this system is a pre-diagnosis system for casual pet dog owners to monitor abnormal behavior in their pets without having deep knowledge, robust inference power in pet dog information systems is essential for owners.

However, the limitation of this research is that the proposed fuzzy inference system has not been tested on real dog patient data. To validate the clinical effectiveness of the system, we need to further test using more extensive clinical data of dog patients, which requires veterinarian hospital participation.

ACKNOWLEDGMENTS

This research was supported by a grant of the Citizen participatory service R&D project, funded by the Busan Innovation Institute of Industry, Science & Technology Planning (BISTEP) and the Busan Metropolitan City of the Republic of Korea.

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