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Optimization of Certainty Factor in Cat Disease Diagnosis Using Particle Swarm Optimization

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Abstract

The increasing prevalence of diseases in pet cats highlights the need for a diagnostic support system that is both fast and accurate. The Certainty Factor (CF) method is widely used in expert systems to represent uncertainty in decision-making. However, its reliance on subjective expert judgment can reduce diagnostic accuracy and system confidence. This study aims to optimize CF values using the Particle Swarm Optimization (PSO) algorithm, enabling the system to adapt better to actual medical data. CF values were initially collected from two veterinary experts and combined using the median method to minimize bias. These values were then optimized using PSO, with parameter tuning performed individually for each disease to maximize fitness. The dataset used for validation consisted of 100 medical records of cats diagnosed with one of nine common feline diseases, including Ringworm, Scabies, Helminthiasis, and others. The results show an increase in diagnostic accuracy from 85% (using original CF) to 88% (after PSO optimization). Moreover, 70.73% of the cases with consistent diagnoses before and after optimization showed an increase in final CF values, indicating greater confidence in the system's diagnostic decisions. These findings suggest that the integration of CF with PSO not only improves diagnostic accuracy but also strengthens the reliability of expert systems in the veterinary field, particularly for early and efficient identification of cat diseases.

I. Introduction

In recent years, cats have become one of the most favored pets among Indonesians, surpassing other common choices such as birds and fish. A survey conducted by Rakuten Insight and reported by GoodStats revealed that 67% of over 10,000 Indonesian respondents own at least one pet, with cats being the most popular [1]. This growing trend in cat ownership has also driven increased awareness regarding the health and wellbeing of domestic cats. Pet owners are no longer focused solely on basic needs such as food and shelter but are also increasingly attentive to preventive care, early symptom detection, and overall medical attention for their pets.

According to a study conducted by Drh. Syaiful Ratmus, out of 1,130 cats studied, 73.2% were diagnosed with health issues. His research identified nine major diseases that frequently occur in cats: Ringworm, Scabies, Helminthiasis, Otitis, Ancylostomiasis, Enteritis, Toxocariasis, Vulnus, and Toxoplasmosis [2]. Accurate and early diagnosis is essential in veterinary practice, particularly for prevalent feline diseases. Timely identification not only improves treatment outcomes and recovery rates but also helps prevent complications, control the spread of infectious diseases, and reduce treatment costs, thereby enhancing overall animal welfare.

To address this issue, expert systems have been developed as decision support tools capable of assisting in disease diagnosis. These systems simulate the reasoning process of a human expert using a predefined knowledge base. One of the widely used methods in expert systems is the Certainty Factor (CF) method, which is designed to handle uncertainty by representing the level of confidence in the association between observed symptoms and possible diseases [3]. CF values are generally assigned by domain experts based on their experience and judgment.

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However, this introduces subjectivity, especially in veterinary diagnostics where many symptoms overlap across diseases. For example, vomiting, diarrhea, and appetite loss commonly appear in both Helminthiasis and Enteritis, but different experts may assign different CF values to these symptoms. This variation can reduce diagnostic reliability and lead to inconsistent outcomes. Certainty Factor methods are designed to express degrees of confidence based on expert input [4], but this approach depends heavily on individual judgment, which may vary widely in practice.

Several studies have sought to address the limitations of subjectivity in CF-based systems. Optimization algorithms, particularly those inspired by natural and biological processes, have shown promise in refining CF values to better match real-world diagnosis patterns. One such algorithm is Particle Swarm Optimization (PSO), a population-based stochastic optimization technique modeled on the social behavior of birds and fish. PSO is known for its simplicity and strong global search capability, making it a suitable candidate for parameter optimization in expert systems [5].

The effectiveness of PSO has been demonstrated in various domains. For instance, a study by Yadav et al. found that PSO outperformed other bio-inspired algorithms such as Ant Colony Optimization, Firefly Algorithm, and Cuckoo Search in sentiment analysis tasks, achieving a classification accuracy of 93.84% [6]. PSO's strengths in convergence speed and solution quality make it highly adaptable for improving system performance across different fields. In another study by Pambudi et al., PSO was successfully used to optimize CF values in diagnosing fish health conditions. Their results showed a 10% improvement in accuracy when compared to using CF without optimization [7].

However, prior research, such as Pambudi's, often relied on a single expert to define CF values. While this approach simplifies the modeling process, it lacks robustness and may not fully capture the variability found in medical knowledge. Medical diagnosis, especially for animals, is inherently complex and often involves varying opinions among experts. Therefore, this study proposes an alternative approach by combining CF values from two veterinary experts to create a more comprehensive and reliable knowledge base.

The primary objective of this study is to implement a CF-based expert system enhanced with PSO to diagnose common cat diseases more accurately. By integrating the perspectives of multiple experts and applying PSO to fine-tune CF values, the system aims to minimize subjectivity and improve both accuracy and confidence in the diagnostic outcomes. It is expected that the proposed method will contribute to the development of more reliable veterinary expert systems that can assist both pet owners and veterinarians in identifying diseases promptly and accurately.

II. Related Works/Literature Review

Several previous studies have contributed significantly to the development of expert systems and optimization techniques for diagnostic purposes. One study by Dian et al. developed a rule-based expert system for identifying dental problems in children using a combination of Forward Chaining and Certainty Factor. The system utilized both rule inference and confidence weighting, which led to high diagnostic accuracy exceeding 91%. This hybrid method demonstrated the potential of combining reasoning techniques with uncertainty handling to support early diagnosis and treatment planning [8].

In the agricultural domain, Wiliam et al. applied Particle Swarm Optimization to improve the performance of the K-Nearest Neighbor (KNN) algorithm for citrus pest detection. PSO was used to optimize the value of *k* and perform feature selection, resulting in an increased classification accuracy from 90% to over 96%. The study showed how PSO could effectively enhance performance in classification-based expert systems by fine-tuning parameters and input selection [5].

Gupta et al. proposed a hybrid model combining PSO with Convolutional Neural Networks (CNN) for plant leaf disease detection. Their approach leveraged PSO to optimize neural network parameters and achieved near-perfect performance with 99.98% accuracy. Although the research focused on agriculture, the methodology demonstrated PSO's adaptability and effectiveness in optimizing complex AI models in various diagnosis-related applications [9].

Closer to the veterinary context, Pambudi et al. combined the Certainty Factor method with PSO to identify health conditions in catfish. The optimization led to a 10% improvement in accuracy compared to CF alone, proving the advantage of hybridization. However, their system relied on a single expert and addressed a relatively narrow domain, focusing only on one species and one disease which limits its scalability and effectiveness in more complex diagnostic scenarios [7].

While these studies highlight the effectiveness of both Certainty Factor and PSO in improving expert systems, many still rely on a single-expert knowledge base or focus on narrowly defined problems. This reveals a gap in building diagnostic systems that incorporate multiple expert perspectives and operate in broader, more variable domains. The present study addresses this gap by integrating CF values from two veterinary experts and applying PSO optimization separately for each disease. Additionally, the system is designed to diagnose nine common feline diseases, making it more comprehensive and representative of real-world veterinary diagnostic challenges.

III. METHODS

This study was carried out through a series of systematic stages, starting from literature review, data collection and processing, system analysis, testing scenarios, implementation, and system evaluation. The complete research workflow is illustrated in Figure 1.

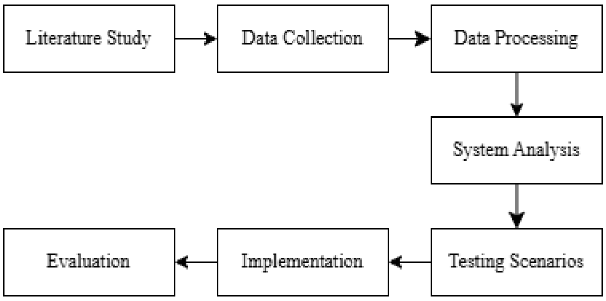

Fig 1 Research Flow

A. Literature Study

1. Certainty Factor

Certainty Factor (CF) is a knowledge representation method used in expert systems to handle uncertainty in decision-making processes. The concept was first introduced in the MYCIN expert system by Shortliffe and Buchanan, which was developed to diagnose bacterial infections and recommend appropriate antibiotic therapies in the medical field. The CF method quantifies an expert's confidence in a hypothesis based on available evidence[10]. he basic CF formulation is given by Equation (1).

$$CF[h,e] = MB[h,e] - MD[h,e] \tag{1}$$

Where *MB[h,e]* is the measure of belief in hypothesis *h* given evidence *e* and *MD[h,e]* is the measure of disbelief in hypothesis *h* given evidence *e* [11].

If a single piece of evidence supports a hypothesis, the CF value can be calculated by multiplying the user's belief level (*CF_user*) with the expert's confidence in the rule (*CF_expert*), as shown in Equation (2).

$$CF[h,e] = CF[e] \times CF[rule] = CF[user] \times CF[expert] \tag{2}$$

When multiple symptoms support the same hypothesis, the CF values can be combined using Equation (3).

$$CF_{combined}[CF_1, CF_2] = CF_1 + CF_2 \times (1 - CF_1) \tag{3}$$

The CF method offers a straightforward yet effective approach to managing uncertainty in expert systems. It is easy to implement and allows for numerical representation of belief. However, it has limitations, especially in dealing with complex relationships among multiple variables, as it relies solely on two parameters: *MB* and *MD* [12].

2. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based optimization algorithm inspired by the social behavior of bird flocks and fish schools in search of food [13]. Introduced by Kennedy and Eberhart in 1995, PSO has been widely applied in various domains, including expert systems, artificial intelligence, and function optimization [14]. In PSO, each candidate solution is represented as a particle that moves through the search space. Each particle has a position and velocity, which are iteratively updated based on its personal best position (*pBest*) and the global best position (*gBest*) discovered by the swarm [15].

The velocity update rule incorporates three components: the inertia component (ω), the cognitive component (*pBest*), and the social component (*gBest*), as defined in Equation (4) [16][17].

$$v_i(t+1) = \omega . v_i(t) + c_1 . r_1 . (pBest_i - x_i) + c_2 . r_2 . (gBest_i - x_i) \tag{4}$$

The updated velocity is then used to update the particle's position, as shown in Equation (5).

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{5}$$

Where x_i is the position of the *i-th* particle, v_i is the velocity, c_1, c_2 are the cognitive and social acceleration coefficients and r_1, r_2 are random values between 0 and 1

The inertia factor ω is adjusted linearly based on the iteration, as shown in Equation (6) [18].

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min}) \times Iter}{Iter_{max}} \tag{6}$$

In each iteration, a fitness value is calculated to evaluate the performance of each particle. This study uses Mean Squared Error (MSE) as the fitness function to measure the difference between expert CF values and optimized CF values, defined in Equation (7) [19].
Where $(Y_i - F(X_i))^2$ is the squared error between actual and predicted CF values.
The optimization process terminates when the maximum number of iterations is reached or when there is no significant improvement in *gBest*. The position of the best-performing particle is used as the final optimized CF value in the diagnostic system.

3. Expert System

An expert system is a computer-based application designed to replicate the decision-making ability of a human expert in a specific domain [20]. It utilizes a set of rules and knowledge acquired from experts to analyze data and provide recommendations or conclusions. Generally, an expert system comprises two environments: the development environment and the consultation environment. The development environment is used by system developers to acquire knowledge and construct the knowledge base. Meanwhile, the consultation environment allows users to interact with the system as if consulting with a real expert [21].

Expert systems have been implemented in various fields such as medicine, agriculture, manufacturing, and education, particularly to support decision-making in complex and time-sensitive situations [20], [21],[22]. One of their key advantages is the ability to provide consistent recommendations based on the encoded expert knowledge. However, expert systems are not without limitations. The quality of their output heavily depends on the accuracy and completeness of the knowledge base. Incomplete or inaccurate information may lead to suboptimal or incorrect recommendations.

B. Data Collection

The data used in this study were obtained from two primary sources. The first source is expert knowledge collected from the Puskeswan Jiwan in Madiun. This includes a list of nine common feline diseases, namely Ringworm (P01), Scabies (P02), Helminthiasis (P03), Otitis (P04), Ancylostomiasis (P05), Enteritis (P06), Toxocariasis (P07), Vulnus (P08), and Toxoplasmosis (P09), along with 31 related symptoms (Table 1) and CF values provided by two veterinarians for each disease-symptom pair (Table 2). These CF values form the initial knowledge base used by the expert system. The second source consists of 100 medical records obtained from the Animal Hospital of the East Java Provincial Livestock Service. This dataset was used to evaluate the system's diagnostic accuracy before and after the optimization process.

TABLE 1
SYMPTOM

Symptom Code	Symptom Name	Symptom Code	Symptom Name	Symptom Code	Symptom Name
G01	Decreased appetite	G12	Reddish rash	G22	Foul odor in the ear
G02	Hair loss	G13	Thickened/hardened skin	G23	Redness/swelling in the ear
G03	Vomiting	G14	Under 1 year old	G24	Torn wound
G04	Fever	G15	Soft or watery stool	G25	Pus in the wound
G05	Diarrhea	G16	Black stool	G26	Adult age
G06	Weakness	G17	Stool with blood	G27	Difficulty breathing
G07	Lethargy	G18	Mucous in stool	G28	Restlessness
G08	Bloated abdomen	G19	Weight loss	G29	Vomiting with worms
G09	Circular spots on the skin	G20	Frequent ear scratching/rubbing	G30	Frequent head shaking
G10	Crusty skin	G21	Ear discharge	G31	Aged 1–5 years
G11	Frequent scratching				

TABLE 2
CF VALUES

Disease Code	Symptom Code	CF Value 1	CF Value 2	Disease Code	Symptom Code	CF Value 1	CF Value 2	Disease Code	Symptom Code	CF Value 1	CF Value 2
P01	G02	0.6	1.0	P04	G14	0.4	0.0	P07	G03	0.8	1.0
	G09	1.0	0.8		G20	0.8	1.0		G05	0.6	1.0
	G10	0.8	1.0		G21	1.0	1.0		G08	0.8	1.0
	G11	0.6	1.0		G22	1.0	1.0		G14	0.6	0.0
	G12	0.6	1.0		G23	0.8	0.8		G15	0.8	1.0

Disease Code	Symptom Code	CF Value 1	CF Value 2
P02	G02	0.6	1.0
	G10	0.6	0.6
	G11	0.8	1.0
	G12	0.6	0.8
	G13	1.0	1.0
	G28	0.2	1.0
P03	G01	0.6	0.6
	G02	0.6	1.0
	G03	0.4	0.8
	G05	0.4	0.8
	G08	0.8	1.0
	G14	0.4	0.0
	G15	0.4	1.0
	G29	1.0	0.8

Disease Code	Symptom Code	CF Value 1	CF Value 2
	G30	0.6	1.0
	G31	0.2	0.8
P05	G02	0.6	1.0
	G03	0.6	1.0
	G05	0.6	1.0
	G06	0.6	1.0
	G07	0.6	1.0
	G08	0.8	0.8
	G16	1.0	1.0
	G17	1.0	1.0
P06	G01	0.6	1.0
	G03	0.8	0.6
	G04	0.8	0.8
	G05	1.0	1.0
	G14	0.4	0.0
	G15	1.0	1.0
	G17	1.0	0.4
	G18	1.0	0.8
	G19	0.8	1.0

Disease Code	Symptom Code	CF Value 1	CF Value 2
P08	G01	0.6	1.0
	G04	0.6	1.0
	G06	0.6	0.8
	G24	1.0	1.0
	G25	1.0	1.0
	G31	0.6	0.0
P09	G01	0.8	1.0
	G04	0.8	1.0
	G05	0.6	1.0
	G26	0.6	1.0
	G27	1.0	1.0

Each CF value provided by the experts corresponds to a specific level of certainty, as outlined in the interpretation guideline proposed by Setyaputri et al [23]. A value of 1.0 indicates very confident, meaning the expert believes the symptom-disease relationship is certainly convincing. A score of 0.8 reflects high confidence, while 0.6 indicates moderate confidence, where the relationship is likely but not guaranteed. A value of 0.4 represents low confidence, suggesting a weak but possible correlation. Meanwhile, 0.2 denotes very weak or almost no confidence, and 0.0 implies no belief or no knowledge regarding the symptom's relevance to the disease.

C. Data Processing

The CF values obtained from two veterinary experts were processed to generate a single final certainty value to be used in the optimization stage. Since discrepancies may exist between the experts' assessments, the median method was applied to merge the values. The median was chosen for its robustness against outliers and, in this case with only two values, yields the same result as the mean [24].

After the merging step, a normalization process was conducted to align the resulting CF values with the predefined certainty level categories. Each value was rounded up to the nearest defined level on the interpretation scale. For example, a value of 0.9 would be rounded to 1.0, and 0.7 would be adjusted to 0.8. This scale uses a fixed interval of 0.2, as defined in the confidence level reference (see Table 4). This step ensures that every CF value used in the system falls within a clearly defined and interpretable range.

The second data source consists of 100 feline medical records collected in 2024 from the Veterinary Hospital of the East Java Provincial Livestock Service. These records were used to evaluate the system's diagnostic performance before and after CF optimization. Sampling was conducted using a purposive sampling technique, where only cases with complete symptom documentation and confirmed veterinary diagnoses were included. This method was chosen to ensure data quality and relevance for validating the expert system's decision-making process.

D. System Analysis

The system analysis stage aims to develop a diagnostic model by integrating the CF method with PSO. This hybrid model is designed to improve the accuracy of diagnosing common feline diseases by optimizing expert-defined CF values provided by two veterinary professionals. The combination of CF and PSO enables the system to better handle uncertainty in the knowledge base and enhances the confidence level of its diagnostic output.

The process begins with the system receiving input symptoms and confidence levels from the user. Each input is then combined with expert CF values that have been previously optimized using the PSO algorithm. Optimization is carried out separately for each disease using predefined parameters, including maximum and minimum inertia weights (ω_max, ω_min), cognitive and social acceleration coefficients (C_1 and C_2), swarm size, and the number of iterations.

PSO operates by initializing a swarm of particles randomly within the search space. Each particle represents a candidate solution in the form of expert CF values. A fitness function based on Mean Squared Error (MSE) is used to evaluate how closely each particle matches the expert reference. The particles' velocities and positions are updated iteratively based on personal best (pBest) and global best (gBest) positions. This process continues until the maximum number of iterations is reached or the optimal solution is found.

Once the optimized expert CF values are obtained, the system calculates a combined CF for each symptom by multiplying the user's confidence level (CF_user) with the optimized expert value (CF_expert). These values are then aggregated using the CF combination formula to produce a final CF score for each disease. The disease with the highest final CF score is presented as the primary diagnosis, along with a description and recommended initial treatment. The full workflow of this CF-PSO-based diagnostic model is illustrated in Figure 2.

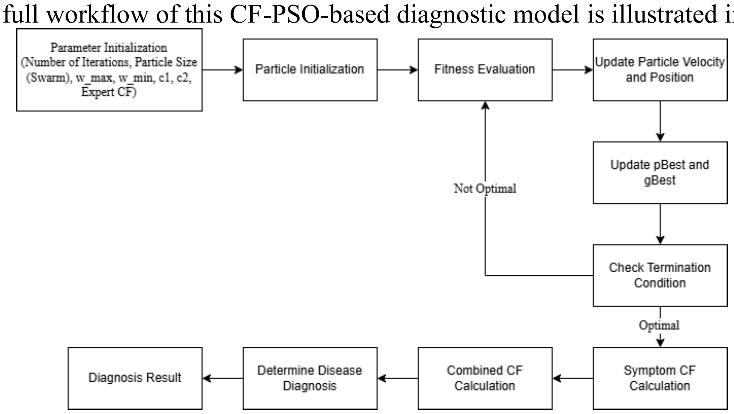

Fig 2 CF-PSO Model Flow

E. Testing Scenarios

This study implements a testing scenario to evaluate the performance of the PSO algorithm in optimizing CF values and to measure the diagnostic accuracy of the system before and after optimization.

1. PSO Parameter Testing

The PSO parameter testing aimed to determine the optimal configuration that yields the lowest average fitness value. The parameters tested included inertia weight (ω_max and ω_min), acceleration coefficients (C_1 and C_2), swarm size, and number of iterations. Testing was carried out sequentially, starting from inertia weight, followed by acceleration coefficients, swarm size, and iterations. For each test, the remaining parameters were kept constant using default values: $C_1 = 2.0$, $C_2 = 2.0$, swarm size = 10, and iterations = 10. Once the best value was found, it was used as a fixed value for the next test.

The variations included ω_max values of 0.9, 0.8, and 0.7, each paired with ω_min values of 0.2, 0.3, and 0.4. Acceleration coefficients ranged from 1.0 to 2.0 for both C_1 and C_2, tested in both symmetric and asymmetric pairs. Swarm size and iterations were varied from 10 to 100 with a step size of 5. Each combination was tested 10 times, and the average of the best fitness scores was recorded. The testing was performed separately for each disease, resulting in different optimal parameter combinations.

The choice of parameter ranges in this testing process was based on established practices in PSO literature and prior studies. The inertia weight variation adopted the linear decreasing strategy proposed by Shi and Eberhart, where a higher value of ω is used at the beginning and gradually decreased to enhance convergence [25]. The selected ranges for acceleration coefficients (C_1 and C_2 between 1.0 and 2.0) are commonly used to maintain balance between individual and swarm learning. This range is considered safe and effective, as it prevents particles from moving too aggressivel which can lead to oscillations and missed solutions or too slowly, which may hinder convergence [26]. Swarm sizes and iteration counts were chosen to explore the trade-off between optimization performance and computational efficiency, particularly for medium-scale problems such as CF optimization in expert systems. These settings also aligned with configurations used in similar studies, such as those by Pambudi [7], and were validated through empirical testing in this study.

2. Accuracy Testing

Accuracy testing is conducted to evaluate how well the system diagnoses match actual diagnoses recorded in medical records. A total of 100 patient records were used as test data, consisting of symptom inputs and confirmed diagnoses for nine common cat diseases. These records were obtained from the Veterinary Hospital of the East Java Provincial Livestock Department.

The system is tested in two conditions: using unoptimized expert CF values and using CF values optimized with PSO. The system's diagnoses are then compared with actual diagnoses to count how many are correct. Accuracy is calculated using Equation (8) [27]. This comparison is used to assess the effectiveness of PSO in improving diagnostic accuracy.

$$Accuracy = \frac{\text{Number of Correct Diagnoses}}{\text{Total Test Data}} \, x\ 100\% \quad (8)$$

IV. RESULTS

This section presents the results of a series of tests conducted to evaluate the performance of a cat disease diagnosis system using the CF method optimized with PSO.

A. PSO Parameter Testing Results

Each combination of PSO parameters was tested ten times, and the average fitness value was calculated. For efficiency and brevity, not all detailed testing results are presented in this article. As an example, Table 3 shows the results of testing the inertia weight parameter. The bold values in the table indicate the best fitness results for each disease.

TABLE 3
PSO INERTIA WEIGHT TESTING RESULTS

Inertia Weight		Average Fitness Score (10 Trials)								
ωmax	**ωmin**	**P01**	**P02**	**P03**	**P04**	**P05**	**P06**	**P07**	**P08**	**P09**
0.9	0.2	**0.152116**	**0.167354**	0.18364	**0.165659**	0.183203	**0.153445**	0.167139	0.174719	0.175806
	0.3	0.171703	0.192656	0.19688	0.176282	0.174973	0.179337	0.174281	0.183869	0.188284
	0.4	0.175422	0.185571	0.17044	0.17254	0.184536	0.180641	0.166442	**0.154059**	0.169455
0.8	0.2	0.154824	0.18122	0.1857	0.175877	0.185958	0.194893	0.18423	0.171603	0.180705
	0.3	0.188104	0.185323	**0.154976**	0.201853	0.183532	0.157791	0.175147	0.181891	0.180911
	0.4	0.193252	0.169824	0.169513	0.166707	**0.165716**	0.185537	0.175594	0.169327	0.165201
0.7	0.2	0.18298	0.178403	0.185051	0.169366	0.171585	0.174451	0.167401	0.193089	0.173751
	0.3	0.179762	0.192955	0.168006	0.186052	0.198171	0.173203	0.171447	0.17621	**0.148397**
	0.4	0.195749	0.191836	0.155992	0.166718	0.171993	0.185208	**0.159901**	0.175862	0.174999

After testing all PSO parameters, the best parameter combinations for each disease are summarized in Table 4 below.

TABLE 4
OPTIMAL PSO PARAMETER COMBINATIONS EACH DISEASE

Disease Code	ωmax	ωmin	C_1	C_2	Swarm Size	Iteration
P01	0.9	0.2	1.0	1.5	70	40
P02	0.9	0.2	1.5	1.5	85	50
P03	0.8	0.3	2.0	1.5	75	35
P04	0.9	0.2	2.0	1.5	95	25
P05	0.8	0.4	1.0	1.5	95	100
P06	0.9	0.2	1.5	1.5	100	65
P07	0.7	0.4	1.5	1.5	95	25
P08	0.9	0.4	1.0	1.5	100	20
P09	0.7	0.3	1.5	1.5	95	40

B. CF Optimization Results

The optimal PSO parameter combinations identified from the previous tests were then applied to the CF optimization process for each disease. Optimization was conducted individually per disease, using the specific PSO configuration that yielded the best results for each case.Table 5 presents selected examples from the CF optimization results using PSO. Only a portion of the data is displayed to maintain readability.

TABLE 5
OPTIMIZED CF VALUES USING PSO

Disease Code	G01	G02	G03	G04	G05	G06	...	G30	G31	Final Fitness Score
P01	1	0.8	0	0	0.799999	0	...	0	0	0.103225
P02	0	0.799998	0	0	0.799997	0	...	0	1	0.096774
P03	0.600042	0.800032	0.799990	0	0.800031	1	...	0	0	0.051615
...	...	...	...	...	...	...	...	...	...	...

By applying the PSO algorithm separately for each disease, the optimized CF values were found to be more stable and closer to expert-provided values, with lower error (fitness) scores. This indicates that the optimization process successfully adjusted the CF values to better reflect patterns in real-world data, while also reducing reliance on subjective initial expert assessments.

C. System Accuracy Testing Results

After optimizing the expert CF values using PSO, the system proceeded to calculate the final CF for each patient. The first step involved multiplying the user's confidence level in a symptom (as recorded in the medical data) with the optimized CF value for that symptom. These values were then combined using the CF combination formula to generate a final CF score for each disease. The final diagnosis was determined based on the disease with the highest CF value. Table 6 presents a partial comparison of diagnosis results before and after CF optimization using PSO. Only a sample of patient records is shown for clarity.

TABLE 6
COMPARISON OF DIAGNOSIS RESULTS BEFORE AND AFTER CF OPTIMIZATION

Patient Code	Medical Record Diagnosis	Pre-Optimization Diagnosis	Final CF Value (Before)	Post-Optimization Diagnosis	Final CF Value (After)	CF Value Difference (Before Optimization)
PAS01	P03	P06	0.9782272	P06	0.9856	-
PAS02	P03	P07	0.95104	P06	0.96	-
PAS03	P02	P02	0.96256	P02	0.9925120376	-
PAS04	P04	P04	0.891136	P04	0.9395895517	-
PAS05	P06	P07	0.990208	P06	0.992	-
...	...	...	...	...	...	...
PAS37	P02	P02	0.9856	P02	0.9855999344686	0.000000065
PAS38	P06	P06	0.99328	P06	0.992	0.001280
...	...	...	...	...	...	...

These results were used to evaluate the accuracy of the system. The final accuracy was calculated by comparing the system's diagnosis to the actual diagnosis recorded in the medical data. Accuracy was determined as the percentage of correctly diagnosed cases over the total number of test cases. To provide a more comprehensive evaluation beyond accuracy, we analyzed the system's performance using classification metrics such as precision, recall, and F1-score. This analysis was conducted for both pre- and post-optimization predictions. The results showed that before optimization, the system achieved an overall accuracy of 85%, but some diseases, particularly Helminthiasis (P03) and Enteritis (P06), had relatively low recall values (0.59 and 0.84, respectively). This indicates that many true cases of these diseases were not correctly detected.

After CF optimization using Particle Swarm Optimization (PSO), the overall system accuracy increased to 88%. In addition to this increase, the recall for P03 improved significantly from 0.59 to 0.71, and for P06 from 0.84 to 0.96. The F1-score of P06 also rose from 0.78 to 0.89, demonstrating better balance between sensitivity and precision. These improvements confirm that the PSO-based optimization process enhanced the diagnostic sensitivity of the expert system, particularly for diseases with overlapping symptoms.

The classification report also highlighted that the system maintained high precision across most disease classes, with F1-scores above 0.85 in key categories such as P02, P04, and P08. This means that the improved accuracy was not only due to better detection rates (recall) but also from the system's ability to avoid incorrect diagnoses (precision).

In addition to the numeric metrics, the confusion matrices in Figure 3 and Figure 4 visualize the distribution of predictions across disease classes. Figure 3 shows the confusion matrix before CF optimization, where several misclassifications are observed, especially between P03 (*Helminthiasis*) and other diseases. In contrast, Figure 4 demonstrates improved classification performance after PSO optimization, with more accurate predictions and a stronger diagonal dominance, indicating higher alignment between predicted and actual diagnoses.

Although most cases showed an increase in final CF values after optimization, a few cases experienced a decrease despite the predicted diagnosis remaining correct. This may occur when the PSO algorithm adjusts the CF weights downward for symptoms that are less consistent or less informative across the dataset. Such reductions do not imply a decrease in diagnostic performance, but rather reflect the system's refined calibration of confidence, minimizing overestimation and improving generalization.

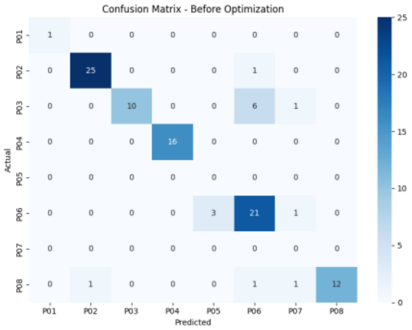

Fig 3 Confusion matrix of diagnosis results before CF optimization

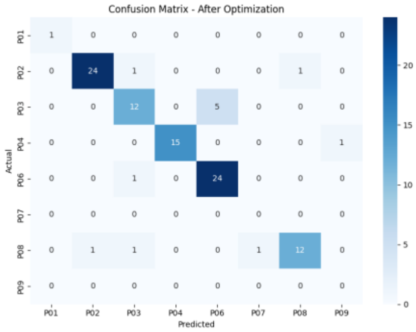

Fig 4 Confusion matrix of diagnosis results after CF optimization

V. DISCUSSION

The evaluation was conducted under two conditions: before and after the optimization of Certainty Factor (CF) values using the Particle Swarm Optimization (PSO) algorithm. Based on 100 patient medical records, the system achieved an accuracy of 85% when using original CF values from experts. After optimization with PSO, the accuracy increased to 88%, indicating that the algorithm contributed to better alignment between system predictions and actual diagnoses.

Further analysis was conducted on a subset of 82 patients whose diagnosis results remained consistent before and after optimization. Among them, 70.73% experienced an increase in final CF values after optimization, suggesting that the system had greater confidence in its diagnostic outputs. While 2.44% of the cases showed no change in CF values, 26.83% experienced a decrease; however, the reductions were minimal (less than 0.01) and did not alter the correctness of the diagnosis.

These findings confirm that integrating PSO into a CF-based expert system can enhance both diagnostic accuracy and confidence. The ability of PSO to adjust CF values based on real-world data patterns helps reduce subjectivity, which is a known limitation of manually assigned CF scores. As a result, the system becomes more adaptive and reliable in handling uncertainty in symptom-disease relationships.

Despite its promising outcomes, this study has several limitations that need to be addressed. The dataset used for evaluation was relatively small, with only 100 patient records, which may limit the generalizability of the results. Additionally, the system currently focuses on only nine common feline diseases; thus, future studies could explore the inclusion of more disease types and consider using alternative optimization methods, such as Genetic Algorithm (GA) or Differential Evolution (DE), to compare their effectiveness against PSO.

VI. CONCLUSIONS

This study demonstrates that integrating the CF method with the PSO algorithm can significantly enhance the performance of an expert system for diagnosing common feline diseases. The primary issue addressed in this research was the subjectivity and variability in expert-assigned CF values, which can reduce the accuracy and reliability of diagnostic systems. By combining CF values from two veterinary experts and optimizing them using PSO, the system was able to produce more representative and objective confidence scores. This approach proved effective in minimizing bias and adapting CF values to better match real-world data.

Experimental results validated the proposed method. The diagnostic accuracy increased from 85% to 88% after CF optimization using PSO, demonstrating a measurable improvement. While a 3% increase may seem modest, it is significant in the context of medical decision support systems, where even small improvements can lead to better clinical outcomes. Furthermore, among patients with unchanged diagnoses before and after optimization, over 70% experienced increased final CF values, indicating enhanced system confidence in its conclusions. Cases with decreased CF values were rare and exhibited only minor reductions that did not affect the correctness of the diagnosis.

In conclusion, this study offers a practical and effective solution to the limitations of traditional CF-based systems by addressing the issue of expert subjectivity and improving system adaptability through PSO. The resulting model not only improves diagnostic accuracy but also increases the robustness of the system in handling uncertainty. Future work could expand this model to include more experts and broader disease categories, ultimately contributing to the development of more reliable and intelligent veterinary diagnostic tools.

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