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Hybrid approach of type-2 fuzzy inference system and PSO in asthma disease

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ABSTRACT

This research work presents a hybrid approach combining a type-2 fuzzy inference system with particle swarm optimization (PSO) to develop a type-2 fuzzy optimized inference system, specifically tailored for asthma patient data. Addressing the inherent uncertainty in medical diagnostics, this model enhances traditional type-1 fuzzy logic by incorporating ambiguity into linguistic variables and utilizing type-2 fuzzy if-then rules. The system is trained to minimize diagnostic error in asthma disease identification. Applied to a dataset comprising eight medical entities from asthma patients, the model demonstrates substantial accuracy improvements. Numerical computations validate the system, showing a decrease in error rate from 1.445 to 0.03, indicating a significant enhancement in diagnostic precision. These results underscore the potential of our model in medical diagnostic problems, providing a novel and effective tool for tackling the complexities of asthma diagnosis.

Introduction

Asthma, a long-time period inflammatory sickness characterized by using triggered bronchospasms and reversible airflow obstruction, offers giant diagnostic challenges because of its complicated and multifactorial nature. Symptoms such as wheezing, chest tightness, coughing, and shortness of breath, frequently exacerbated at night or during exercise, are inspired by means of environmental and genetic factors. As said by the World Health Organization in 2019, asthma impacted approximately 262 million people worldwide, ensuing in 455,000 deaths. This alarming statistic underscores the urgency for progressed diagnostic methodologies to efficiently navigate the uncertainties inherent in scientific diagnostics.

Related works

The prime problem in computational theory is the L.A. Zedah's 1965 foundational paper on 'Fuzzy Sets' with a new approach to cope with uncertainty and imprecision and foundation for the growth of fuzzy logic[1]. In 1975, Zadeh widens the span of fuzzy logic thru 'The Concept of a Linguistic Variable' which presents a brand-new manner of thinking about inexact reasoning and opens up clean prospects for similarly research[2]. In 2005, Sierra and Coello paintings on enhancing PSO based totally multi-goal optimization the usage of crowding, mutation, and ∈-dominance represents a huge leap in optimizing complicated systems[4]. In 2006, Feng delivered the concept of self-producing RBFNs using evolutionary PSO getting to know, mixing neural networks with evolutionary computation in a singular way[5]. In 2008, Huang and Dun's development of a dispensed PSO-SVM hybrid device for characteristic choice and parameter optimization marks a sizable development within the integration of machine mastering and optimization strategies[8]. In 2008, Martínez and Gonzalo's paper on 'The Generalized PSO' opens new doors in PSO evolution, showcasing the adaptability of PSO in fixing complex problems[9]. In 2011, Valdez et al. added a stepped forward evolutionary technique the usage of fuzzy good judgment for combining PSO and genetic algorithms, showcasing the synergy among those optimization techniques[12]. In 2012, Patel et al.'s choice assist gadget for diagnosing allergies severity the usage of fuzzy logic demonstrates the realistic utility of fuzzy good judgment in medical diagnostics[16]. In 2013, Melin et al. Worked at the most effective design of fuzzy category structures using PSO with dynamic parameter version showcases the integration of fuzzy good judgment with optimization strategies[17]. In 2013, Mendel's educational on widespread kind-2 fuzzy good judgment structures simplifies those

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complex standards, making them more available for a broader target audience[18]. In 2014, Namadchian et al.'s balance analysis of nonlinear dynamic systems the use of nonlinear Takagi–Sugeno–Kang fuzzy structures provides a new measurement to the steadiness analysis of dynamic structures[19]. In 2015, Marini and Walczak's worked on PSO is a vital contribution, presenting a complete information of PSO and its packages[20]. In 2016, Gehlot et al.'s development of a PSO-primarily based home security device the use of a wi-fi non-public vicinity community demonstrates the flexibility of PSO in actual-global programs[22]. In 2016, Badnjević et al.'s work on diagnosing allergies, the use of fuzzy rules implemented according with international hints and physician's revel in is a large step inside the sensible application of fuzzy common sense in healthcare[23]. In 2017, Bonyadi and Michalewicz's review of PSO for single objective continuous space problems is an important contribution, providing a deep insight into the applications and limitations of PSO[26]. In 2021, Mancilla et al. research on optimizing fuzzy logic controllers with distributed bio-inspired algorithms marks a significant advancement in controller design[34]. In 2022, Thobiani et al. development of a hybrid PSO and Grey Wolf Optimization algorithm for static and dynamic crack identification demonstrates the potential of combining various optimization techniques for engineering applications[35]. In 2022, Mancilla et al. worked on optimal fuzzy controller design for autonomous robot path tracking using population-based metaheuristics is an innovative application of fuzzy logic in robotics[36]. In 2022, Gupta et al. review of fuzzy logic-based systems for medical diagnosis illustrates the growing importance and applicability of fuzzy logic in healthcare[37]. Additionally, Tahamipour-Z et al. introduced a generalized fuzzy hyperbolic model for controlling nonlinear systems, contributing to the field of complex system management[40]. In 2023, Bi et al. exploration of PSOSVR Pos, a WiFi indoor positioning system using SVR optimized by PSO, showcases the practical application of PSO in location-based services[41]. In 2023, García-Valdez et al. worked on distributed and asynchronous population-based optimization applied to the optimal design of fuzzy controllers represents a significant step in the evolution of optimization techniques[42]. In 2023, Moazen et al.'s introduction of PSO-ELPM, enhancing PSO with elite learning and enhanced parameter updating, marks a novel advancement in optimization algorithms[43]. In 2023, Alagarsamy and Govindaraj introduced an innovative method for brain tumor segmentation in MRI images. Their approach synergizes the Artificial Bee Colony algorithm with Interval Type-II Fuzzy techniques, aiming to enhance the precision and efficiency in identifying brain tumors, which holds significant implications for medical diagnostics and treatment strategies[49].

Related works with Type-2 fuzzy set

In 2002, Mendel and John's paper on Type-2 fuzzy sets simplifies those ideas, making them greater on hand and staining an essential development inside the discipline of fuzzy good judgment[3]. In the 2007 publication by Castillo et al. presented at the IEEE International Conference on Granular Computing, the authors explore the theory and applications of Type-2 Fuzzy Logic. This work offers insights into the complex nature of Type-2 Fuzzy systems and their practical applications in various fields[6]. The following year, in 2008, Castillo and Melin further expanded on this topic in their book, providing a more comprehensive exploration of Type-2 Fuzzy Logic. They delve deeper into both the theoretical aspects and the diverse applications of this advanced fuzzy logic system, bridging the gap between theory and practical implementation[7]. In 2009, Bajestani and Zare's utility of optimized type 2 fuzzy time series for forecasting the Taiwan stock index highlights the predictive power of fuzzy logic in economic markets[10]. In 2010, Martinez et al. optimized type-2 fuzzy controllers using genetic algorithms and PSO[11]. In 2011, Bajestani and Zare presented an improved type 2 fuzzy time collection method for predicting the TAIEX, reinforcing the effectiveness of fuzzy logic in financial forecasting[13]. In 2012, Castillo and Melin's assessment on the design and optimization of interval type-2 fuzzy controllers affords a comprehensive perception into the advancements and challenges inside the area[14]. In 2012, Catillo and Melin reviewed the design and optimization of interval type-2 fuzzy controllers[15]. In 2015, Sanchez et al. Supplied an evaluation of generalized type-2 fuzzy systems with c program language period type-2 and sort-1 fuzzy systems in controlling a cellular robot highlights the nuances and effectiveness of these systems[21]. In 2016, Olivas et al.'s parameter adaptation in PSO using interval type-2 fuzzy logic offers a novel approach to enhancing the efficiency of PSO[24]. In 2016, Baydokhty et al.'s optimal hierarchical type 2 fuzzy controller for load–frequency systems with production rate limitation and governor dead band is a noteworthy application of fuzzy logic in engineering[25]. In 2017, Bajestani et al.'s development of a GA-based type-2 fuzzy regression model for nephropathy forecasting in diabetic patients is a significant application of fuzzy logic in medical forecasting[27]. In 2018, Bajestani et al. prediction of retinopathy in diabetic patients using a type-2 fuzzy regression model further illustrates the potential of fuzzy logic in medical diagnostics[28]. In 2019, Wang and Kumbasar focused on enhancing interval Type-2 fuzzy neural networks. They employed PSO along with BBBC methods to optimize parameters, aiming to improve the network's performance[30]. In 2020, Mittal et al. comprehensive review on type 2 fuzzy logic applications provides a panoramic view of the past, present, and future of this field[31]. In 2020, Valdez et al. survey on Type-2 fuzzy logic controller design using nature-inspired

optimization highlights the fusion of fuzzy logic with modern optimization techniques[32]. In 2020, Namadchian and Zare worked on stability analysis of dynamic nonlinear interval type-2 TSK fuzzy control systems emphasize the importance of robust control systems in engineering[33]. In 2022, the field of interval type-2 fuzzy systems saw notable advancements. Gomes and Serra developed a computational model for real-time Kalman filtering, specifically targeting the dynamic spread of novel Coronavirus 2019, a timely and significant contribution to public health analytics[38]. In the same year, Cuevas et al. innovated in control systems by optimizing membership functions in interval type-2 fuzzy tracking controllers using a shark smell metaheuristic algorithm, demonstrating a novel approach to improving controller accuracy[39]. In 2023, Awotunde et al.'s application of an enhanced Internet of Things-enabled Type-2 Fuzzy Logic for healthcare system applications is a notable fusion of fuzzy logic with IoT for healthcare solutions[44]. In 2023, Sharma and Dhiman's intuitionistic type-2 fuzzy logic-based inference system and its applications to the medical field illustrate the potential of fuzzy logic in complex decision-making environments[45]. In 2023, Rafiei et al.'s interval type-2 Fuzzy control and stochastic modelling of COVID-19 spread based on vaccination and social distancing rates is a timely application of fuzzy logic in pandemic modelling[46]. In 2023, Dhiman et al.'s exploration of artificial neural network-based type-2 fuzzy optimization for medical diagnosis exemplifies the integration of fuzzy logic with neural networks for medical applications[47]. In 2023, Namadchian et al. stability analysis of dynamic general Type-2 fuzzy control systems with uncertainty highlights the ongoing advancements in control theory and its applications in uncertain environments[48].

In response to these developments and the pressing need for effective asthma diagnostics, our research introduces a novel type-2 fuzzy optimized inference system.

Basic objective of the system involves the following points:

- To develop a type-2 fuzzy set-based inference system for the identification of asthma disease over the collected patient data.
- To find the error of the proposed system and check their optimality level in comparison with the targeted value.
- We will discuss the generalized concepts of type-2 fuzzy based logic systems. We will give a novel way to represent the type-2 fuzzy based logic consists 'IF-Then' rules, and the uncertainty is handled by the model.
- Optimize the parameters used in the system by using particle swarm optimization technique.
- Finally, we will describe briefly the utilizations and problem of type-2 fuzzy modelling-based logic.

Our proposed work is structured into nine sections, detailing the foundational concepts of type-2 fuzzy sets, type-2 fuzzy inference systems, and PSO techniques. The algorithm for the type-2 fuzzy logic-based PSO model is outlined, followed by a description of the architecture of the proposed model. The collected data, including factors relevant to asthma diagnosis, and the fuzzy 'IF-Then' rules employed are discussed in subsequent sections. The efficacy and validation of our model are demonstrated through numerical computations, showing a significant reduction in error values post-PSO process.

The proposed type-2 fuzzy logic-based PSO model showcases its proficiency in detecting the severity of asthma and optimizing diagnostic errors. Our approach tackles uncertainty using a three-dimensional space, incorporating elements, primary membership functions, and secondary membership functions. Utilizing realistic asthma patient data, the model considers various critical factors associated with the disease. The results indicate a substantial improvement in diagnostic accuracy, paving the way for future enhancements, potentially exploring the realms of type-3 fuzzy logic systems.

Basic concepts

Having established the relevance and historical context of our research in Section 1, we now delve into the core theoretical constructs that form the foundation of our proposed model. Subsection 2.1 begins by exploring the concept of Type-2 fuzzy sets, an extension of traditional fuzzy sets that allow for handling higher levels of uncertainty. This exploration is crucial as it lays the groundwork for understanding how our model processes complex asthma patient data, setting the stage for the more detailed discussions that follow.

Type-2 fuzzy set[29]

A type-2 fuzzy set, characterized by a fuzzy membership function $\mu_A(x, \mu)$, is represented as in eq.1.

$$A = \{((x, \mu), \mu_A(x, \mu)) : x \in X \text{ and } \mu \in I_x \subseteq \} \quad (1)$$

where, I_x: Primary membership value and $\mu_A(x, \mu)$ is the secondary membership value, also $0 \le \mu_A(x, \mu) \le 1$. A geometrical representation of type-2 fuzzy set is given in Fig. 1.

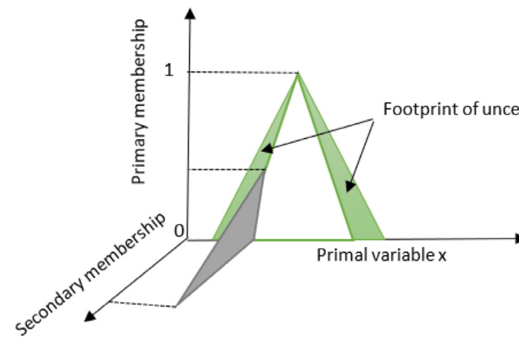

Fig. 1. Type-2 fuzzy set.

Type-2 fuzzy inference system

Type-2 fuzzy system mainly consists six components, namely.

- Input factor
- Fuzzification
- Fuzzy rules
- Type reduction
- Defuzzification
- Output

Fig. 2 represents the various component of type-2 fuzzy inference system.

Particle swarm optimization

In the computation area, the particle swarm optimization (PSO) is a method that minimize or maximize a problem by using iteration process and try to obtain an optimal solution with respect to a given quality measure. It tackles a problem by having a population of optimal solutions which depends upon the particle's position and velocity. In PSO, particle's movement is influenced by p-best (local best) and g-best (global best) value. The positions and velocities of the particle are updated as better positions of other particles. This is predictable to change the swarm near the best solutions.

A best example of PSO is bird flocks in nature. When a bird is flying, it might try several techniques to preserve energy; gliding, jumping or leveraging wind flows to carry it in the right track of travel. Flowchart of the PSO shown in Fig. 3.

Proposed algorithm for the type-2 fuzzy logic based PSO model

The algorithm of type-2 fuzzy logic based PSO model consists eight steps. Each step is described below as;

Step 1: Let us assume a set of input factors I involve in the problem defined as;

$$I = \{I_1, I_2, \dots\dots, I_n\}$$

Step 2: Now fuzzified each input factor into the form of type-2 triangular fuzzy set given below in eq.2.

$$A = \{(\tau, \mu(\tau), \nu(\tau)) : \tau \in I; \mu, \nu : I \to [0, 1]\} \quad (2)$$

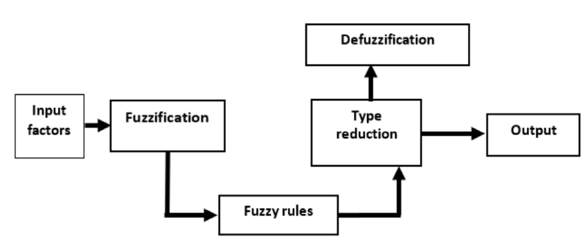

Fig. 2. Type-2 fuzzy inference system.

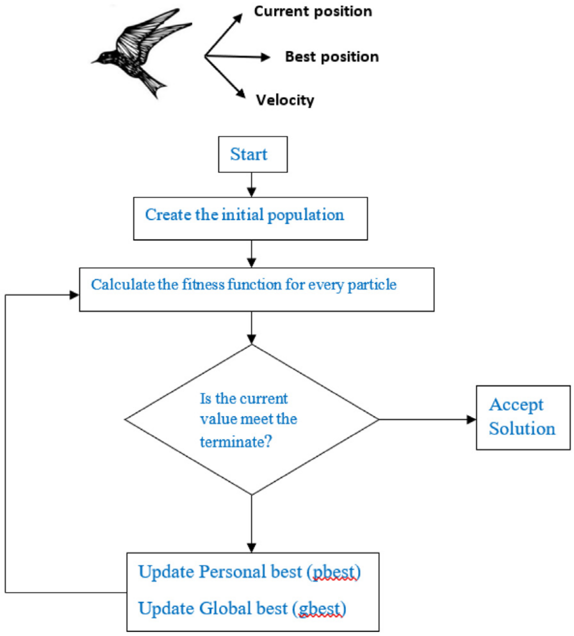

Fig. 3. Architecture of the PSO.

Step 3: Now make fuzzy rules either provided by subject experts or are extracted from numerical data, are expressed as a collection of IF-THEN statements, e.g.,

IF input 1 is X_1, input 2 is X_2, . . ., and input n is X_n, then output is Y.

Step 4: The consequent part obtained from the type-2 fuzzy rule-based system, is now converted input a single crisp value by using the score function given by eq.3.

$$Scorefunction = \frac{[1 + Primary - Secondary]}{2} \tag{3}$$

Step 5: Now, we find the error of the system by using the formula given as in eq. (4).

$$Error = \frac{(Targated\,value - Obtained\,value)^2}{2} \tag{4}$$

Step 6: If the optimal error is achieved then we stop the process else go to step 7.

Step 7: Apply the PSO technique to find optimal error of the system.

Step 8: The PSO process is further divide into three sub-steps given as;

8a) First we take initial randomly chosen values of velocity and position for the involved factors.
8b) In the next sub step, we find the p-best and g-best values by using the values of velocity and positions.
8c) After that, we calculate the updated position and velocities of the particle by using the following equation (5) and (6).

$$v[n] = v[n] + c_1 rand()(pbest - present[n]) + (c_2 rand())(gbest - present) \tag{5}$$

$$\mathrm{v[n] = v[n] + c_1 rand()(pbest - present[n]) + (c_2 rand())(gbest - present)}$$

$$present[n] = present[n] + v[n] \tag{6}$$

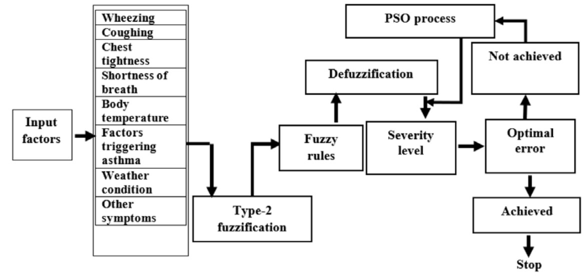

Fig. 4. Architecture of the proposed model.

8d) After the previous sub-step, we go to the next iteration by using updated values of velocities and positions of the particle as initial values for the next iteration. We continue the process, until the optimal solution is achieved.

Architecture of the type-2 fuzzy logic based PSO model

The architecture of the proposed model consists various components, which consists; input factors (wheezing, coughing, chest tightness, shortness of breath, body temperature, factors triggering asthma, weather condition and other symptoms), type-2 fuzzification, fuzzy rules, defuzzification, optimal error and PSO process (as given in Fig. 4).

Collected data for the asthma disease

In this section, we have given a data of asthma patients having the symptoms; wheezing, coughing, chest tightness, shortness of breath (Table 1), this section also consists the number of times wheezing (Table 2), activity-based breathlessness (Table 3), number of times of breathing shortness (Table 4), severity of breathlessness (Table 5), what time patient feel the symptom (Table 6), trigger factor of asthma (Table 7), type of cough (Table 8), weather condition (Table 9), rate of cough (Table 10), body temperature (Table 11), allergy signs (Table 12), and signs of cold or allergies other symptoms (Table 13) (Anxiety, blue nails, blue fingernails etc.). [See the appendix 1 for Tables 1-13].

Given tabular data will apply over the proposed type-2 fuzzy based inference system and after the inference system process the obtained value further be optimized through PSO technique in order to obtained the minimum error.

Including factors related to asthma disease

We have taken eight input factors to identify the severity level of asthma disease. Each input factors i.e., wheezing, coughing, chest tightness, shortness of breath, body temperature, factors triggering asthma, weather condition and other symptoms are further divided into various linguistic categories like; low, medium, high, very-high, sometime, most of the time etc. In the given Table 14, the output factor i.e., the severity level of asthma disease is also divided into four categories. These categories indicated low, moderate, high and very high severity levels of the patient.

Fuzzy rules for the type-2 fuzzy inference system

The proposed type-2 fuzzy inference system consists eight input and one output-based system. Some crucial fuzzy rules for the system are given by Table 15 (Appendix 1).

Numerical computation

In this section, we have taken a patient having values of the symptoms given as; chest tightness is 0.7, shortness of breath is 0.9, wheezing is 0.1, body temperature is 0.1, trigger factor value is 0.9, times of coughing is 0.7, weather condition is 0.2 and anxiety is 0.3. Based on these values, we have the moderate level of the asthma according to the fuzzy rules of the system.

First, we drawn horizontal lines that indicate the fired levels of each input factors. According to these firing lines process, we have eight lines, then we take the minimum ratio of these lines. We calculate the scored value of moderate asthma disease based on the minimum ratio line. (Fig. 5).

We got 0.3 as the scored value of type-2 moderate category of asthma. According to the obtained value the patient is suffering with moderate asthma level. But still the error for this valued needs to be determine. We considering the targeted value as 2 (for low category 1, moderate category 2, high category 3 and very high category 4), based on this the error of the system calculated by the formula given below in eq.7.

$$Error = \frac{(2 - Obtained\, value)^2}{2} \tag{7}$$

$$= \frac{(2 - 0.3)^2}{2} = 1.445$$

We obtain the value 1.445 as the error of the system. To obtained the minimum error, we apply the PSO process.

Particle swarm optimization process:

In this section we applied PSO on the objective function in eq.8**.**

$$y = c_0 + x_1c_1 + x_2c_2 + x_3c_3 + x_4c_4 + x_5c_5 + x_6c_6 + x_7c_7 + x_8c_8 \tag{8}$$

First iteration: In Table 16, we have taken the population size = 6, dimension of the problem = 8, maximum number of iterations = 3,

Table 17 indicates the randomly chosen initial positions of the factors $c_i; i = 1to8$.

Table 18 denotes the p-best positions of the factors $c_i; i = 1to8$.

Table 19 denotes the g-best positions of the factors $c_i; i = 1to8$.

Now, update the velocities for the next iterations, can be find by using the formula (eq.5 & 6):

$$v[n] = v[n] + c_1 rand()(pbest - present[n]) + (c_2 rand())(gbest - present)$$

$$\mathrm{v[n] = v[n] + c_1 rand()(pbest - present[n]) + (c_2 rand())(gbest - present)}$$

$$present[n] = present[n] + v[n]$$

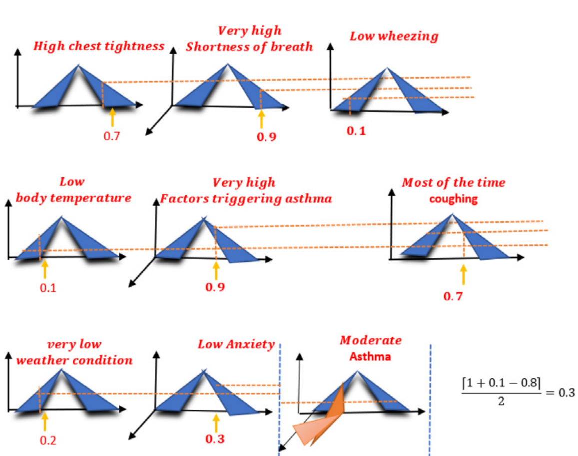

Fig. 5. Obtained 0.3 as the scored value.

where, $c_1 and c_2$ learning factor and rand () is a random number between (0, 1). Here we take $c_1 = 0.2 and c_2 = 0.5$

By using this above equation, we got the updated velocities for this process (see Table 20) (Appendix 1).

Based on, the updated position of the factors $c_i; i = 1to8$ is given by Table 21 (Appendix 1).

Second Iteration: Now in the second iteration, update velocities for 2nd iteration are given by chart 1 (Fig. 6).

The update position for 2nd iteration is given by chart 2 (Fig. 7). We can easily be observed that the maximum value is 1.022305.

Third Iteration: Now update velocities for 3rd iteration is given by chart 3 (Fig. 8).

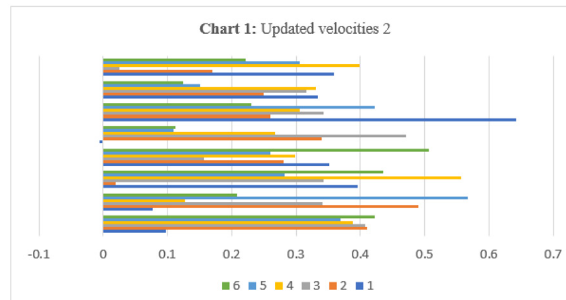

Fig. 6. Update velocities for 2nd iteration.

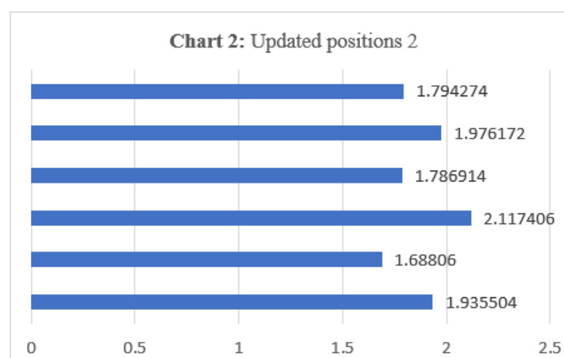

Fig. 7. Update position for 2nd iteration.

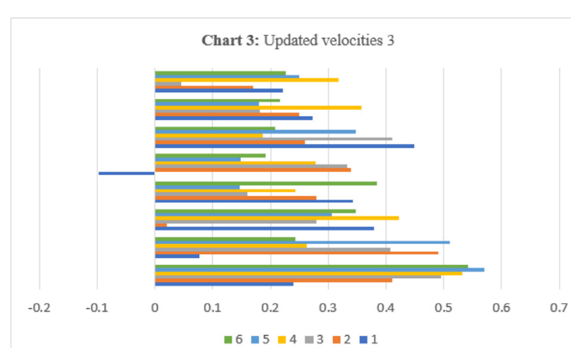

Fig. 8. Update velocities for 3rd iteration.

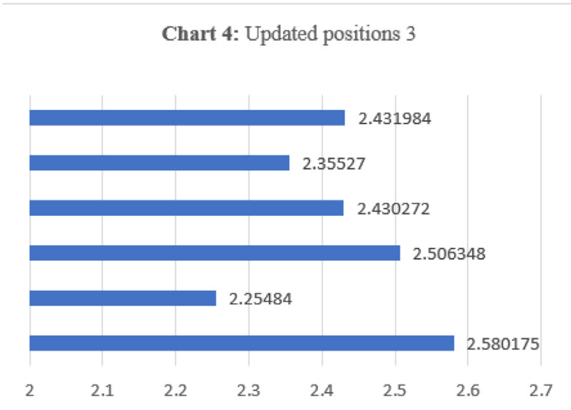

Fig. 9. Update position for 4th iteration.

The update position for 4th iteration is given by chart 4 (Fig. 9). We can easily be observed that the maximum value is 1.023594.

From the chart 4, it can easily be observed that the maximum value of the output is 2.25484. Based on this output the error of the system is given by (eq.4);

$$Error = \frac{(Targated\, value - Obtained\, value)^2}{2}$$

$$= \frac{(2 - 2.25484)^2}{2} = 0.03$$

Finally, we got 0.03 is the value of optimal error for the system.

Conclusion

The proposed model comprises several key components: input factors, type-2 fuzzification, fuzzy rules, defuzzification, optimal error, and the PSO process. This model uniquely integrates the impact of both type-2 fuzzy set and PSO technique, an approach not previously introduced in existing studies. It has the capability to detect disease severity levels and optimize errors within the conducted analysis. The type-2 fuzzy logic system addresses uncertainty using a three-dimensional space (element, primary membership function, and secondary membership function). Realistic data from asthma patients was utilized, considering factors such as wheezing frequency, activity-based breathlessness, and severity of symptoms. This study, unprecedented in its kind, addresses major issues related to asthma. Initially, we applied the inference system and subsequently focused on the errors encountered. Tables 20 and 21 show the updated particle velocities and positions. Charts 1 and 2 display these updates in the context of the second iteration, while charts 3 and 4 present the third iteration updates. The numerical computation section reveals that the initial error value of 1.445 was reduced to 0.03 following the PSO process. The system's ability to infer decisions and optimize via PSO is thus demonstrated. Additionally, we computed the system's error using a traditional fuzzy set for a comparative analysis, as shown in Table 22.

Looking towards future developments, our intention is to advance our research by transitioning from the current type-2 fuzzy logic-based system to a more sophisticated type-3 fuzzy logic-based system. This evolution aims to further refine our model's ability to handle uncertainties and complexities inherent in various datasets. By leveraging the enhanced capabilities of type-3 fuzzy logic, we anticipate providing more nuanced and accurate analysis, particularly in scenarios with higher degrees of uncertainty and vagueness. This progression aligns with the ongoing advancements in fuzzy logic research, promising even more robust and efficient solutions in the realm of computational intelligence.

Limitation of study

This study, while innovative in its approach to asthma disease identification using a Type-2 Fuzzy Optimized Inference System, has certain limitations that should be acknowledged. Firstly, the dataset used may not comprehensively represent the wide variability in asthma symptoms across different populations, possibly affecting the generalizability of the findings. Additionally, the complexity of the type-2 fuzzy logic and PSO models might limit their practical applicability in real-world clinical settings due to computational resource requirements. Furthermore, while the model shows promising results, its performance in real-time clinical environments and across diverse patient datasets remains to be evaluated. Finally, this study focuses solely on asthma and may not be directly applicable to other diseases without significant modifications and additional validation.

Author Credit Statement

- **Tarun Kumar:** Led the paper conceptualization and methodology development. Contributed to the design and implementation of the research methodology. Played a pivotal role in the data analysis and interpretation of the results.
- **Anirudh Kumar Bhargav:** Played a key role in data collection, analysis, and interpretation of results.
- **M.K. Sharma:** Oversaw the overall research direction and strategy. Managed the administrative and logistical aspects of the research and contributed to drafting and revising the manuscript.
- **Nitesh Dhiman:** Involved in the development of the analytical models and tools. Played a significant role in the data processing and validation. Assisted in the literature review and provided critical revisions of the manuscript.
- **Neha Nain:** Contributed to the development of the methodology and the execution of computational models.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1

Table 1
Symptoms.

Patient	Low	Medium	High	Very high
	Wheezing	Coughing	Chest tightness	Shortness of breath
1.				1
2.	1	1	1	2
3.	2	2	2	–
4.	3	–	3	3
5.	4	–	4	4
6.	–	–	5	–
7.	–	3	6	–
8.	5	4	–	–
9.	6	5	7	–
10.	–	–	–	5
11.	–	–	8	6
12.	–	–	9	–
13.	–	–	10	7
14.	–	–	–	8
15.	–	–	11	9
16.	–	–	12	–
17.	7	8	13	–
18.	8	9	–	–
19.	9	10	14	–
20.	–	11	–	–
21.	–	–	–	10
22.	–	–	–	11
23.	–	–	15	–

Table 2
Time of wheezing.

Patient	Low One time	Medium A little of time	High A moderate amount of time	Very high Most of the time
1.	–	1	–	–
2.	–	–	–	–
3.	–	–	1	–
4.	–	–	2	–
5.	–	–	3	–
6.	–	–	4	–
7.	–	2	–	–
8.	–	3	–	–
9.	–	–	5	–
10.	–	–	–	1
11.	–	–	6	–
12.	1	–	–	–
13.	–	4	–	–
14.	–	–	–	2
15.	–	5	–	–
16.	–	6	–	–
17.	–	–	7	–
18.	–	–	8	–
19.	–	–	–	3
20.	–	7	–	–
21.	–	8	–	–
22.	–	–	–	4
23.	2	–	–	–

Table 3
Activity affecting breathlessness.

Patient	Low After eating	Medium While sleeping	High While walking/ running	Very high While talking/ laughing
1.	1	–	1	–
2.	–	1	–	–
3.	–	2	2	1
4.	–	3	3	
5.	–	4	–	2
6.	–	–	4	–
7.	–	5	–	–
8.	–	–	5	–
9.	–	–	6	3
10.	–	6	7	–
11.	–	7	–	–
12.	–	–	8	–
13.	–	–	9	–
14.	–	–	10	–
15.	–	–	11	–
16.	–	8	–	–
17.	–	–	12	4
18.	–	9	–	–
19.	–	10	13	–
20.	–	–	14	–
21.	–	–	–	–
22.	–	11	–	–
23.	–	–	15	–

Table 4
Shortness of breath.

Patient	Low Never	Medium Once in month	High Once in a week	Very high Daily
1.	–	–	1	–
2.	–	–	–	1
3.	–	–	–	2
4.	–	–	2	–
5.	–	–	–	3
6.	–	–	3	–
7.	–	–	4	–
8.	–	–	5	–
9.	–	–	6	–
10.	–	–	–	4
11.	–	–	–	5
12.	–	–	7	
13.	–	–	–	6
14.	–	–	–	7
15.	–	–	–	8
16.	–	–	8	–
17.	–	1	–	9
18.	–	–	–	10
19.	–	–	–	11
20.	–	–	9	–
21.	–	–	–	12
22.	–	–	–	13
23.	–	2	–	–

Table 5
Severe level of feeling of breathlessness.

Patient	Low Mild	Medium Moderate	High High	Very high Very high
1.	–	1	–	–
2.	–	2	–	–
3.	–	–	1	–
4.	–	3		–
5.	–	–	2	–
6.	–	4		–
7.	1		3	–
8.	–	5	–	–
9.	–	6	–	–
10.	–	–	–	1
11.	–	–	4	
12.	–	7	–	
13.	–	–	–	2
14.	–	–	–	3
15.	–	8	–	–
16.	–	9	–	–
17.	–	10	–	–
18.	–	–	5	–
19.	–	–	6	–
20.	2	–	–	–
21.		11	–	–
22.		–	–	4
23.	3	–	–	–

Table 7
Trigger asthma symptoms.

Patient	Dust mites	Pets	Smoke	Strong fumes (Chemicals, perfume)
1.	1	–		–
2.	2	–	1	–
3.	3	1	2	1
4.	4		3	2
5.	5	2	4	–
6.	–	3	5	–
7.	6	–	–	–
8.	7	–	–	–
9.	8	–	6	–
10.	9	–	–	–
11.	10	–	–	–
12.	11	–	–	–
13.	–	–	7	3
14.	12	–	8	–
15.	13	–		–
16.	–	–	9	–
17.	–	4	10	4
18.	–	–	11	5
19.	–	–	12	–
20.	14	–	–	–
21.	15	–	–	–
22.	16	–	–	–
23.	17	–	–	–

Table 6
Time of feeling the symptoms most.

Patient	Low At early morning	Medium Before noon	High After noon	Very high At night
1.	–	–	–	1
2.	–	–	1	–
3.	1	–	–	2
4.	2	–	–	3
5.		–	–	4
6.	3	–	–	–
7.	4	–	–	–
8.	5	–	–	–
9.	–	1	–	–
10.	–	–	2	5
11.	–	–	–	–
12.	–	2	–	–
13.	–		–	6
14.	–	3	–	7
15.	6	–	–	–
16.	–	–	–	8
17.	–	4	3	–
18.	–	–	–	9
19.	–	–	–	10
20.	7	–	–	–
21.	–	–	–	11
22.	–	–	–	12
23.	–	–	–	13

Table 8
Weather conditions affects your health most.

Patient	Very low Cold	Nearest low Dry air	Low Hot	Medium Humid air	High Wet weather	Very high Windy weather
1.	1	–		–	–	–
2.	2	1		–	–	–
3.	3	2		–	–	1
4.	4	3		–	–	2
5.	5	–		–	1	–
6.	–	4		–	–	–
7.	–	5		–	–	–
8.	–	6		–	–	–
9.	–	7	1	–	–	–
10.	–	–		–	–	3
11.	–	–		–	–	4
12.	–	–		–	–	5
13.	6	–		–	–	
14.	7	–		–	–	–
15.	8	–		–	–	–
16.	–	8		–	–	–
17.	–		2	–	–	–
18.	–	9	–	1	2	–
19.	–	–		–	3	–
20.	9	–		–	–	–
21.	10	–		–	–	–
22.	11	–		–	–	–
23.	12	–		–	–	–

Table 9
Type of cough.

Patient	Low Dry	Medium Wet	High Chest cough	Very high Tickly cough
1.		1	–	–
2.	1	–	–	–
3.	–	–	1	–
4.	–	2	–	–
5.	–	3	–	–
6.	2		–	–
7.	–	4	–	–
8.	–	5	–	–
9.	–	6	–	–
10.	3		–	–
11.	–	7	–	–
12.	–		1	–
13.	–	8		–
14.	–	–	2	–
15.	4		–	–
16.	–	9	–	–
17.	–	10	–	–
18.	–	–	–	–
19.	–	–	3	–
20.	5	–	–	–
21.	6	–	–	–
22.		–	4	–
23.	7	–		–

Table 10
Rate of cough in a day.

Patient	Low Rarely	Medium For some time in the morning and night	High 4–5 h/day	Very high Persistent (All the time)
1.	1	–	–	–
2.	–	1	–	–
3.	–	–	1	–
4.	–	2	–	–
5.	–	3	–	–
6.	–	4	–	–
7.	–	5	–	–
8.	–	6	–	–
9.	–	7	–	–
10.	2		–	–
11.	–	8	–	–
12.	3	–	–	–
13.	4	–	–	–
14.	–	–	2	–
15.	5	–	–	–
16.	–	9	–	–
17.	–	–	3	–
18.	–	10		–
19.	–	–	4	–
20.	–	11		–
21.	–	–	5	–
22.	–	–	–	1
23.	6	–	–	–

Table 11
Body temperature.

Patient	Low Less than 98.6^{0}F	Medium 98.6^{0}F - 100^{0}F	High 100^{0}F - 102^{0}F	Very high Greater than 102^{0}F
1.	1	–	–	–
2.		–	–	–
3.	2	–	–	–
4.	–	1	–	–
5.	–	2	–	–
6.	–	3	–	–
7.	–	4	–	–
8.	3	–	–	–
9.	4	–	–	–
10.	–	5	–	–
11.	5		–	–
12.	6		–	–
13.	–	6	–	–
14.	–		1	–
15.	–	7	–	–
16.	7	–	–	–
17.	–	8	–	–
18.	–	9	–	–
19.	–	10	–	–
20.	–	11	–	–
21.	8	–	–	–
22.	9	–	–	–
23.	10	–	–	–

Table 12
Signs of cold or allergies.

Patient	Low Runny nose	Medium Nasal congestion	High Sore throat	Very high Headaches
1.	–	–	1	1
2.	–	1	2	–
3.	–	2	–	–
4.	1	3	–	2
5.	–	4	5	
6.	–	5	–	–
7.	–	6	–	–
8.	2	–	–	–
9.	3	7	6	–
10.		8		–
11.	4	–	7	3
12.	–	–	–	4
13.	–	9	8	–
14.	–	–	–	–
15.	–	–	–	5
16.	–	10	–	–
17.	5	11	9	–
18.	6	12	–	–
19.		13	–	–
20.	7	–	–	–
21.	–	–	–	–
22.	–	–	–	–
23.	–	14	–	6

Table 13
Other symptoms.

Patient	Very low Chest pain	Low Feeling of anxiety /panic	Medium Pales/sweaty face	High Blue lips	Very high Blue fingernails
1.	1	–	–	–	–
2.	–	1	–	–	–
3.	–	2	1	–	–
4.	2	–	–	–	–
5.	3	3	–	–	–
6.	4	–	–	–	–
7.	–	–	2	–	–
8.	5	–	–	–	–
9.	–	4	–	–	–
10.	–	–	–	–	–
11.	6	–	–	–	–
12.	7	–	–	–	–
13.	8	5	–	–	–
14.	–	–	–	–	–
15.	9	6	3	–	–
16.	10	7	–	–	–
17.	11	8	–	–	–
18.	–	9	4	–	–
19.	–	10	–	–	–
20.	–	–	–	–	–
21.	–	–	–	–	–
22.	–	–	–	–	–
23.	–	–	–	–	–

Table 14
Including parameters.

S. No.	Factors	Linguistic categories
1.	Wheezing	One time [0–0.25], a little of time [0.2–0.6], a moderate amount of time [0.58–0.8], most of the time [0.78–1]
2.	Coughing	Rarely [0–0.25], sometime [0.2–0.6], most of the time [0.58–0.8], persistent [0.78–1]
3.	Chest tightness	Low [0–0.25], medium [0.2–0.6], high [0.58–0.8], very high [0.78–1]
4.	Shortness of breath	Never [0–0.3], once in a time [0.28–0.7], once in a week daily [0.68–1]
5.	Body temperature	Low [0–0.25], medium [0.2–0.6], high [0.58–0.8], very high [0.78–1]
6.	Factors triggering asthma	Dust mites [0–0.3], pets, smoke [0.28–0.7], strong fumes [0.68–1]
7.	Weather condition	Cold [0–0.2], dry air [0.18–0.5], hot, humid air [0.48–0.7], wet weather [0.68–9], windy weather [0.9–1]
8.	Other symptoms	Chest pain [0–0.2], feeling of anxiety [0.18–0.5], pales/sweaty face [0.48–0.7], blue lips [0.68–9], blue fingernails [0.9–1]
9.	Severity level of asthma	Low [0–0.25], moderate [0.2–0.6], high [0.58–0.8], very high [0.78–1.2]

Table 15
Fuzzy rules.

Wheezing	Coughing	Chest tightness	Shortness of breath	Body temperature	Triggering factor	Weather condition	Other factors	Severity of Asthma
Ones	Rarely	Low	Never	Low	Dust	Cold	Chest pain	Low
Little bit	Some time	Medium	Ones	Medium	Pets	Dry	Anxiety	Moderate
Moderate	4–5 h	High	One in a week	High	Smoke	Hot	Pales	High
Most	Persistent	High	Never	High	Strong fumes	Humid	Sweaty face	Very high
Little bit	Some time	Low	Ones	Low	Pets	Wet	Blue lips	Moderate
Most	Rarely	Medium	One in a week	Medium	Smoke	Windy	Blue fingernails	Moderate
Moderate	Persistent	Low	Never	Low	Strong fumes	Cold	Anxiety	Moderate

Table 16
Randomly chosen initial velocities.

	$\boldsymbol{v}_1$	$\boldsymbol{v}_2$	$\boldsymbol{v}_3$	$\boldsymbol{v}_4$	$\boldsymbol{v}_5$	$\boldsymbol{v}_6$	$\boldsymbol{v}_7$	$\boldsymbol{v}_8$
1	**0.2**	**0.32**	**0.3**	**0.28**	**0.4**	**0.5**	**0.45**	**0.5**
2	**0.5**	0.4	0.2	0.25	0.31	0.2	0.31	0.23
3	**0.35**	0.26	0.37	0.22	0.57	0.1	0.55	0.17
4	**0.25**	0.1	0.53	0.35	0.28	0.41	0.28	0.41
5	**0.15**	0.51	0.21	0.44	0.2	0.36	0.24	0.35
6	**0.3**	0.29	0.43	0.5	0.13	0.23	0.13	0.23

Table 17
Randomly chosen initial positions.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	y
1	**0.7**	**0.9**	**0.1**	**0.1**	**0.9**	**0.7**	**0.2**	**0.3**	0.4691
2	**0.5**	0.2	0.7	0.2	0.1	0.4	0.3	0.3	0.5545
3	**0.3**	0.3	0.3	0.4	0.2	0.1	0.5	0.5	0.9384
4	**0.2**	0.5	0.1	0.3	0.2	0.6	0.1	0.1	0.4431
5	**0.1**	0.2	0.2	0.5	0.4	0.3	0.4	0.2	0.9283
6	**0.2**	0.6	0.2	0.1	0.3	0.5	0.3	0.2	0.4541

Table 18
p-best positions.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
1	**0.7**	**0.9**	**0.1**	**0.1**	**0.9**	**0.2**	**0.3**	**0.3**
2	**0.5**	0.2	0.7	0.2	0.1	0.4	0.3	0.3
3	**0.3**	0.3	0.3	0.4	0.2	0.1	0.5	0.5
4	**0.2**	0.5	0.1	0.3	0.2	0.6	0.1	0.1
5	**0.1**	0.2	0.2	0.5	0.4	0.3	0.4	0.2
6	**0.2**	0.6	0.2	0.1	0.3	0.5	0.3	0.2

Table 19
Global positions.

c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
0.2	0.5	0.1	0.3	0.2	0.6	0.1	0.1

Table 20
Updated velocities.

	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8
1	0.040234	0.06411	0.060126	0.056198	0.080098	0.100352	0.090238	0.100238
2	0.10029	0.08032	0.040222	0.050256	0.062162	0.040384	0.062238	0.046238
3	0.070266	0.05235	0.074238	0.044312	0.114224	0.020306	0.11027	0.03427
4	0.050224	0.02035	0.106126	0.070294	0.056224	0.082336	0.056126	0.082126
5	0.030162	0.10232	0.042192	0.08831	0.040288	0.072378	0.048264	0.070192
6	0.060224	0.05832	0.086192	0.100198	0.026266	0.04637	0.026238	0.046192

Table 21
Updated positions.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	y
1	0.740234	0.96411	0.160126	0.156198	0.980098	0.300352	0.390238	0.400238	0.651446
2	0.60029	0.28032	0.740222	0.250256	0.162162	0.440384	0.362238	0.346238	0.714706
3	0.370266	0.35235	0.374238	0.444312	0.314224	0.120306	0.61027	0.53427	1.111819
4	0.250224	0.52035	0.206126	0.370294	0.256224	0.682336	0.156126	0.182126	0.639123
5	0.130162	0.30232	0.242192	0.58831	0.440288	0.372378	0.448264	0.270192	1.108003
6	0.260224	0.65832	0.286192	0.200198	0.326266	0.54637	0.326238	0.246192	0.638525

Table 22
Comparative study

	Traditional fuzzy set-based model	Type-2 fuzzy set-based model
Obtained value of error	1.05	**0.03**

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