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Fuzzy hybrid approach for advanced teaching learning technique with particle swarm optimization in the diagnostic of dengue disease

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ABSTRACT

Dengue fever is a serious public health issue worldwide, particularly in tropical and subtropical areas. Early detection and accurate diagnosis are essential for effective management and control of the disease. In this study, we present a fuzzy hybrid approach (F-TLBO-APSO) for the detection and diagnosis of dengue disease using an advanced teaching-learning technique with adaptive particle swarm optimization. The proposed method combines the strengths of fuzzy logic, teaching learning-based optimization (TLBO), and adaptive particle swarm optimization (APSO) to improve the accuracy and efficiency of dengue detection based on symptoms. A key challenge addressed is the management of uncertain information existing in the problem. To validate the proposed technique, we applied it to a case study, demonstrating its robustness. The results indicate the versatility of the F-TLBO-APSO algorithm and highlight its value in detecting dengue based on symptoms. Our numerical computations reveal the advantages of the F-TLBO-APSO algorithm compared to TLBO and APSO.

1. Introduction

Dengue is a mosquito-borne virus-related disease caused by the dengue virus. The dengue virus is spread by female mosquitoes – Aedes aegypti. These dengue mosquitoes usually bite during the day and are found both inside and outside the house. These mosquitoes are found to be at the peak of their activity at dawn and dusk. The symptoms can develop in the next 6 to 10 days after being bitten by an infected mosquito. Four different serotypes of the virus that transmit dengue fever can infect humans. These serotypes constitute a group of viruses that are closely related to one another. These viruses can only be distinguished because they contain antigens that are relatively dissimilar to our own antigens, which are substances that influence our bodies and cause us to develop antibodies. In our country as well as other subtropical and tropical regions of the world, dengue cases are more prevalent. The severity and mortality of dengue are significantly reduced by early detection and prompt treatment. However, because of the disease's complexity and non-linear nature, correct diagnosis is often difficult. Traditional diagnostic techniques may have drawbacks in terms of accuracy, efficiency, and computational cost.

Teaching-learning-based optimization (TLBO) is a well-known population-based optimization technique where the population can be considered as a class of learners. Due to the teacher's hard work, the students interact with them to further change and expand their knowledge. The TLBO algorithm is a discovery **for a** large number of applications in diverse fields of engineering, science, and technology. Rao et al. [1] introduced the concept of TLBO to solve constrained mechanical design problems. The TLBO algorithm involves only common monitoring structures like the number of generations and population size for the process. The TLBO algorithm has gained popularity with variations alongside the existing optimization techniques. TLBO involves a smaller number of function evaluations **as** compared to **the** other optimization techniques [2–4]. Rao et al. [5] chose a comparatively smaller number of evaluation functions and demonstrated the better performance of TLBO. Rao et al. [6] introduced an enhanced version of the TLBO algorithm for solving unconstrained and constrained real-parameter optimization problems. The modifications made to TLBO, including the randomization mechanism and diverse population initialization strategy, improved its exploration and exploitation capabilities. Rao et al. [7] showcased the application of the TLBO algorithm for solving composite test functions. The results indicated that TLBO is a promising optimization technique, demonstrating competitive

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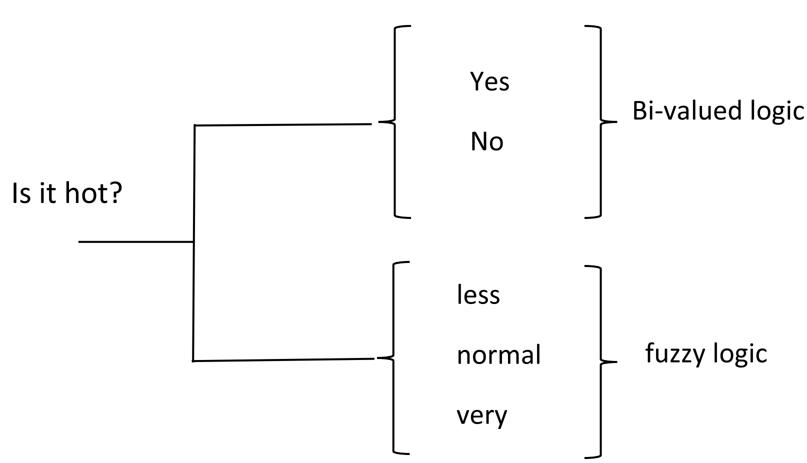
performance and efficiency in solving complex optimization problems represented by composite functions. Rao et al. [8] proposed the application of the TLBO technique for the multi-objective design optimization of a robot gripper. The results demonstrate the capability of TLBO in finding a set of Pareto-optimal solutions, representing the optimal trade-offs between conflicting objectives. Zeuxan et al. [9] introduced a new variant of the TLBO algorithm that incorporates a course selection mechanism. The integration of course selection enhances the optimization process by allowing students (solutions) to adapt their strategies and dynamically adjust their behavior. TLBO has also been applied in the optimization of ORP [10] and in testing the performance of combinatorial problems [11].

On the other hand, in the Particle Swarm Optimization (PSO) process, we require the inertial weight and acceleration constants as our desired structures. Kennedy & Eberhart [12] introduced Particle Swarm Optimization (PSO). PSO is a population-based stochastic algorithm used for continuous optimization problems. PSO consists of a swarm of bird-like particles, each particle residing at a position in the search space and initialized with position and velocity in a random manner. In the PSO technique, all particles move based on their own experiences. Opposition-based PSO with Cauchy Mutation [13] and for Noisy Problems [14] have been applied in existing studies. The basics and fundamentals of Computational Swarm Intelligence [15] techniques have also been studied. A modified PSO [16] and filtering machinery-based PSO [17] have also been used for optimization purposes.

But in real-life problems, things that are not so clear, i.e., vague in nature, refer to the term fuzzy. Many times, we come across a situation when we cannot determine whether the condition is either true or false; in such cases, fuzzy logic [18–20] offers the flexibility for appreciated reasoning [21]. In the bi-valued system, '1′ represents the complete truth value and '0′ represents the complete false value. However, in the fuzzy logic system, there is no space for completely true and false values. In fuzzy logic, there is a midway solution to represent partially true and partially false values. Fuzzy logic was introduced by Professor L. A. Zadeh in 1965 [22]. Fuzzy logic is used to describe a vague common-sense system in which the truth values are subsets of unit intervals, and linguistic labels include quite true, true, very true, etc. The following figure differentiates bi-valued logic from fuzzy logic.



Fuzzy logic, combined with other techniques, has shown its robustness in various fields. Zhang et al. in [23] introduced a combination of fuzzy optimization strategy and fuzzy adaptive particle swarm optimization (PSO) to address the complex and conflicting objectives of reactive power and voltage control. To examine distribution feeder reconfiguration, a modified HBMO method [24] has also been introduced. A reactive power flow study using an artificial bee colony approach [25] is also conducted to optimize active power loss in the scheme. A reactive power dispatch based on quasi-oppositional TLBO [26] has also been used for the optimization process. A fuzzy-TLBO [27] for reactive power control parameter scheduling has also been utilized in the existing literature. The objective of this research paper is to propose and develop a novel optimization approach for tackling the challenges associated with the control and prevention of dengue disease. The paper aims to combine the benefits of fuzzy logic, advanced teaching-learning techniques, and particle swarm optimization (PSO) to create an effective and efficient methodology for dengue control.

An innovative approach that integrates fuzzy logic with particle swarm optimization (PSO) [28] to enhance vector quantization learning schemes in the field of image compression. The combination of these methods allows for more adaptive and efficient optimization, reducing both error rates and computational costs associated with image compression. This hybrid approach demonstrates significant improvements in compression quality, making it a robust solution for large-scale image data processing. The application of discrete particle swarm optimization (DPSO) [29] to feature selection in binary classification tasks. This method not only enhances computational efficiency but also addresses the challenge of finding optimal feature subsets in high-dimensional data, which is vital for improving the performance of machine learning models in classification problems. A hybrid clustering method that integrates fuzzy c-means (FCM) with an enhanced version of particle swarm optimization [30]. The improved PSO algorithm enhances the search for optimal clustering parameters, leading to more accurate and robust clustering outcomes. This hybrid method proves especially effective in complex datasets where traditional clustering techniques may struggle. A novel method using convolutional neural networks (CNNs) [31] combined with PSO for reducing false positives in lung nodule detection on CT images. This combination enhances the reliability of automated systems in identifying lung nodules, ultimately contributing to better early detection of lung cancer through computed tomography. A hybrid algorithm combining fuzzy c-means (FCM) and PSO for brain image segmentation [32]. This technique proves particularly beneficial for handling the complex and fuzzy boundaries of brain tissues, where traditional segmentation methods often fall short. The hybrid FCM-PSO algorithm significantly enhances the precision of brain image analysis, facilitating more accurate medical diagnoses. A multi-objective PSO-based feature selection method that integrates node centrality for analysing medical datasets [33]. This approach proves highly effective for improving classification performance in medical datasets, offering a more nuanced and powerful feature selection strategy. The practical applications of fuzzy control systems in industrial environments [34]. Fuzzy control is widely used for managing processes that involve uncertainty and imprecise information. This foundational work laid the groundwork for many modern applications of fuzzy logic in both industrial and technological contexts.

The Score-Based Artificial Fish Swarm Algorithm (SAFSA) [36] for the diagnosis of Parkinson's disease. Their study introduced a novel intelligent approach that merges SAFSA with traditional diagnostic techniques. SAFSA, a variant of the traditional Artificial Fish Swarm Algorithm (AFSA), enhances optimization processes by simulating fish behaviours such as foraging, swarming, and following. In their work, this algorithm was applied to patient data, effectively improving the accuracy and speed of diagnosis. PSO-based Adaptive Neuro-Fuzzy Inference System (ANFIS) model [37] to predict Chikungunya outbreaks. Their work focused on using PSO to optimize the fuzzy rules and membership functions within the ANFIS model, leading to improved accuracy in forecasting disease outbreaks. Chikungunya, a vector-borne disease, presents challenges in early detection due to its symptom overlap with other diseases. The hybrid approach combining PSO with neuro-fuzzy inference allowed the model to handle the uncertainty in symptom presentation and environmental factors. This system demonstrated improved predictive power compared to traditional models, making it a valuable tool for healthcare professionals dealing with disease prevention and management. A systematic review of swarm intelligence techniques [38] applied to intrusion detection systems, including applications in healthcare data security. Although their primary focus was on network security, the principles of swarm intelligence—especially PSO—are applicable to medical systems requiring real-time data analysis and anomaly detection. This approach could be extended to healthcare systems where the detection of anomalies in patient data, such as irregularities in vital signs or medical imaging, is critical for diagnosing diseases early. A comprehensive survey on the applications of swarm intelligence, particularly the hybridization of PSO with Ant Colony Optimization (ACO), in healthcare [39]. The paper reviewed multiple implementations of these techniques in medical image analysis and disease surveillance systems. This survey also outlined the potential of these optimization techniques in real-time disease monitoring systems.

A hybrid method combining Particle Swarm Optimization (PSO) with Artificial Neural Networks (ANN) [40] for cancer detection. Their research focused on the classification of microRNA patterns, which are crucial in early-stage cancer detection. By using PSO to optimize the weights of ANN, the proposed method efficiently reduced computational costs and improved classification accuracy. This hybrid approach is especially significant in medical diagnostics where accuracy and early detection are critical.

The specific objectives of the paper are as follows:

i. **Introduce** a fuzzy hybrid approach: The paper aims to propose a hybrid approach that integrates fuzzy logic with advanced teaching-learning techniques and PSO. This hybrid approach leverages the strengths of each technique to effectively address the complexities and uncertainties associated with dengue disease control.
ii. **Enhance** optimization capabilities: The objective is to enhance the optimization capabilities of the proposed approach by utilizing advanced teaching-learning techniques. This technique stimulates the teaching and learning interactions between students and teachers to improve the search process and convergence to optimal solutions.
iii. **Incorporate** fuzzy logic: The paper aims to incorporate fuzzy logic to handle the inherent uncertainties and imprecise information associated with dengue disease control. Fuzzy logic allows for the representation and manipulation of vague and uncertain data, enabling more robust decision-making and control strategies.
iv. **Utilize** particle swarm optimization: The objective is to utilize the particle swarm optimization technique to optimize the parameters and variables involved in dengue disease control. PSO is a population-based optimization algorithm inspired by social behavior, which facilitates efficient exploration and exploitation of the solution space.
v. **Evaluate** the proposed approach: The paper intends to evaluate the effectiveness and performance of the fuzzy hybrid approach using real-world data and case studies related to dengue disease control. The objective is to compare the results obtained from the proposed approach with existing approaches or techniques to demonstrate its superiority in terms of accuracy, efficiency, and effectiveness.

The present research work consists of nine segments. Segment 2 covers the fundamental concepts of fuzzy sets, fuzzy numbers, TLBO, and advanced PSO. In Segment 3, we introduce our novel optimization technique, Fuzzy Hybrid Advanced TLBPSO (F-TLBO-APSO). Segment 4 applies this technique to data on dengue-infected patients [35]. The mathematical formulation of the F-TLBO-APSO algorithm is presented in Segment 5. Segment 6 includes numerical computations of the proposed work. A comparative study is conducted in Segment 7. Segment 8 provides a discussion and conclusion of the entire manuscript. The last and ninth segment describes the limitations and future directions of this work.

2. Basic concepts

2.1. Fuzzy set

A fuzzy set A defined on a universal set U denoted as:

$$A = \{(x,\ \mu_A(x)) : \quad x \in U\} \tag{1}$$

where, $\mu_A(x) : \ U \rightarrow [0,\ 1]$ represents the membership value of x given in universal set U.

2.2. Fuzzy number

A fuzzy set A defined on a universal set U is known as a fuzzy number if it satisfies the following three properties defined as:

i. It is "normal" i.e., there exists a point $x \in U$ such that $\mu_A(x) = 1$.
ii. $\alpha -$ cut of A i.e., A^α is a closed interval, $\alpha \in [0,\ 1]$.
iii. Support of A i.e., $\{x \epsilon \text{ R}: \mu_A(x) > 0\}$ is bounded.

A triangular fuzzy number $\mu_{\text{tri}}(\tau)$ is given as:

$$\mu_{\text{tri}}(\tau) = \begin{cases} \dfrac{\tau - a}{b - a},\ a \leq \tau \leq b \\ \dfrac{c - \tau}{c - b}, b \leq \tau \leq c \\ 0 \text{ else} \end{cases}$$

where $a < b < c$ on real line.

2.3. Teaching learning-based optimization (TLBO)

TLBO is inspired by the teaching-learning process, where the teacher's knowledge influences the learner's output. This algorithm eliminates the need for specific parameters and only relies on basic control parameters such as population size. The TLBO algorithm divides the selected population into two phases: the teacher phase and the learner phase. In this approach, population size represents the learners, and various design variables from different subject types are assigned to the learners. The fitness value corresponds to the optimization problem's learners' results. The equation number 1 to 9 in this section is taken from [1].

TLBO operates in two phases: the Teacher phase and the Learner phase.

a) Teacher phase: In the teacher phase of TLBO, learners acquire knowledge from the teacher. At iteration 'n', considering the number of subjects 'μ' (design variables), 'x' Please check.learners (population size, $P = 1, 2, 3, \ldots x$), and $\lambda_{m,n}$ the mean result of learners in a specific subject 'm' ($m = 1, 2, 3, \ldots \mu$), the best learner's overall result $\chi_{total} - P_{best,n}$ obtained collectively across all subjects, is considered as the result of the best learner. The algorithm designates this best learner as the teacher, who aims to enhance the learners' results. The difference between the mean result of each subject and the corresponding result of the teacher is calculated using Eq. (2):

$$\text{Difference \_mean}_{m,P,n} = R_n\left(\chi_{m,P_{best},n} - \tau_F\lambda_{m,n}\right) \tag{2}$$

where $\chi_{m,P_{best},n}$ is the result of best learner in subject m, τ_F is the teaching factor which decides the value of mean to be changed and R_n is the random number in the range [0,1]. Value of τ_F is decided randomly with equal probability as,

$$\tau_F = round[1 + rrand(0,1)\{2-1\}] \tag{3}$$

τ_F is not given as an input to the algorithm and its value is randomly decided by the algorithm from Eq. (3). After conducting many experiments on many benchmark functions, it is concluded that this algorithm performs better if τ_F is between 1 and 2. However the algorithm is found to perform much better if the value of τ_F is either 1 or 2 and hence to simplify this algorithm, τ_F is suggested to take either 1 or 2 depending on the estimation (approx.) criteria given by Eq. (2). Based on Difference $\_\text{mean}_{m,P,n}$ the existing solution is updated in the teacher phase according to the following expression.

$$\chi'_{m,P,n} = \chi_{m,P,n} + \text{Difference \_mean}_{m,P,n} \tag{4}$$

In the above Eq. (4), $\chi'_{m,P,n}$is the updated value of $\chi_{m,P,n}$. $\chi'_{m,P,n}$is accepted if it gives the better functional value. All the accepted functional values at the end of the teacher's phase are maintained and these values are the input to learner phase. The learner phase depends upon the teacher phase.

a) Learner phase: In the second part of this algorithm, learners expand their knowledge through interactions with each other. They randomly interact with other learners to enhance their knowledge. A learner acquires new information if other learners possess greater knowledge. The learning process in this phase, involving a population size of n, is described below. Randomly choose two learners, A and B, such that

$$\chi'_{total-A,n} \neq \chi'_{total-B,n} \tag{5}$$

In the above Eq. (5), the randomly select two updated functional values, $\chi'_{total-A,n}$ and $\chi'_{total-B,n}$, which represent the values of learner A and learner B, respectively, at the end of the teacher's phase.

$$\chi''_{m,A,n} = \chi'_{m,A,n} + R_n(\chi'_{m,A,n} - \chi'_{m,B,n}),\quad if \chi'_{total-A,n} < \chi'_{total-B,n} \tag{6}$$

$$\chi''_{m,A,n} = \chi'_{m,A,n} + R_n(\chi'_{m,B,n} - \chi'_{m,A,n}),\quad if \chi'_{total-B,n} < \chi'_{total-A,n} \tag{7}$$

If $\chi''_{m,A,n}$ -(m, A, n) yields a superior unction value, it is accepted. Eqs. (6) and (7) are utilized for problem minimization, while Eqs. (8) and (9) are employed for problem maximization.

$$\chi''_{m,A,n} = \chi'_{m,A,n} + R_n(\chi'_{m,A,n} - \chi'_{m,B,n}),\quad if \chi'_{total-B,n} < \chi'_{total-A,n} \tag{8}$$

$$\chi''_{m,A,n} = \chi'_{m,A,n} + R_n(\chi'_{m,B,n} - \chi'_{m,A,n}),\quad if \chi'_{total-A,n} < \chi'_{total-\boldsymbol{B},n} \tag{9}$$

2.4. Advanced particle swarm optimization (APSO)

Incorporating considerations such as the benefits, drawbacks, and parameter impacts of PSO, this study includes advanced PSO (APSO). APSO utilizes novel parameters ($\omega, \ \alpha_1, \ \alpha_2$) that gradually vary (decrease/increase) and are defined as follows (The equation number 10 to 12 in this section is taken from [23]):

$$\omega = \omega_z + (\omega_a - \omega_z)\left(\frac{i}{i_{max}}\right)^2;\ \alpha_1 = \alpha_{1Z}\left(\frac{\alpha_{1a}}{\alpha_{1Z}}\right)^{\left(\frac{i}{i_{max}}\right)^2}$$

$$\text{and } \alpha_2 = \alpha_{2Z}\left(\frac{\alpha_{2a}}{\alpha_{2Z}}\right)^{\left(\frac{i}{i_{max}}\right)^2} \tag{10}$$

In the above Eq. (10), ω_a and ω_z represent the initial and final values of ω, respectively. α_{1a} and α_{1z} correspond to the initial and final values of α_1, while α_{2a} *and* α_{2z} represent the initial and final values of α_2. The iteration index is denoted by i, and i_{max} indicates the maximum number of iterations. The velocity $\vartheta_{k,l}^{i+1}$ and position $y_{k,\ l}^{i+1}$ of the kth particle are updated using the following equations in APSO (shown by Eqs. (11) & 12).

$$\vartheta_{k,l}^{i+1} = \left(\omega_z + (\omega_a - \omega_z)\left(\frac{i}{i_{max}}\right)^2\right)\vartheta_{k,l}^{i} + \left(\alpha_{1Z}\left(\frac{\alpha_{1a}}{\alpha_{1Z}}\right)^{\left(\frac{i}{i_{max}}\right)^2}\right)R_1\left(P_{bestk,l}^{i} - y_{k,\ l}^{i}\right)$$

$$\left(\alpha_{2Z}\left(\frac{\alpha_{2a}}{\alpha_{2Z}}\right)^{\left(\frac{\mathrm{i}}{\mathrm{i_{max}}}\right)^2}\right)\mathrm{R}_2\left(\mathrm{g}_{\mathrm{best}}^{\mathrm{i}} - \mathrm{y}_{\mathrm{k},\ 1}^{\mathrm{i}}\right) \tag{11}$$

$$y_{k,\ l}^{i+1} = y_{k,\ l}^{i} + \vartheta_{k,l}^{i+1} \tag{12}$$

The pseudocode for APSO is presented below:

Initialize particle positions and velocities
Initialize personal best positions and global best position
Set iteration index $i = 0$
Set maximum number of iterations i_{max}
while $i < i_{max}$ do:
for each particle in the population do:
Update velocity using Eq. (11)
Update position using Eq. (12)
Evaluate fitness of the current position
Update personal best position if necessary
Update global best position if necessary
Update gradually varying parameters $\omega, \ \alpha_1, \ and\ \alpha_2$ using Eq. (10)
Increment iteration index i by 1
End loop
Return global best position as the solution

3. Proposed technique fuzzy hybrid advanced TLBPSO (F-TLBO-APSO)

A step-by-step algorithmic procedure for the proposed technique “Fuzzy Hybrid Advanced TLBPSO (F-TLBO-PSO)” for detecting dengue disease based on symptoms is presented as follows:

a. **Fuzzification:**
   a. Define the symptoms associated with dengue disease and specify their corresponding values.
   b. Establish membership functions for each symptom variable to capture the degree of membership for each value.
   c. Assign the symptom values to their respective membership functions, resulting in the generation of fuzzy sets for each symptom.
b. **Sugeno Inference System:**
   a. Define the fuzzy rules that establish the connection between the fuzzy symptoms and the diagnosis of dengue disease.
   b. Combine the fuzzy symptoms using fuzzy logic operations (AND, OR, NOT) to construct the antecedent part of each rule.
   c. Specify the consequent part of each rule based on the diagnosis of dengue disease.
   d. Employ the Sugeno inference system to ascertain the overall diagnosis by considering the fuzzy rules and fuzzy symptoms.
c. **Linear Objective Function:**
   a. Transform the fuzzy diagnosis obtained from the Sugeno inference system into a precise, crisp value.
   b. Establish a linear objective function that measures the accuracy or quality of the diagnosis, considering specific evaluation criteria (e.g., sensitivity, specificity, accuracy).
   c. The objective function should accept the crisp diagnosis and the actual diagnosis as inputs, generating a quantitative measure that assesses the level of concordance between the diagnosis and the actual condition.
d. **Hybrid TLBO-APSO Optimization:**
   a. Initialize a population of potential solutions (patients). The population is split into two sub-populations: P1 (the top half) and P2 (the remaining portion), enabling global and local search capabilities.
   b. Evaluate the fitness of each solution by computing the objective function value.
   c. Select the best and gbest solutions from the population P1 and P2 respectively.
   d. If best is better than gbest merge P1 with P2 and Facilitate a teaching and learning process to enhance solution quality. Otherwise merge P2 with P1 and apply advanced Particle Swarm Optimization (APSO) to refine the objective function by adjusting positions and velocities based on individual and swarm best positions.
   e. Repeat steps b to f until a termination condition is met (e.g., maximum iterations or satisfactory solution).
e. **Final Diagnosis:**

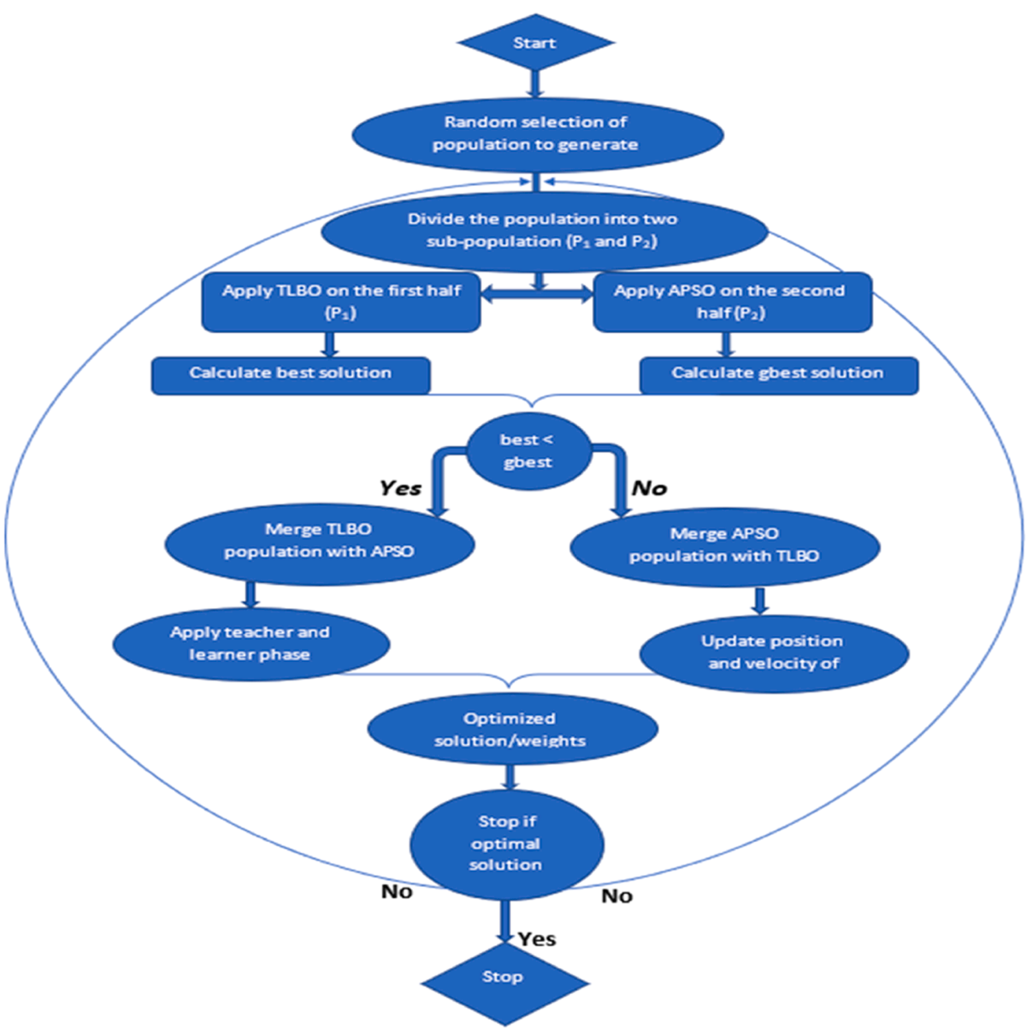


Fig. 1. Flow chart for the Proposed Algorithm F-TLBO-APSO.

a. Retrieve the optimal solution obtained through TLBO-APSO optimization, indicating the optimized diagnosis.
b. Translate the crisp diagnosis into meaningful information for dengue disease detection, such as determining a positive or negative diagnosis and assessing the severity level.
c. Communicate the final diagnosis to the healthcare professional or system user.

Please note that this algorithmic procedure is a general outline based on the information provided. The specific implementation details and parameters may vary depending on the research or application context. Introducing the advanced TLBPSO, a hybrid algorithm, called Fuzzy Hybrid Advanced Teaching Learning Based Particle Swarm Optimization (F-TLBO-APSO), is proposed for further optimization improvements., F-TLBO-APSO is developed by combining APSO with TLBO, aiming for superior performance. The flowchart of F-TLBO-APSO is illustrated in Fig. 1.

4. Data collection

Data collection for dengue patients involves gathering relevant information about diagnosed individuals. The process includes the following steps:

1. **Identification:** Patients are identified through hospital records, clinics, or public health surveillance systems, with health authorities and medical professionals playing a crucial role.
2. **Patient Information:** Demographic details like age, gender, address, and contact information are collected to maintain accurate records and enable communication and follow-up.
3. **Medical History:** Detailed histories are obtained, covering symptoms, onset dates, disease severity, prior medical conditions, and treatments. This information helps to understand the patient's health status and disease progression.
4. **Laboratory Tests**: Diagnostic tests, such as blood tests, confirm the presence of dengue virus or antibodies, categorizing the infection type (e.g., dengue fever, dengue haemorrhagic fever).
5. **Clinical Assessment**: Healthcare professionals evaluate patients through physical examinations and symptom assessments to determine disease severity and appropriate treatment.
6. **Follow-up**: Some patients require follow-up visits or monitoring to track recovery progress and identify potential complications. These visits ensure comprehensive care and ongoing data collection.

It is important to comply with ethical and privacy considerations, ensuring patient confidentiality and anonymity. Adherence to healthcare regulations and guidelines is crucial during the data collection process.

Here, the process of secondary data collection for dengue-infected patients involved gathering data from Lala Lajpat Rai Memorial Medical College in Meerut, India. The data focused on six key symptoms: blood sugar levels, temperature, pulse rate, weight, age, and blood pressure.

5. Mathematical formulation of the proposed F-TLBO-APSO algorithm

Let us consider a set of patients

$$S = \{s_1,\ s_2, \ldots s_n\}$$

of a dengue infected patient p. Now, express each symptom of the patient in the form of trapezoidal fuzzy number

$$A = (a_{11}, a_{22}, a_{33},\ a_{44}\ )$$

as shown in Fig. 2 for each input factors;

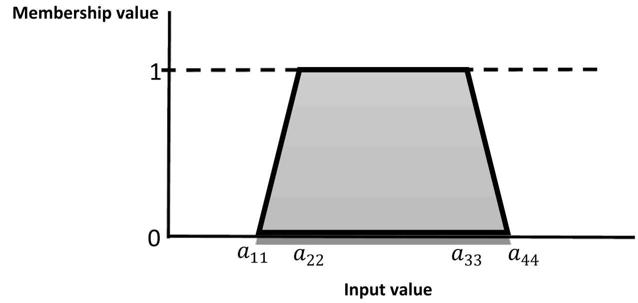


Fig. 2. Geometrical representation of trapezoidal fuzzy number

Input factors are categorized into two linguistic categories based on medical experts' knowledge. Temperature is classified as normal ([**95–99**]) and severe ([**≥98**]). Sugar is categorized as normal ([**130–150**]) and severe ([**≥140**]). Pulse rate is classified as controlled ([**85–95**]) and severe ([**≥90**]). Age is categorized as low ([35-45]) and high ([**≥40**]). Weight is classified as low ([**48–55**]) and high ([**≥54**]). Lastly, blood pressure is categorized as normal ([**90–118**]) and severe ([**≥115**]).

A fuzzy rule base is considered for the Sugeno's inference system, following a specific form:

R : Antecedent part
x_1 is A_1 and x_2 is A_2 and x_3 is A_3 and x_4 is A_4
and x_5 is A_5 and x_6 is A_6
Consequent part
$\boldsymbol{y = a_0 + x_1 a_1 + x_2 a_2 + x_3 a_3 + x_4 a_4 + x_5 a_5 + x_6 a_6}$

where, $A_i;\ i = 1, 2, \ldots 6$ are trapezoidal fuzzy numbers for each input factor expressed by

$$\mu_{A_i}(\tau) = \begin{cases} \dfrac{\tau - a_{11}}{a_{22}\ -\ a_{11}};\ a_{11} \le \tau \le a_{22} \\ 1;\ \ a_{22} \le \tau \le a_{33} \\ \dfrac{a_{44} - \tau}{a_{44} -\ a_{33}};\ a_{33} \le \tau \le a_{44} \\ 0;\ \text{else} \end{cases}$$

and $a_i;\ i = 0,\ 1, \ldots 6$ are the weights. The obtained output will be used as the objective function for the proposed F-TLBO-APSO algorithm. Next, let's analyze a patient's data and determine the membership values for each input factor using the trapezoidal membership function. Subsequently, we will consider an objective function in a specific form.

$$y = a_0 + x_1 a_1 + x_2 a_2 + x_3 a_3 + x_4 a_4 + x_5 a_5 + x_6 a_6 \tag{13}$$

In Eq. (13), For the optimization of weights $a_i;\ i = 0,\ 1, \ldots 6$, we will apply the TLBO technique. Now, we calculate the difference mean value by the Eq. (2)

$$\text{Difference \_mean}_{m,P,n} = R_n\left(\chi_{m,P_{best},n} - \tau_F \lambda_{m,n}\right)$$

Based on this, the solution can be updated by Eq. (4)

$$\chi'_{m,P,n} = \chi_{m,P,n} + \text{Difference \_mean}_{m,P,n}$$

Now, we calculate randomly select two updated functional values, $\chi'_{total-A,n}$ and $\chi'_{total-B,n}$, which represent the values of learner A and learner B, respectively, such that

$$\chi'_{total-A,n} \ne \chi'_{total-B,n}$$

Now, we calculate the value of $\chi''_{m,A,n}$ at the end of the teacher's phase (using Eqs. (6)-9).

$$\chi''_{m,A,n} = \begin{cases} \chi'_{m,A,n} + R_n\left(\chi'_{m,A,n} - \chi'_{m,B,n}\right), \text{if} \chi'_{total-A,n} < \chi'_{total-B,n} \\ \chi'_{m,A,n} + R_n\left(\chi'_{m,B,n} - \chi'_{m,A,n}\right),\ \text{if} \chi'_{total-B,n} < \chi'_{total-A,n} \end{cases}$$

Table 1
Initial population.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.1	0.3	0.1	0.6	0.2	0.15	1.3125
2	0.5	0.2	0.7	0.2	0.1	0.4	1.5875
3	0.3	0.1	0.3	0.4	0.25	0.15	1.2375
4	0.25	0.5	0.15	0.3	0.2	0.6	1.54375
5	0.1	0.25	0.2	0.5	0.4	0.3	1.5375
6	0.25	0.7	0.25	0.1	0.3	0.5	1.69375
Mean	0.25	0.342	0.284	0.35	0.35	0.35	1.48542

$$\chi''_{m,A,n} = \begin{cases} \chi'_{m,A,n} + R_n\left(\chi'_{m,A,n} - \chi'_{m,B,n}\right), if \chi'_{total-B,n} < \chi'_{total-A,n} \\ \chi'_{m,A,n} + R_n\left(\chi'_{m,B,n} - \chi'_{m,A,n}\right), if \chi'_{total-A,n} < \chi'_{total-B,n} \end{cases}$$

Now apply the APSO and find the value of $\omega,\ \alpha_1,\ and\ \alpha_2$ by the given expression (using Eq. (10));

$$\omega = \omega_z + (\omega_a - \omega_z)\left(\frac{i}{i_{max}}\right)^2;\ \alpha_1 = \alpha_{1Z}\left(\frac{\alpha_{1a}}{\alpha_{1Z}}\right)^{\left(\frac{i}{i_{max}}\right)^2}$$

and $\alpha_2 = \alpha_{2Z}\left(\frac{\alpha_{2a}}{\alpha_{2Z}}\right)^{\left(\frac{i}{i_{max}}\right)^2}$

The updated velocity of proposed APSO is calculated by Eq. (11)

$$\vartheta_{k,l}^{i+1} = \left(\omega_z + (\omega_a - \omega_z)\left(\frac{i}{i_{max}}\right)^2\right)\vartheta_{k,l}^{i} + \left(\alpha_{1Z}\left(\frac{\alpha_{1a}}{\alpha_{1Z}}\right)^{\left(\frac{i}{i_{max}}\right)^2}\right)R_1\left(P_{bestk,l}^{i} - y_{k,\ l}^{i}\right) + \left(\alpha_{2Z}\left(\frac{\alpha_{2a}}{\alpha_{2Z}}\right)^{\left(\frac{i}{i_{max}}\right)^2}\right)R_2\left(g_{best}^{i} - y_{k,\ l}^{i}\right)$$

The error of the algorithm can be obtained by the following equation (14)

$$e = \left|\frac{experimental\ value\ -\ expected\ value}{expected\ value} \times 100\right| \tag{14}$$

6. Numerical computation

To conduct this computational analysis, we collected data from a total of 25 dengue patients. Among these patients, 20 were used to train our model, while the remaining 5 were utilized for testing purposes. In this section, we applied our proposed technique F-TLBO-APSO over a set of dengue patients.

In this computational section, we initiated the process by applying Sugeno's fuzzy inference system to the patients' data. This resulted in an objective function, denoted as (using Eq. (13)):

$$y = f(x) = a_0 + x_1a_1 + x_2a_2 + x_3a_3 + x_4a_4 + x_5a_5 + x_6a_6$$

Subsequently, our focus shifted towards optimizing the weights (a_0, a_1, a_2, a_3, a_4, a_5, and a_6) extracted from the objective function. We accomplished this optimization through a two-step approach, employing the TLBO algorithm followed by APSO. The iteration-by-iteration process is presented as follows:

TLBO Process: first Iteration

Teaching phase:

$$y = f(x) = a_0 + x_1a_1 + x_2a_2 + x_3a_3 + x_4a_4 + x_5a_5 + x_6a_6$$

$$\text{Difference \_mean}_{m,P,n} = R_n\left(\chi_{m,P_{best},n} - \tau_F\lambda_{m,n}\right)$$

$$\chi'_{m,P,n} = \chi_{m,P,n} + \text{Difference \_mean}_{m,P,n}$$

Take initial assumptions; TF: $\lambda_F = 1$. Random numbers: $R_1 = 0.25$, $R_2 = 0.43$, $R_3 = 0.53$, $R_4 = 0.34$, $R_5 = 0.61$ and $R_6 = 0.15$ and let us assume that the expected value is 1.

By using this above equation, we got the new values for the weights of objective function.

Learner Phase:

Peer to Peer learning: Interaction between the slow learners and better learners in which peer to peer learning between the learners as follows: (1&3) for learner 1, (2&3) for learner 2, (1&4) for learner 4, (3&5) for learner 5 and (1&6) for learner 6.

$$\chi''_{m,A,n} = \begin{cases} \chi'_{m,A,n} + R_n\left(\chi'_{m,A,n} - \chi'_{m,B,n}\right), if \chi'_{total-A,n} < \chi'_{total-B,n} \\ \chi'_{m,A,n} + R_n\left(\chi'_{m,B,n} - \chi'_{m,A,n}\right),\ if \chi'_{total-B,n} < \chi'_{total-A,n} \end{cases}$$

Assuming random numbers: $R_1 = 0.47$, $R_2 = 0.33$, $R_3 = 0.25$, $R_4 = 0.76$, $R_5 = 0.53$, $R_6 = 0.16$

By using these above equations, we got the new values for the weights after Peer-to-Peer learning between the learners

Second Iteration: Repeating the whole process from Table 1 to Table 6 for better result.

APSO Process:

In this section we applied APSO on the Objective function, $y = a_0 + x_1a_1 + x_2a_2 + x_3a_3 + x_4a_4 + x_5a_5 + x_6a_6$.

First iteration:

In which we have taken Population size = 6, Dimension of the problem = 6, Max. Iteration = 3, Inertia weight (ω = 0.9), Correction factor (α_1&α_2 = 1.5) Random numbers ($R_1 = 0.43$, $R_2 = 0.18$)

	ϑ_1	ϑ_2	ϑ_3	ϑ_4	ϑ_5	ϑ_6
1	0.25	0.34	0.27	0.18	0.43	0.51
2	0.55	0.48	0.19	0.25	0.31	0.23
3	0.46	0.26	0.37	0.22	0.57	0.17
4	0.28	0.11	0.54	0.35	0.28	0.41
5	0.12	0.51	0.21	0.44	0.24	0.36
6	0.33	0.29	0.43	0.5	0.13	0.23

Now, update the velocities for 1st iteration:

$$\vartheta_{k,l}^{i+1} = \left(\omega_z + (\omega_a - \omega_z)\left(\frac{i}{i_{max}}\right)^2\right)\vartheta_{k,l}^{i} + \left(\alpha_{1Z}\left(\frac{\alpha_{1a}}{\alpha_{1Z}}\right)^{\left(\frac{i}{i_{max}}\right)^2}\right)R_1\left(P_{bestk,l}^{i} - y_{k,\ l}^{i}\right) + \left(\alpha_{2Z}\left(\frac{\alpha_{2a}}{\alpha_{2Z}}\right)^{\left(\frac{i}{i_{max}}\right)^2}\right)R_2\left(g_{best}^{i} - y_{k,\ l}^{i}\right)$$

Table 2
New values for the weights of objective function.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.0625	0.28194	0.00248	0.685	0.17438	0.12	1.2272375
2	0.5625	0.13894	0.92048	0.148	0.01338	0.4075	1.6354875
3	0.3125	−0.00406	0.30848	0.417	0.25488	0.12	1.1534875
4	0.25	0.56794	0.07898	0.283	0.17438	0.63	1.51305
5	0.0625	0.21044	0.15548	0.551	0.49638	0.2925	1.5829875
6	0.25	0.85394	0.23198	0.015	0.33538	0.5225	1.7913

Table 3
Updated values of the weights after comparing Table 1 & 2.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.0625	0.28194	0.00248	0.685	0.17438	0.12	1.2272375
2	0.5	0.2	0.7	0.2	0.1	0.4	1.5875
3	0.3125	−0.00406	0.30848	0.417	0.25488	0.12	1.1534875
4	0.25	0.56794	0.07898	0.283	0.17438	0.63	1.51305
5	0.1	0.25	0.2	0.5	0.4	0.3	1.5375
6	0.25	0.7	0.25	0.1	0.3	0.5	1.69375

Table 4
Initial population for peer-to-peer learning taken from Table 3.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$	Peer to Peer learning
1	0.0625	0.28194	0.00248	0.685	0.17438	0.12	1.2272375	(1&3)
2	0.5	0.2	0.7	0.2	0.1	0.4	1.5875	(2&3)
3	0.3125	−0.00406	0.30848	0.417	0.25488	0.12	1.1534875	
4	0.25	0.56794	0.07898	0.283	0.17438	0.63	1.51305	(1&4)
5	0.1	0.25	0.2	0.5	0.4	0.3	1.5375	(3&5)
6	0.25	0.7	0.25	0.1	0.3	0.5	1.69375	(1&6)

Table 5
New values for the weights after peer-to-peer learning.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.18	0.18756	0.07898	0.48132	0.21705	0.12	1.09241
2	0.411875	0.13266	0.60212	0.36492	0.182044	0.3552	1.613797
3	0.3125	−0.00406	0.30848	0.417	0.25488	0.12	1.153488
4	0.161875	0.46366	0.05986	0.58852	0.17438	0.5484	1.621323
5	0.199875	0.16616	0.22712	0.43692	0.32309	0.2712	1.363843
6	0.161875	0.56204	0.18812	0.5446	0.2334	0.4392	1.808463

Table 6
Updated values for the weights after comparing Table 4 & 5.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.18	0.18756	0.07898	0.48132	0.21705	0.12	1.09241
2	0.5	0.2	0.7	0.2	0.1	0.4	1.5875
3	0.3125	−0.00406	0.30848	0.417	0.25488	0.12	1.1534875
4	0.25	0.56794	0.07898	0.283	0.17438	0.63	1.51305
5	0.199875	0.16616	0.22712	0.43692	0.32309	0.2712	1.363843
6	0.25	0.7	0.25	0.1	0.3	0.5	1.69375

Table 7
Updated values for the Second Iteration.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.18	0.18756	0.07898	0.48132	0.21705	0.12	1.09241
2	0.04325	0.170458	0.75956	0.181518	−0.01205	0.48073	1.356069
3	0.0100533	−0.01573	0.270156	0.465902	0.220054	0.076761	**0.982534**
4	−0.1731882	0.521034	0.051098	0.375452	0.143474	0.714006	1.383115
5	−0.2318856	0.052672	0.231654	0.466214	0.286707	0.258051	1.079315
6	−0.2330126	0.64496	0.214336	0.251927	0.262977	0.551571	1.562605

Table 8
Randomly chosen Initial velocities (**$\vartheta = L + $ Rand*(U-L)**)

	ϑ_1	ϑ_2	ϑ_3	ϑ_4	ϑ_5	ϑ_6
1	0.25	0.34	0.27	0.18	0.43	0.51
2	0.55	0.48	0.19	0.25	0.31	0.23
3	0.46	0.26	0.37	0.22	0.57	0.17
4	0.28	0.11	0.54	0.35	0.28	0.41
5	0.12	0.51	0.21	0.44	0.24	0.36
6	0.33	0.29	0.43	0.5	0.13	0.23

where, $R_1 = 0.43$, $R_2 = 0.18$, $\omega = 0.9$ andα_1& $\alpha_2 = 1.5$

By using this above equation, we got the updated velocities for this process.

By using the equation $y^{i+1}_{k,l} = y^{i}_{k,l} + \vartheta^{i+1}_{k,l}$, we got the updated positions for this process.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.379	0.552	0.397	0.708	0.6005	0.609	2.704125
2	0.941	0.605	0.763	0.479	0.4195	0.5395	2.889125
3	0.714	0.334	0.633	0.598	0.763	0.303	2.74725
4	0.5155	0.491	0.6765	0.642	0.4655	0.8475	2.892063
5	0.262	0.6685	0.416	0.869	0.5755	0.5835	2.919
6	0.5605	0.799	0.6505	0.631	0.4035	0.6125	3.000438

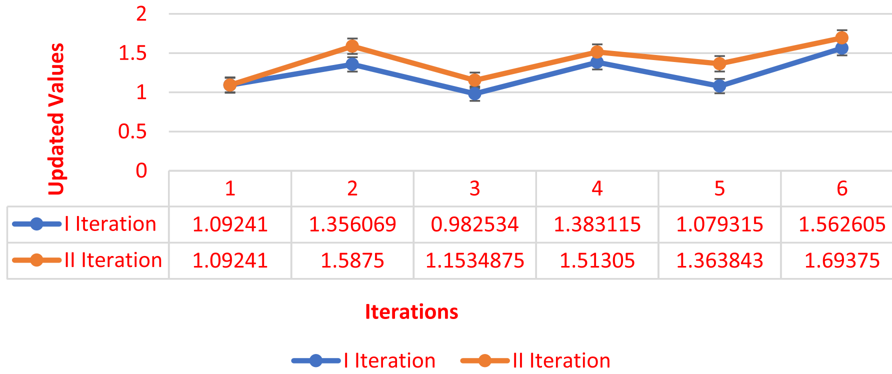


Fig. 3. Comparison between Iterations and their values.

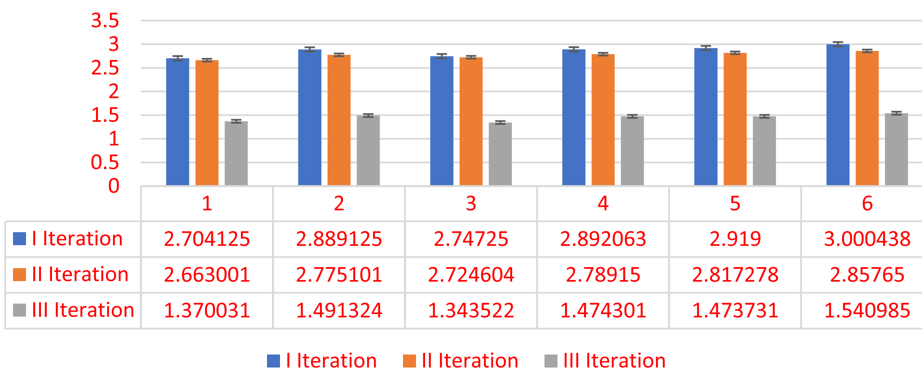


Fig. 4. Comparison between Iterations and their values.

Second Iteration:

Now in this iteration, update velocities for 2ndtime same as above

Third Iteration:

Now update velocities for 3rd iteration same as above

Apply TLBO on the Updated values of APSO:

In this section we have applied the TLBO on the updated values of APSO with the help of peer-to-peer learning.

Learner Phase:

Peer to Peer learning: Interaction between the slow learners and better learners in which peer to peer learning between the learners as follows: (1&3) for learner 1, (2&1) for learner 2, (1&4) for learner 4, (3&5) for learner 5 and (3&6) for learner 6. Assuming random numbers: $R_1 = 0.42$, $R_2 = 0.36$, $R_3 = 0.25$, $R_4 = 0.18$, $R_5 = 0.45$, $R_6 = 0.31$

Repeating the whole process from Table 18 to Table 21 for better result in further iterations:

The obtained updated values after ten iterations:

Tenth Iteration:

7. Comparative study

A comparative study between the existing approaches and proposed approach is given in Fig. 6.

The Fig. 6. Shows that the estimated values obtained by different techniques (i.e., TLBO, APSO, and F-TLBO-APSO) are 0.982534, 1.343522 and 1.000755 respectively. It can be easily observed that in case of F-TLBO-APSO the obtained error is minimum as compare to TLBO and APSO.

Verifying the results of a Fuzzy Hybrid Approach for Advanced

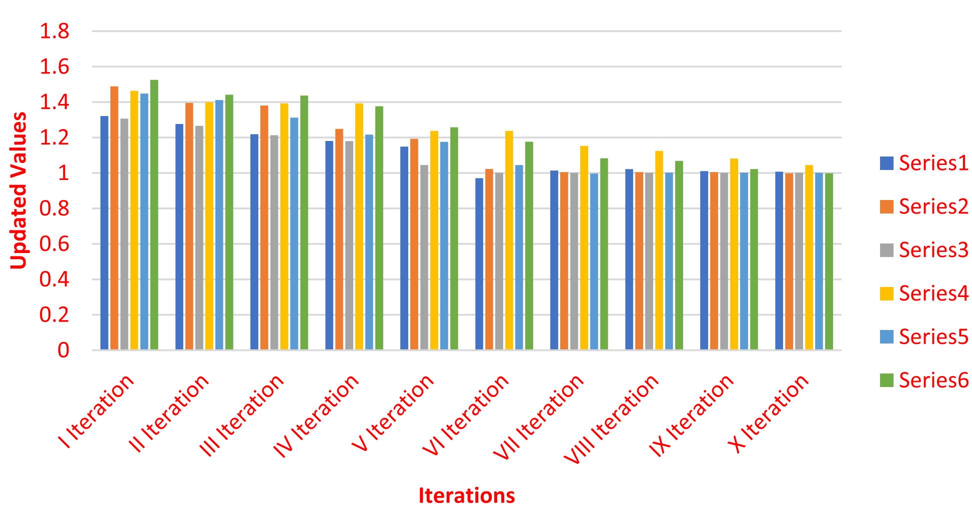


Fig. 5. Comparison between Iterations and their values.

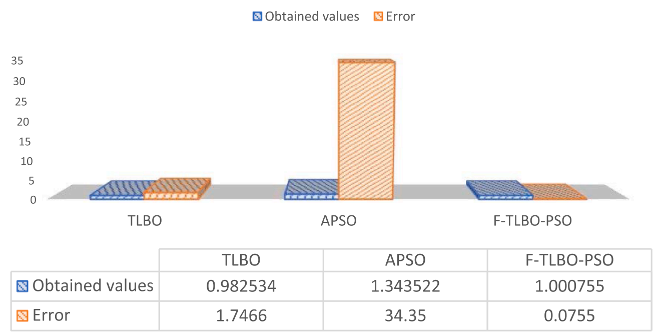


Fig. 6. Comparative Study.

Teaching Learning Technique with Particle Swarm Optimization (F-TLBO-APSO) for the diagnosis of Dengue disease against other published works would typically involve a systematic comparison using key metrics such as accuracy, sensitivity, specificity and computational time (see tab 23).

Algorithm	Accuracy	Sensitivity	Specificity	Computation Time
F-TLBO-APSO (Proposed Work)	**96.5 %**	**95.8 %**	**97.2 %**	**Moderate**
SVM with PSO [41]	91.5 %	90.8 %	92.2 %	Moderate
ANN with PSO [42]	93.4 %	92.8 %	94.2 %	High
Hybrid GA-PSO Approach [43]	94.1 %	93.5 %	94.6 %	High

8. Conclusion and discussion

In this work, we developed the Fuzzy Hybrid Advanced Teaching Learning Based Particle Swarm Optimization (F-TLBO-APSO) algorithm and applied it to a real-life application. By merging the TLBO technique with advanced APSO, we obtained optimized values and developed the F-TLBO-APSO algorithm. We applied the TLBO approach to the updated weights of APSO. To validate the performance of the proposed F-TLBO-APSO algorithm, we utilized secondary data from dengue-infected patients. In the computation section, the following observations were made:

i. Tabs 1-3 represent the teaching phase of the first iteration, and Tabs 4-6 represent the learner phase of the first iteration.
ii. Tab 7 shows the updated values for the second iteration.
iii. Tabs 8-11 represent the randomly initialized velocity, initial position, p-best position, and global best position for the first iteration of the APSO process.
iv. Tabs 12-13 show the updated initial velocity and initial position for the APSO process in the first iteration.
v. Tab 14 represents the updated values, Tab 15 represents the updated positions for the second iteration, and Tab 16 represents the updated values, and Tab 17 represents the updated positions for the third iteration of the APSO process.
vi. Tab 18 and 20 represent the teaching phase of the first iteration, where Tab 18 shows the updated values of weight taken from APSO (acting as the initial population of the teaching phase). Tab 20 and 21 represent the learner phase of the first iteration by merging TLBO with APSO.
vii. Tab 22 represents the updated values of the tenth iteration of the hybrid process.
viii. Fig. 3, Fig. 4, and Fig. 5 depict the comparison between iterations and their respective values.
ix. Tab 23, represents the comparative analysis through accuracy, sensitivity, specificity and computation time.

The value 1.000755 obtained from the Table 22 is nearest to the targeted value 1. On behalf of the estimated error obtained by

$$e = \left| \frac{experimental\ value\ -\ expected\ value}{expected\ value} \times 100 \right|$$
$$= \frac{1.000755\ -\ 1}{1} \times 100 = \ 0.0755\%.$$

The obtained results show that the proposed F-TLBO-PSO algorithm is able to produce improved optimal results compared to TLBO and APSO. It can be concluded that the proposed algorithm is applicable in engineering filed, economics, industry, medicine and many more (Tables 9, 10, 19).

Most recent PSO and TLBO based algorithms do not offer the advanced learning strategies when the involved factors adjust their weights during the process. The advantage of this proposed F-TLBO-PSO in the medical area over the existing methodology is the hybridization of two approaches (TLBO and PSO). It given more degree of freedom to address the uncertainty present in the disease diagnostic problem.

Table 9
Randomly chosen Initial positions ($\mathbf{a_n}$).

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.1	0.3	0.1	0.6	0.2	0.15	1.3125
2	0.5	0.2	0.7	0.2	0.1	0.4	1.5875
3	0.3	0.1	0.3	0.4	0.25	0.15	1.2375
4	0.25	0.5	0.15	0.3	0.2	0.6	1.54375
5	0.1	0.25	0.2	0.5	0.4	0.3	1.5375
6	0.25	0.7	0.25	0.1	0.3	0.5	1.69375

Table 10
P_i(p-best) positions.

	a_1	a_2	a_3	a_4	a_5	a_6
1	0.1	0.3	0.1	0.6	0.2	0.15
2	0.5	0.2	0.7	0.2	0.1	0.4
3	0.3	0.1	0.3	0.4	0.25	0.15
4	0.25	0.5	0.15	0.3	0.2	0.6
5	0.1	0.25	0.2	0.5	0.4	0.3
6	0.25	0.7	0.25	0.1	0.3	0.5

Table 11
$\mathbf{P^g}$ (g-best) global positions.

	a_2	a_3	a_4	a_5	a_6
0.3	0.1	0.3	0.4	0 0.25	0.15

Table 12
Updated velocities.

	ϑ_1	ϑ_2	ϑ_3	ϑ_4	ϑ_5	ϑ_6
1	0.279	0.252	0.297	0.108	0.4005	0.459
2	0.441	0.405	0.063	0.279	0.3195	0.1395
3	0.414	0.234	0.333	0.198	0.513	0.153
4	0.2655	−0.009	0.5265	0.342	0.2655	0.2475
5	0.162	0.4185	0.216	0.369	0.1755	0.2835
6	0.3105	0.099	0.4005	0.531	0.1035	0.1125

Table 13
Updated positions

	a_1	a_2	a_3	a_4	a_5	a_6	Y = f(x)
1	0.379	0.552	0.397	0.708	0.6005	0.609	2.704125
2	0.941	0.605	0.763	0.479	0.4195	0.5395	2.889125
3	0.714	0.334	0.633	0.598	0.763	0.303	2.74725
4	0.5155	0.491	0.6765	0.642	0.4655	0.8475	2.892063
5	0.262	0.6685	0.416	0.869	0.5755	0.5835	2.919
6	0.5605	0.799	0.6505	0.631	0.4035	0.6125	3.000438

Table 14
Updated velocities.

	ϑ_1	ϑ_2	ϑ_3	ϑ_4	ϑ_5	ϑ_6
1	0.049815	−0.05778	0.049545	−0.05562	0.007493	−0.00688
2	−0.06062	−0.03308	−0.10895	0.049815	0.035708	−0.06959
3	−0.00621	−0.00351	−0.005	−0.00297	−0.0077	−0.0023
4	0.009518	−0.10787	0.032603	0.02187	0.009518	−0.12521
5	0.05157	−0.04678	0.02376	−0.03254	−0.04313	−0.04475
6	0.008843	−0.16349	0.007492	0.073035	−0.01505	−0.09619

Table 15
Updated positions.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = (x)$
1	0.428815	0.49422	0.446545	0.65238	0.607993	0.602115	2.663001
2	0.880385	0.571925	0.654055	0.528815	0.455208	0.469908	2.775101
3	0.70779	0.33049	0.628005	0.59503	0.755305	0.300705	2.724604
4	0.525018	0.383135	0.709103	0.66387	0.475018	0.722288	2.78915
5	0.31357	0.621723	0.43976	0.836465	0.532368	0.538748	2.817278
6	0.569343	0.635515	0.657993	0.704035	0.388448	0.516313	2.85765

Table 16
Updated velocities.

	ϑ_1	ϑ_2	ϑ_3	ϑ_4	ϑ_5	ϑ_6
1	−0.20203	−0.28371	−0.2185	−0.15199	−0.35307	−0.41988
2	−0.45661	−0.39708	−0.16401	−0.20203	−0.25238	−0.1941
3	−0.37872	−0.21406	−0.30462	−0.18113	−0.46928	−0.13996
4	−0.22958	−0.09815	−0.44174	−0.28626	−0.22958	−0.34608
5	−0.095	−0.42273	−0.171	−0.36415	−0.20044	−0.29923
6	−0.27074	−0.25013	−0.35307	−0.40596	−0.10798	−0.19599

Table 17
Updated positions.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.226783	0.210507	0.228047	0.500394	0.254923	0.182233	1.370031
2	0.423779	0.174846	0.490044	0.326783	0.202829	0.275809	1.491324
3	0.329073	0.116433	0.323385	0.413905	0.286025	0.160744	1.343522
4	0.295442	0.284988	0.267366	0.377612	0.245442	0.376203	1.474301
5	0.218566	0.198997	0.268764	0.472318	0.331932	0.239516	1.473731
6	0.298602	0.385382	0.304923	0.298074	0.280471	0.320318	1.540985

Table 18
Initial population taken from (Table 17) for using Teaching phase to optimize the values of weights in APSO process.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.226783	0.210507	0.228047	0.500394	0.254923	0.182233	1.370031
2	0.423779	0.174846	0.490044	0.326783	0.202829	0.275809	1.491324
3	0.329073	0.116433	0.323385	0.413905	0.286025	0.160744	1.343522
4	0.295442	0.284988	0.267366	0.377612	0.245442	0.376203	1.474301
5	0.218566	0.198997	0.268764	0.472318	0.331932	0.239516	1.473731
6	0.298602	0.385382	0.304923	0.298074	0.280471	0.320318	1.540985
Mean	0.3001913	0.228525	0.313755	0.398181	0.266937	0.259137	1.44954

Table 19
Updated values of the weights after comparing.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.195951	0.20402	0.20662	0.518793	0.249516	0.158393	1.331627
2	0.423779	0.174846	0.490044	0.326783	0.202829	0.275809	1.491324
3	0.341204	0.076079	0.325792	0.416735	0.294615	0.130243	**1.306294**
4	0.295442	0.284988	0.267366	0.377612	0.245442	0.376203	1.474301
5	0.227468	0.198997	0.268764	0.472318	0.331932	0.239516	1.477069
6	0.298602	0.385382	0.304923	0.298074	0.280471	0.320318	1.540985

Table 20
Initial population for peer-to-peer learning taken from Table 19.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$	
1	0.195951	0.20402	0.20662	0.518793	0.249516	0.158393	1.331627	1 & 3
2	0.423779	0.174846	0.490044	0.326783	0.202829	0.275809	1.491324	2 & 1
3	0.341204	0.076079	0.325792	0.416735	0.294615	0.130243	**1.306294**	
4	0.295442	0.284988	0.267366	0.377612	0.245442	0.376203	1.474301	4 & 1
5	0.227468	0.198997	0.268764	0.472318	0.331932	0.239516	1.477069	5 & 3
6	0.298602	0.385382	0.304923	0.298074	0.280471	0.320318	1.540985	6 & 3

Table 21
Updated values for the weights after comparing.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.2004	0.1938	0.2221	0.4974	0.2572	0.1519	1.3216
2	0.417	0.1771	0.4532	0.3671	0.2107	0.2488	1.488875
3	0.3412035	0.076079	0.325792	0.416735	0.294615	0.130243	1.306294
4	0.2924	0.278	0.2595	0.4073	0.2461	0.3261	1.4636
5	0.2309	0.1892	0.2785	0.4606	0.3256	0.2144	1.447688
6	0.2999	0.3607	0.3076	0.323	0.2829	0.2766	1.524963

Table 22
Updated values for the Tenth Iteration.

	a_1	a_2	a_3	a_4	a_5	a_6	$Y = f(x)$
1	0.492852	−0.268	0.309069	0.427888	0.34481	0.017623	1.007399
2	0.329141	−0.18985	0.321051	0.417082	0.319405	0.013829	0.998027
3	0.48737	−0.28821	0.311171	0.43801	0.347767	0.019192	1.001099
4	0.300259	−0.15844	0.321265	0.424133	0.335792	0.018741	1.044717
5	0.476073	−0.27682	0.31162	0.435519	0.342665	0.01848	**1.000755**
6	0.375186	−0.23595	0.318158	0.429949	0.336524	0.018485	0.99862

9. Limitations and future directions of this work

While a Fuzzy Hybrid Approach with PSO and TLBO holds promise for enhancing diagnostic accuracy and decision-making, it comes with several limitations that must be addressed, including computational complexity, data availability, and the need for extensive parameter tuning. Additionally, real-world constraints in the medical field, such as interpretability, reliability, and latency, pose significant challenges to its successful implementation in dengue disease diagnosis. Issues with patient data quality and completeness including; missing entries, variability in collection methods is a major difficulty while doing such data collection research work. The compatibility with doctor and concern authority also been the crucial part of this study. A positive interaction with patient is essential while doing such kind of data collection work.

Future aspects of this proposed technique i.e., Fuzzy Hybrid Approach for Dengue Disease Diagnosis has the potential to significantly improve medical diagnostics and patient outcomes. Key directions include enhancing algorithm performance, expanding to other diseases, leveraging real-time and edge computing, and addressing the clinical, ethical, and regulatory challenges associated with artificial intelligence in healthcare. Further research could also explore integrating this approach into personalized and precision medicine, allowing for more tailored and effective healthcare solutions. This work may be extended over many engineering and technical fields.

CRediT authorship contribution statement

Nivedita: Formal analysis, Methodology, Writing – original draft. **Riddhi Garg:** Formal analysis, Investigation, Software. **Seema Agrawal:** Data curation, Supervision, Validation. **Ajendra Sharma:** Formal analysis, Investigation, Visualization. **M.K. Sharma:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

M K Sharma reports financial support was provided by Chaudhary Charan Singh University. M K Sharma reports a relationship with Chaudhary Charan Singh University that includes: employment.

Data availability

The data of dengue patients for this work is collected from Lala Lajpat Rai Memorial Medical College, Meerut, India. The data is available in the manuscript itself.

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