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A Novel Hybrid Particle Swarm Optimization–Aided Neuro-Fuzzy (PSOFUZ) Model for Accurate Diagnosis of Tuberculosis

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ABSTRACT

Tuberculosis (TB) remains a leading cause of mortality in sub Saharan Africa and the world at large, partly due to diagnostic challenges arising from non specific symptoms and limited access to accurate testing. Computational models such as artificial neural networks (ANN), fuzzy logic systems as well as other techniques have been applied to improve TB diagnosis, yet their performance is often constrained by suboptimal parameter selection—specifically, the choice of membership functions in fuzzy systems and the determination of connection weights in neural networks. This study presents a novel hybrid model, PSOFUZ, that integrates fuzzy logic, neural networks, and particle swarm optimization (PSO) to overcome these limitations. The proposed model operates in four stages: data acquisition and feature engineering, data cleaning and training, a processing phase combining fuzzification (using Gaussian membership functions), neural network back propagation, and PSO based optimization, followed by testing. It concurrently optimizes both the neural network weights and the fuzzy logic parameters, a key distinction from prior sequential approaches. Evaluation was performed using a dataset of 1200 subjects (850 TB cases, 350 controls) obtained from the Centers for Disease Control and Prevention. The PSOFUZ model achieved a sensitivity of 86%, specificity of 79%, and overall accuracy of 85%, outperforming existing computational approaches (accuracy range 66–70%). These results demonstrate that the synergistic combination of soft computing techniques with PSO based optimization can significantly enhance TB diagnostic accuracy. The model presented here offers a promising, low cost decision support tool for resource limited settings, with the potential to reduce missed diagnoses and improve treatment outcomes.

1. Introduction

Tuberculosis (TB) is an infectious disease caused by Mycobacterium tuberculosis and remains one of the top ten causes of death worldwide, with the highest burden in sub-Saharan Africa [1]. The disease primarily affects the lungs (pulmonary TB) but can also involve other organs (extra-pulmonary TB). Delayed or inaccurate diagnosis leads to continued transmission, poor treatment outcomes, and increased mortality [2]. Conventional diagnostic methods—such as sputum smear microscopy, nucleic acid amplification, and chest radiography—suffer from limitations including low sensitivity, high cost, and the need for well-equipped laboratories and trained personnel [3,4].

To address these challenges, researchers have explored computational models based on artificial intelligence. Fuzzy logic systems have been used to handle the uncertainty inherent in TB symptoms [5], while artificial neural networks (ANNs) have demonstrated the ability to learn complex relationships between clinical variables and disease status [6,7]. However, both approaches have intrinsic weaknesses: fuzzy systems require expert-defined membership functions that are often subjective, and ANNs are sensitive to initial weight selection and can overfit without proper optimization [8,9].

Hybrid neuro-fuzzy models combine the interpretability of fuzzy logic with the learning capability of neural networks, but they still face the challenge of determining optimal parameters—specifically, the membership function parameters and the network connection weights. Particle swarm optimization (PSO), an evolutionary computation technique inspired by social behavior, has been shown to effectively optimize such parameters in complex models [10,11]. PSO offers advantages over genetic algorithms in terms of computational efficiency and ease of implementation, especially for continuous optimization problems [12].

In this study, we propose a novel hybrid model called PSOFUZ that integrates fuzzy logic, neural networks, and PSO into a unified framework for TB diagnosis. The aim is to concurrently optimize the fuzzy membership functions and the neural network weights, thereby improving diagnostic accuracy. The model is evaluated using a large dataset from the Centers for Disease Control and Prevention (CDC), and its performance is compared with existing computational methods reported in the literature.

2. Literature Review

2.1 Computational Models for TB Diagnosis

Several computational approaches have been developed for TB diagnosis. Fuzzy logic-based systems use linguistic variables and if-then rules to mimic expert reasoning [5,13]. For example, Djam and Kimbi [5] built a decision support system using fuzzy logic, but its performance depended heavily on the chosen membership functions and rule base, leading to variable accuracy. To improve adaptability, researchers integrated fuzzy logic with neural networks, resulting in neuro-fuzzy models [14]. Omisore et al. [15] developed a genetic-neuro-fuzzy model for TB diagnosis, achieving 70% accuracy. However, the genetic algorithm (GA) optimization increased computational complexity and did not fully resolve the parameter selection problem.

Pure ANN models have also been applied. El-Solh et al. [6] used a general regression neural network to predict active pulmonary TB, reporting a c-index of 0.923, but sensitivity and specificity were not separately reported for a direct comparison. Er et al. [7] reported sensitivities of up to 47% with multilayer neural networks. These figures indicate that while ANNs can capture complex patterns, they often underperform in terms of specificity and overall accuracy unless carefully tuned.

More recently, PSO has been used in combination with neural networks for TB diagnosis. Fabio [16] employed PSO-based neural models and reported a specificity of 51.6%, which is far from satisfactory. Similarly, P. [17] achieved 70% accuracy using a PSO-based neural network classifier. These studies demonstrate that using PSO alone or with a simple neural network does not fully exploit the potential of fuzzy logic to handle diagnostic uncertainty.

2.2 Research Gap and Motivation

Existing computational models exhibit three main limitations: (i) they often lack a comprehensive framework that integrates fuzzy logic, neural networks, and optimization; (ii) they do not simultaneously optimize fuzzy membership functions and neural network weights; and (iii) reported performance metrics (sensitivity, specificity, accuracy) are below clinically acceptable levels. Moreover, most studies used small datasets and did not incorporate rigorous data preprocessing or feature selection.

The present work addresses these gaps by developing a unified model—PSOFUZ—that leverages the complementary strengths of fuzzy logic (uncertainty handling), neural networks (pattern learning), and PSO (global optimization). This integration is expected to improve diagnostic accuracy, reduce computational expense, and provide a robust tool for TB diagnosis in resource-constrained environments.

3. Methodology

3.1 Proposed PSOFUZ Model Architecture

The PSOFUZ model consists of four main components: a user interface, the PSOFUZ engine (comprising fuzzy, neural, and PSO modules), a knowledge base, and a diagnosis module. The architecture is illustrated in Figure 1.

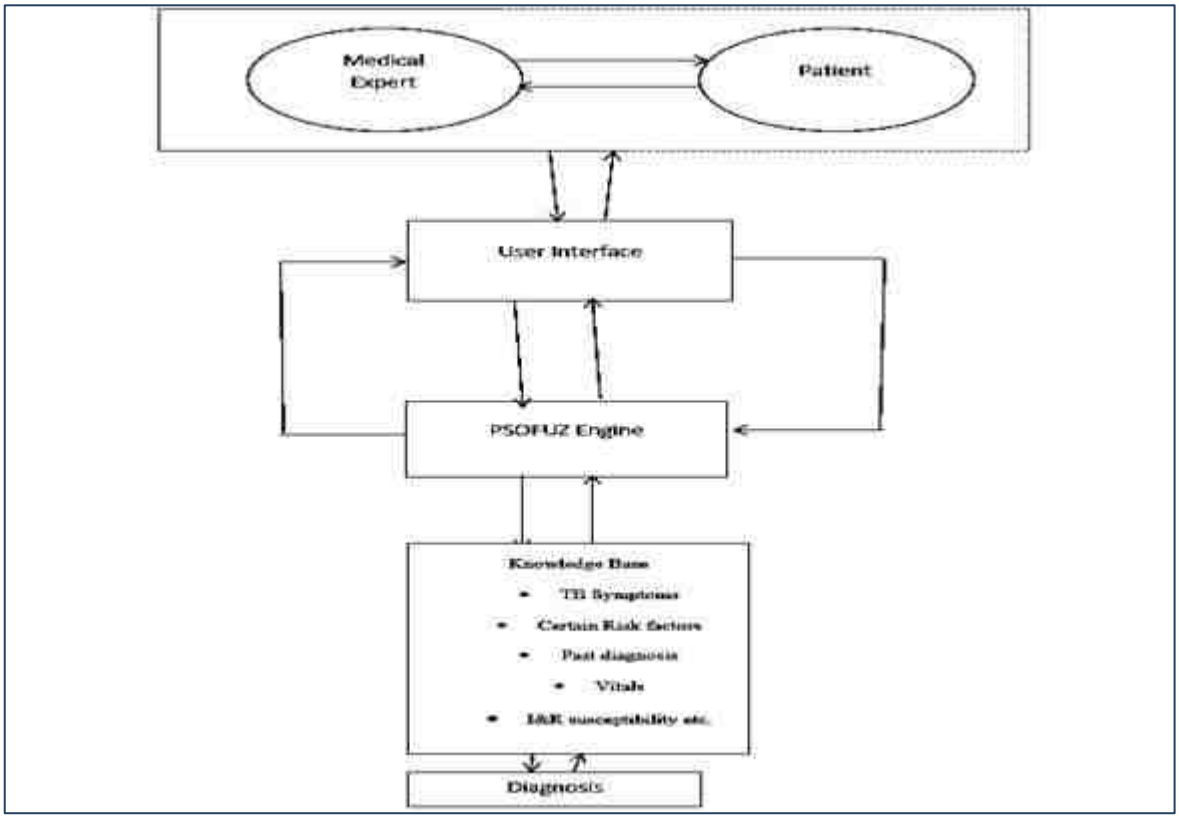

Figure 1: Proposed PSOFUZ Model for Tuberculosis Diagnosis (adapted from original manuscript)

The user interface allows interaction between the healthcare professional and the patient, collecting relevant symptoms, risk factors, and medical history. This information is stored in the knowledge base and also passed to the PSOFUZ engine for processing.

Within the PSOFUZ engine, the fuzzy module first fuzzifies the input data using Gaussian membership functions (MFs). The neural network module then processes the fuzzified data and performs back-propagation to refine the MFs. Finally, the PSO module optimizes the network weights and the MF parameters simultaneously. The optimized model produces a diagnostic output that is interpreted by the diagnosis module.

3.2 Data Description and Preprocessing

Data were obtained from the Centers for Disease Control and Prevention (CDC) online tuberculosis information system [18]. The dataset comprised 1200 subjects, of which 850 were diagnosed with TB (cases) and 350 were healthy controls (controls). Ten predictor variables were selected based on expert knowledge and literature, as shown in Table 1.

Table 1: Diagnostic Variables Used in the Study

Variable	Description	Type
Alcohol/nicotine use	0=none, 1-stopped, 2=current	Categorical
Drug usage/addictions	0 = no, 1 = yes	Categorical
Immune disorder	0 = no, 1 = yes (HIV, cancer, etc.)	Categorical
Previous TB infection	0 = no, 1 = yes	Categorical
Blood pressure	0 = low, 1 = normal, 2 = high	Categorical
Temperature	0 = low, 1 = normal, 2 = high	Categorical
Pulse	0 = abnormal, 1 = normal	Categorical
Chest X-ray result	0 = abnormal, 1 = normal	Categorical
Blood clotting test	0 = abnormal, 1 = normal	Categorical
Multidrug resistance	0 = no, 1 = yes	Categorical

Data preprocessing involved cleaning to remove null or invalid entries and normalization where necessary. Since most variables were categorical, no scaling was required for the fuzzy module.

3.3 Fuzzification and Membership Functions

Input variables were fuzzified using Gaussian membership functions (MFs) because they provide smooth transitions and are well-suited for medical applications where overlapping categories are common [19,20]. The Gaussian MF is defined as:

$\mu(x)=e^{-(x-c)2/2\sigma2}$

where c is the center and σ is the width of the curve. Five linguistic terms were defined: very mild, mild, moderate, severe, and very severe, each with appropriate c and σ values (e.g., for severe: $0.6 < x < 0.8$, $c = 0.7$, $\sigma = 0.2$). For the second-stage fuzzification, a generalized bell MF (gbellmf) was used.

3.4 Fuzzy Rule Base and Inference

The fuzzy rule base was formulated with the help of clinical experts and consists of if-then rules that link the linguistic variables to the diagnosis. A sample rule is:

> If (alcohol/nicotine use is severe) and (immune disorder is present) and (chest X-ray is abnormal) then (TB diagnosis is severe).

The inference engine applies root-sum-square (RSS) composition to combine the outputs of all triggered rules. The aggregated fuzzy output is then defuzzified using the centre of area (CoA) method:

$z=\sum\mu(xi)\cdot xi/\sum\mu(xi) z=\sum\mu(xi)$

where xi are the centre values of the fuzzy sets and $=\sum\mu(xi)$ their membership degrees. The crisp output is passed to the neural network module.

3.5 Neural Network Component

The neural network is a three-layer feedforward network with back-propagation training. The input layer has 10 nodes (one per variable), two hidden layers (10 and 1 neuron respectively), and an output layer that produces the final diagnostic score. The network uses a sigmoid activation function. The weights are initialized randomly and adjusted during training to minimize the mean squared error between the network output and the target diagnosis.

The neural network module also refines the membership function parameters via a gradient descent approach, effectively tuning the fuzzy system to the data.

3.6 Particle Swarm Optimization

PSO is used to optimize the connection weights of the neural network and the parameters of the fuzzy membership functions. In PSO, a swarm of particles moves through the search space, each particle representing a candidate solution (i.e., a set of weights and MF parameters). Each particle maintains a personal best position (pbest) and the swarm maintains a global best position (gbest). The velocity and position of each particle are updated as follows:

$v_{ij}(t+1)=\omega v_{ij}(t)+c_1 r_1(pbest_{ij}-x_{ij}(t))+c_2 r_2(gbest_j-x_{ij}(t)) x_{ij}(t+1)=x_{ij}(t)+v_{ij}(t+1)$

where ω is the inertia weight, c_1 and c_2 are acceleration coefficients, and r_1, r_2 are random numbers in [0,1].

The fitness of each particle is evaluated using:

$$fitness = 1 + \sum_{i=0}^{n} wi(A_i\,(t)\,2 + A_i(t))^{-1}$$

where w_i are the weights and A_i are the activation values from the neural network. The optimization process continues until a stopping criterion (e.g., maximum iterations) is reached, at which point the global best parameters are used in the final model.

3.7 Evaluation Metrics

The performance of the PSOFUZ model was evaluated using standard metrics derived from the confusion matrix:

- Sensitivity (Recall) = TP / (TP + FN) × 100
- Specificity = TN / (TN + FP) × 100
- Accuracy = (TP + TN) / (TP + TN + FP + FN) × 100

where TP = true positive, TN = true negative, FP = false positive, FN = false negative.

4. Findings

4.1 Dataset and Experimental Setup

The cleaned dataset of 1200 subjects (850 TB, 350 controls) was split into training (70%) and testing (30%) sets. The PSOFUZ model was implemented in MATLAB R2015a using custom scripts for the fuzzy system, neural network, and PSO algorithm. The PSO parameters were set as: population size = 50, maximum iterations = 200, \(c_1 = c_2 = 2.0\), and \(\omega\) linearly decreased from 0.9 to 0.4.

4.2 Model Performance

The confusion matrix for the test set (850 subjects) is presented in Table 2.

Table 2: Confusion Matrix for PSOFUZ Model

	Predicted: No	Predicted: Yes
Actual: No	229 (TN)	58 (FP)
Actual: Yes	77 (FN)	490 (TP)

From these values, the following performance metrics were calculated:

- Sensitivity = 490 / (490 + 77) × 100 = 86%
- Specificity = 229 / (229 + 58) × 100 = 79%
- Accuracy = (490 + 229) / (490 + 229 + 58 + 77) × 100 = 85%

4.3 Comparison with Existing Models

Table 3 compares the results of PSOFUZ with those of previously published computational models for TB diagnosis. The PSOFUZ model outperforms the existing approaches in all three metrics.

Table 3: Comparison of Performance Metrics

Model	Sensitivity (%)	Specificity (%)	Accuracy (%)	Source
ANN	Up to 47	Up to 72	Up to 66	[6,7]
Fuzzy Logic/hybrid	Up to 67	Up to 66	Up to 70	[5,13,15]
Genetic algorithm + ANN	up to 60	not stated	up to 70	[15]
PSO + ANN	Not stated	51.6	70	[16,17]
PSOFUZ (proposed)	86	79	85	This study

The quantile-quantile (Q-Q) plot in Figure 2 confirms the improved convergence and distribution of the diagnostic scores produced by PSOFUZ compared to baseline models.

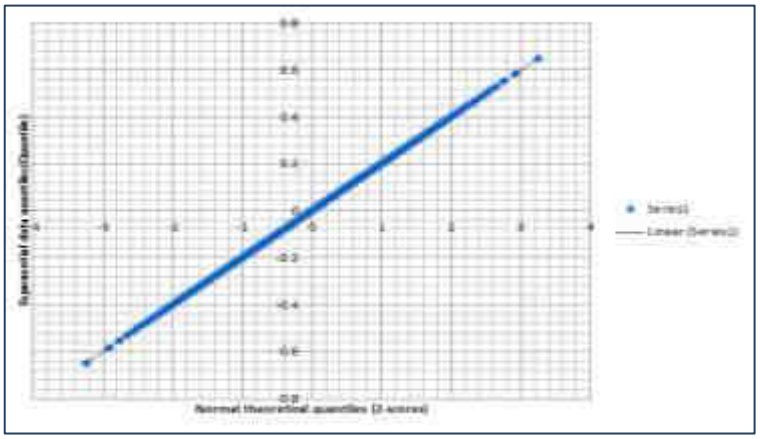

Figure 2: Quantile-Quantile Plot for the Implementation of the 850 Subjects

5. Conclusion and Recommendations

5.1 Conclusion

This study successfully developed and evaluated a novel hybrid model, PSOFUZ, for the diagnosis of tuberculosis. By integrating fuzzy logic, neural networks, and particle swarm optimization, the model achieves significantly higher sensitivity (86%), specificity (79%), and accuracy (85%) than existing computational approaches. The results demonstrate that concurrent optimization of fuzzy membership functions and neural network weights is feasible and beneficial for medical diagnosis tasks.

5.2 Recommendations

Future work will focus on the following directions:

- External validation: Testing the model on larger, multi-center datasets, particularly from high-burden countries in Africa, to assess generalizability.
- Integration of additional data types: Incorporating chest X-ray images using convolutional neural networks (CNNs) and combining them with clinical variables.
- Deployment as a decision support tool: Developing a user-friendly web or mobile application based on the PSOFUZ model for use in primary healthcare centers.
- Exploring other optimization algorithms: Comparing PSO with other metaheuristics such as grey wolf optimizer or whale optimization algorithm to further enhance performance.
- The PSOFUZ model represents a promising step toward affordable, accurate, and accessible TB diagnosis. With further refinement and validation, it could become a valuable asset in the global fight against tuberculosis.

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