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Neuro-Fuzzy Optimization Technique for Enhancing Accuracy of Predication Hepatitis Disease

Rasol H. Rweily[1] , Qusay O. Mosa[2] , Alaa Hussein Hammadi[3]

[1]*College of Computer science & information technology, University of AL-Qadisiyah, Iraq. cm.post23.16@qu.edu.iq*

[2]*College of Computer science & information technology, University of AL-Qadisiyah, Iraq. qusay.mosa@qu.edu.iq*

[3]*College of Computer science & information technology, University of AL-Qadisiyah, Iraq. alaa.hammadi@qu.edu.iq*

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ABSTRACT

Hepatitis remains one of the most widespread infectious diseases globally, posing significant challenges to public health systems and the WHO(WHO). Its inherent ambiguity, clinical variability, and data heterogeneity make accurate diagnosis a complex task. This study presents a hybrid optimization model that integrates Particle Swarm Optimization (PSO) with the Dragonfly Algorithm (DA) to improve the performance of an Adaptive Neuro-Fuzzy Inference System (ANFIS). The proposed hybrid algorithm, referred to as PSODA, is designed to optimize two critical components in the ANFIS structure: the number of membership functions in the initial layer and the model's learning rate. By balancing the exploration behavior of DA and the exploitation capabilities of PSO, the PSODA framework enhances both the stability and accuracy of the diagnostic system. Experimental results suggest that the PSODA-ANFIS model achieves a classification accuracy of 90%, outperforming standard ANFIS as well as models optimized individually by PSO or Grey Wolf Optimizer (GWO). This hybrid model demonstrates promising potential for clinical decision support in the diagnosis of hepatitis and similar medical conditions characterized by uncertainty and complexity.

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1. Introduction

Hepatitis is a global challenge, and addressing it is a critical public health priority. Hepatitis is the most common liver infection, usually caused by viral infection affecting about 1.5 million deaths annually. It is classified into 5 different types, but B & C are considered to be the two which are responsible for cirrhosis and liver cancer, according to the WHO [1] . Hepatitis C virus (HCV) initially targets the liver, causing inflammation, which may progress to cirrhosis and liver cancer. The disease is classified according to the extent of liver injury resulting from the infection. It can expand from a simple form of chronic hepatitis to more serious liver situations like fibrosis and hepatocellular carcinoma. The virus can persist in the human body for a period ranging from 10 to 20 years [2]. A small number of individuals recover spontaneously within approximately six months; however, the majority about

∗Corresponding author

Email addresses:

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70% develop a chronic viral infection. The main danger of this virus lies in its silent progression. According to the WHO, only 20% of people with hepatitis C are aware of their condition. This occurs because the disease progresses asymptomatically, with no noticeable symptoms in the early stages. Instead, patients experience symptoms that do not necessarily indicate infection, such as fatigue, sleep disturbances, or loss of appetite, which are often attributed to work or academic stress. The disease is diagnosed through a liver biopsy, liver function tests, and sometimes imaging techniques [3] .The other type of hepatitis viruses that is also of concern to healthcare providers is hepatitis B because of its serious consequences, causing cirrhosis and liver cancer if not diagnosed early. The viral infection that causes the disease is transmitted through blood fluids or sexual contact. It is often similar to hepatitis C, as there are no symptoms in the early stages. However, the infected person feels nausea, fatigue, and jaundice. It may develop into a chronic disease after six months. The most effective way to prevent the virus is early vaccination [4] .

The disease is diagnosed through several methods, including a liver biopsy, which is considered one of the most dangerous methods for the infected person, as specialists take a small amount of liver tissue and examine it. Alternatively, non-surgical diagnostic methods have been adopted, such as blood biomarkers, imaging techniques, and genetic tests [5]. However, the ambiguity and uncertainty associated with the disease negatively impact the accuracy and reliability of these diagnostic methods, which have gained widespread acceptance in clinical practice. Patients often cannot precisely articulate how they feel or what has happened to them. Physicians often cannot precisely comprehend or explain what they hear from patients, and indicators and symptoms of the disease could be vague or nonspecific. Laboratory test results can be highly variable, and medical researchers cannot determine precisely how diseases affect the body standard biological functions. Therefore, representing this data using deterministic (explicit) values is not a logical approach. Furthermore, every patient has much historical data, however doctors don’t find enough time to review it. For these reasons, precise and timely medical diagnosis is vital, because rapid and precise diagnosis and treatment initiation at a timely phase reduces the danger of complications and costs [6].

To address the ambiguity and diagnostic challenges associated with hepatitis, computational models capable of handling imprecision and uncertainty are essential in supporting medical decision making. From these, neuro-fuzzy inference systems, and the Adaptive Neuro-Fuzzy Interference System (ANFIS) in particular, have shown to have good potential in handling complex and indistinctive medical data.[7].In recent years, meta-heuristic methods that are based on collective behavior developed among animals (like flocks of birds, swarms of bees and schools of fishes) have been increasingly used as an efficient way of solving difficult optimization problems. These swarm intelligent systems are based on the decentralized and self-organizing behavior found in nature. Unlike conventional deterministic approaches that may be computationally expensive or susceptible to local optima, swarm intelligence algorithms provide a robust tradeoff between exploration and exploitation in the study field [8]. Examples of metaheuristic optimization algorithms are particle swarm algorithm (PSO), ant colony algorithm (ACO) and dragonfly algorithm (DA) and other (PSO, ACO and DA) are proposed based on certain animal behavior by solving canny and intelligent problem by cooperation and adjustment their flexibility in dealing with high-dimensional and uncertain space represents an advantage that have make them suitable in upgrading learning model like ANFIS with the goal to perform medical diagnosis tasks [9] .In this study, we propose an improved ANFIS model using a hybrid metaheuristic algorithm called PSODA, which merges the exploration abilities of the dragonfly algorithm (DA) with the exploitation power of the particle swarm algorithm (PSO). This model aims to enhance the prediction accurateness and correctness of hepatitis diagnosis, relying on real clinical data obtained from the Kaggle platform.

2. Related work

Several studies examined to diagnose infectious viral hepatitis by creating powerful diagnostic models. This section reviews some of the previous related work which is done to detection of this life-threatening disease through individual and hybrid computational models. Optimization-based methods, and in particular their hybrids with meta-heuristic techniques, have gained over recent years growing interest among researchers because of their capability of providing precise diagnosis. This section discusses the major contributions and earlier discoveries made by the researchers in this area.

Zahra et al. (2019) proposed a multi-layer neuro-fuzzy expert system that integrates fuzzy logic and a feedforward neural network for the classification of liver disease severity into ranges from normal to dangerous. Based on major biochemical markers such as ALT, AST, albumin, and bilirubin, the system processes uncertain and linguistic information using fuzzy rules and membership functions. With clinical data testing in MATLAB, the system proved to have high diagnostic accuracy of 96%, showing its superiority to conventional expert systems.[10].

Singh et al. (2023) suggested a fuzzy logic system integrated with machine learning algorithms to enhance the prognosis of hepatitis B through early detection of viral inflammation and reducing advancement towards chronic diseases such as cirrhosis and cancer. Their multi-layer fuzzy inference system gives priority to the detection of crucial risk factors in order to achieve maximum classification accuracy. The findings demonstrated high accuracy with outstanding performance in early detection. The authors recommend incorporating neuro-fuzzy inference abilities in order to increase prediction accuracy and system performance [11].

Qasim Altashi et al. (2019) suggested a hybrid binary feature selection algorithm, BGWOPSO, that integrated Grey Wolf Optimization (GWO) and (PSO) heuristics. This approach, belonging to the PSOGWO hybrid family, aims to work well in binary search spaces. The research compared BGWOPSO with various binary algorithms such as PSO, GWO, Genetic Algorithm (GA), Differential Evolution (DE), and Simulated Annealing (SA), indicating that hybrid binary outperforms single-rule approaches. When tested on 18 UCI datasets, BGWOPSO achieved high accuracy, chose fewer features, and took less computation time in comparison to other available methods, demonstrating its competence for feature selection procedures. [12].

El-Sappagh et al. (2018) proposed a clinical decision support system (CDSS) that predicts liver fibrosis stages in HCV patients through two intelligent computing techniques: fuzzy analytic hierarchy process (FAHP) and adaptive neuro-fuzzy inference system (ANFIS). Evaluated on actual data of 119 patients with chronic hepatitis C, FAHP allocated diagnostic weights based on fuzzy logic from expert opinion, whereas ANFIS integrated neural learning and fuzzy inference to design an automatic diagnosis model. Both models performed with 93.3% classification accuracy, which was better compared to conventional medical indices such as APRI and other fuzzy logic-based models such as Wang-Mendel and fuzzy decision trees. The findings show that FAHP and ANFIS are able to deal with uncertainty and fuzziness in clinical data and can be used as strong support tools in medical decision-making for the classification of liver fibrosis stages.[13].

Al-Hasnouni et al. (2020) proposed method a new hybrid optimization model called ANFIS PSOGWO for Parkinson's disease prediction in an IoT-based fog computing environment. The model combines (PSO) and Grey Wolf Optimization (GWO) to optimize ANFIS parameters with ease, utilizing a chaotic tent map to enhance parameter initialization. By bringing together the exploitative power of PSO with the exploratory power of GWO, the model attempts to improve the accuracy of disease classification. It performed better than traditional ANFIS and other optimization methods such as GA, DE, ACO, PSO, and GWO separately Evaluated on five different disease datasets from the University of California, Irvine UCI it achieved an accuracy of 87.5% in diagnosing Parkinson's disease. These observations show its promising potential for AI-based medical diagnosis in today's computing paradigm [14].

Majeed and Ramo (2022) proposed a feature selection method with the Dragonfly Optimization Algorithm (DA) to enhance breast cancer diagnosis. They combined DA with ensemble voting classifier using SVM, K-NN, Naïve Bayes, Decision Tree, and Random Forest. With classification accuracy used as the fitness function, they evaluated the model against the Wisconsin Diagnostic Breast Cancer dataset. Results indicated that the choice of 17 best features with DA had an accuracy of 98.24%, which surpassed the accuracy of the complete 30-feature set at 96.49%. This indicates DA's capacity to minimize dimensionality while preserving or enhancing prediction performance, which supports the significance of metaheuristic optimization and swarm intelligence in medical feature selection problems[15].

Unlike previous works such as [10] and [14], which focused on using PSO or PSOGWO to tune ANFIS parameters in different medical applications (e.g., breast cancer and Parkinson's diagnosis), our study introduces a novel hybrid approach named PSODA that combines the exploration capabilities of the Dragonfly Algorithm (DA) with the exploitation efficiency of the Particle Swarm Optimization (PSO). Moreover, while [10] and [14] did not incorporate feature selection or address dataset imbalance, our proposed method integrates a Random Forest-based feature selection step and uses SMOTE to handle class imbalance.

3. Methodology

In this section, a highly efficient hybrid classification model for hepatitis diagnosis is developed using ANFIS, optimized by a hybrid algorithm consisting of two metaheuristic algorithms: the Dragonfly Algorithm and the (PSO) algorithm. This methodology was applied to hepatitis data obtained from the Kaggle repository, as shown in Fig 2.

3.1. Adaptive Neuro Fuzzy Inference System (ANFIS)

Jang introduced ANFIS in 1993 by, is a hybrid model that merges the learning abilities of artificial neural networks (ANNs) with the explainable features and uncertain data processing abilities of fuzzy systems, using fuzzy inference functions based on the Takagi-Sugeno inference architecture. ANFIS consists of a five-layer network with a number of fixed and adaptive nodes. This system enables the optimization of fuzzy system indicators, such as the number and type of membership functions in the first layer (called the fuzz layer), as well as the optimization of inference rules through backpropagation or hybrid learning machine learning algorithms. This reduces reliance on human expertise and produces a system capable of learning and adapting the layers are[16].

1-Fuzzy layer (Fuzzy transform): In this layer, which contains adaptive nodes, each of the explicit inputs is transformed into functions and belonging scores using functions such as the Gaussian (bell-shaped) function.

2- Rules application layer: All nodes in this layer are fixed and calculate the firing power of fuzzy rules based on (AND, OR) algebraic operations.

3- Normalization Layer: The fixed nodes, in this layer, also convert the weights of the rules into uniform percentage values through the values obtained from the previous layer.

4- Defuzzification Layer :IN this layer, the nodes are adaptive ones that calculate outputs based on their own indicators.

5- Output Layer: This layer merges the outputs of all the rules and transforms the fuzzy results into clear values.

ANFIS is capable of learning complex input-output relationships by adjusting the internal indicators using training algorithms commonly based on gradient descent or hybrid methods that combine supervised learning with regression analysis. Due to its unique structure and abilities ANFIS is commonly employed in various domains that require flexibility and precision particularly in medical domains where data is often uncertain or expert driven such as disease diagnosis and outcome prediction[17].

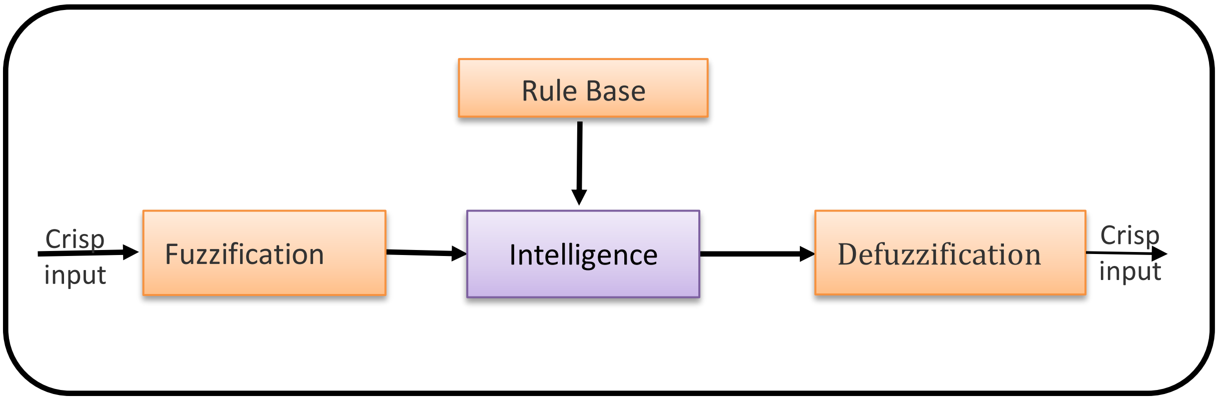

Fig. 1: scheme of ANFIS

3.2. The Proposed method (ANFIS +PSODA)

In this study, we propose a classification model based on the Adaptive Neuro-Fuzzy Inference System (ANFIS), where its performance is enhanced using a hybrid metaheuristic optimization technique that integrates Particle Swarm Optimization (PSO) with the Dragonfly Algorithm (DA). This hybrid technique is referred to as PSODA. The objective is to improve classification accuracy in hepatitis diagnosis using clinical data obtained from the Kaggle platform [18]. The methodology begins with standard data preprocessing steps. Unnecessary attributes such as patient identifiers were removed, target class labels were converted into binary format, and missing values were imputed using the KNN imputer. The dataset was then normalized using min max Scaler to standardize feature ranges and facilitate model training[19] .

Feature selection was carried out using a Random Forest classifier to reduce dimensionality and retain the most informative features, thereby improving the model's effectiveness and interpretability[20].

A customized ANFIS model was implemented using TensorFlow, where fuzzy rules were constructed based on Gaussian membership functions. The firing strengths of the rules were normalized and combined with tunable weights. The final output was passed through a sigmoid activation function to generate probabilistic classification outcomes[21] .

To optimize the model parameters, the PSODA algorithm was employed. PSODA integrates the exploration dynamics of DA with the exploitation strength of PSO. The Dragonfly Algorithm simulates the dynamic movement of swarms based on behaviors such as alignment, cohesion, separation, attraction toward food, and distraction from enemies. These rules are particularly effective during the exploration phase. In contrast, PSO updates particles based on the best-known personal and global positions, making it more efficient in exploitation[22].

The key contribution of this study lies in the proposed hybrid update mechanism, which combines the two strategies as follows:

$$V_{i.d}^{t+1} = \omega v_{i.d}^{t} + c_1 r_1 (pbest_{i,d}^{t} - x_{i,d}^{t}) + c_2 r_2 (DA - x_{i,d}^{t}) \quad (3.1)$$

$$X_i^{t+1} = X_{i.d}^{t} + V_{i.d}^{t+1} \quad (3.2)$$

Where

$V_{i.d}^{t+1}$: updated velocity of the particle

ω : inertia weight

$x^{t}_{i,d}$: current position of the particle

$pbest^{t}_{i,d}$; personal best position of the particle

DA: the position obtained from the DA rule

c_1,c_2 :acceleration coefficients

r_1,r_2 :random values in [0,1]

This formulation allows each particle to benefit from both the local and global experience in PSO, while simultaneously being influenced by DA's swarm movement rules.

The optimization process was conducted over 100 iterations. In each iteration, particle positions and velocities were updated, and the best-found solution was stored. Once the optimal weights were determined, they were assigned to the ANFIS model for final evaluation on the test dataset.

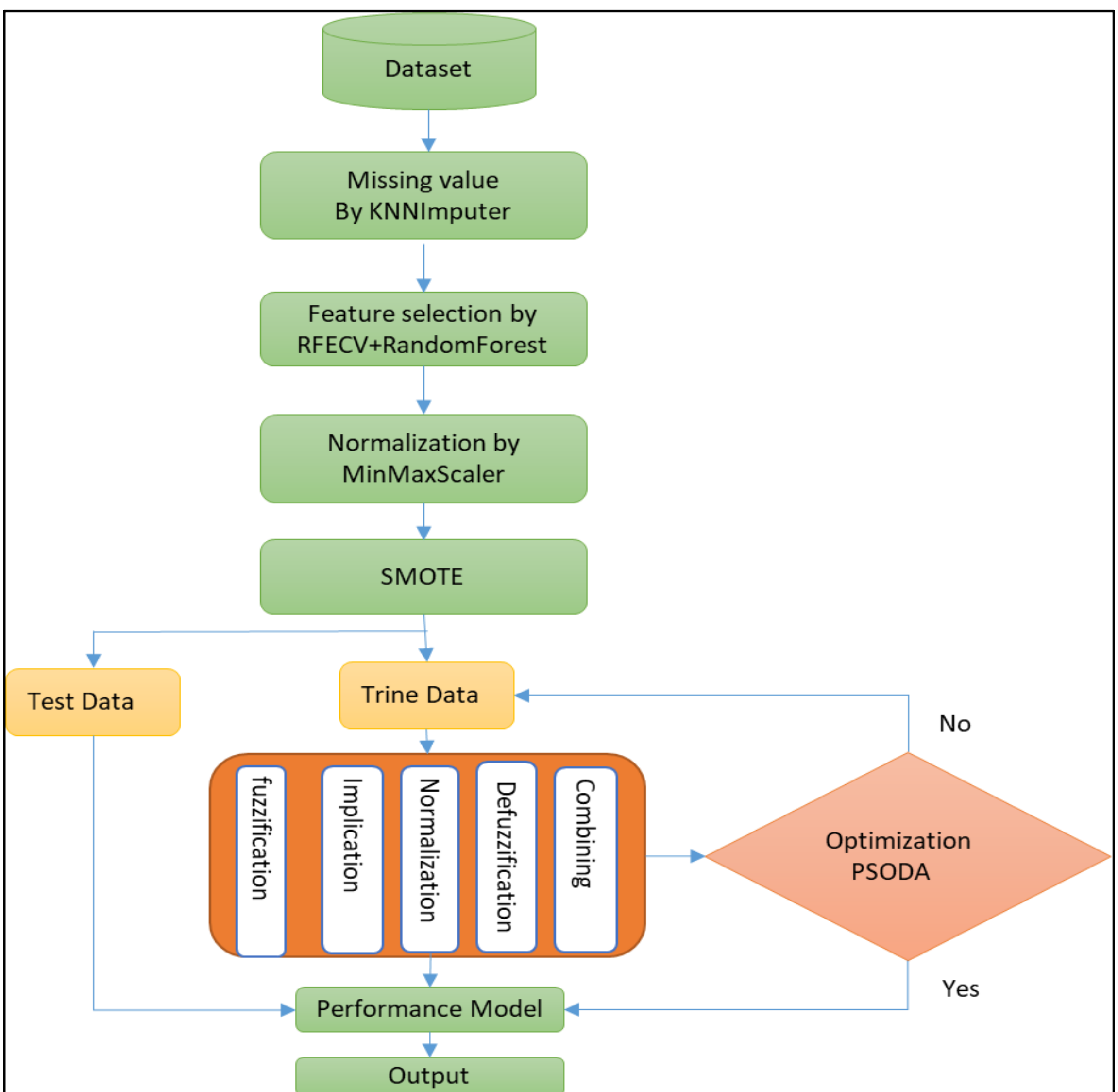

Fig. 2: The Proposed Method Scheme

4.Discussion of Results

Several experiments were achieved to evaluate ANFIS model performance and its hybrid variants enhanced with different optimization algorithms: PSO, GWO, DA, and PSODA. These evaluations were carried out on the hepatitis dataset using various data splitting ratios: 80% training and 20% testing (Table 1) and 70% training and 30% testing (Table 2). Based on the outcomes in Table 1, the hybrid ANFIS+PSODA model achieved the highest accuracy of 90% and was accompanied by relatively lower values of error metrics (MSE, RMSE) during testing. Other hybrid models, such as ANFIS+PSO and ANFIS+DA, showed comparatively lower accuracies ranging between 82% and 88%. In Table 2, which corresponds to the 70/30 training/testing split, the ANFIS+PSODA model continued to demonstrate superior performance, achieving the highest Accuracy of 86%, surpassing all other configurations. Notably, it was more effective than ANFIS+PSO (82%), ANFIS+GWO (81%), and ANFIS+DA (81%) models, validating the effectiveness of the PSODA algorithm in maintaining maximum performance even as the training dataset shrinks. These results demonstrate the strong dynamic abilities of the PSODA algorithm in achieving equilibrium between exploration and exploitation stages in the search process. This hybridization enabled the model to converge to optimal solutions with higher Accuracy and stability. The improved performance is attributed to the suggested update equation, which is the primary contribution of this study by integrating the exploration behavior of the Dragonfly Algorithm (DA) and the attraction mechanism of (PSO).

Table 1: The results of MSE, RMSE, SD, and Accuracy for six models on the hepatitis dataset split (80% training,20% testing)

Algorithm	**Training**			**Testing**			**Accuracy**
	MES	RMES	SD	MES	RMES	SD	
ANFIS	0.0897	0.2995	0.2003	0.1083	0.3291	0.2987	82%
ANFIS+GWO	0.1200	0.3465	0.3414	0.1160	0.3405	0.3394	84%
ANFIS+DA	0.1277	0.3573	0.3458	0.1007	0.3173	0.3585	86%
ANFIS+PSO	0.1179	0.3459	0.3515	0.1001	0.3163	0.3651	88%
ANFIS + PSODA	0.1006	0.3145	0.3145	0.0761	0.2759	0.2724	90%

Table 2: The result of MES, RMSE, SD, and Accuracy for six models on the hepatitis dataset split (70% training,30% testing)

Algorithm	Training			Testing			Accuracy
	MES	RMES	SD	MES	RMES	SD	
ANFIS	0.0892	0.2986	0.2108	0.1206	0.3473	0.2849	79%
ANFIS+GWO	0.1442	0.3797	0.2883	0.1478	0.3845	0.2832	81%
ANFIS+DA	0.1474	0.3840	0.2942	0.1559	0.3949	0.2864	81%
ANFIS+PSO	0.1312	0.3622	0.3576	0.1416	0.3764	0.3363	82%
ANFIS + PSODA	0.0830	0.2881	0.2874	0.1069	0.3270	0.3270	86%

5- Evaluate the model

The model was evaluated using a wide spectrum of performance metrics including classification precision, log loss, F1-score, mean squared error (MSE), root mean squared error (RMSE), and standard deviation (SD) of prediction errors. The evaluation was carried out on several train-test split configurations (80/20, 70/30) to determine the model's robustness and generalization abilities. The results of the experiments consistently prove the superiority of the PSODA-based ANFIS model over all the baseline and hybrid models in the various configurations considered. These include the standalone ANFIS model as well as hybrid variants such as ANFIS+PSO, ANFIS+DA, and ANFIS+GWO. Apart from delivering optimal classification accuracy, the new approach also demonstrated reduced error rates and increased stability of prediction performance, an improved trade-off between accuracy fitting and generalizability. The outcomes in Tables 1 and 2 confirm the efficiency and superiority of the optimization approach based on PSODA across a set of varying experimental conditions.

6.Conclusion and future work

In this study, a combined model for classification that hybridizes the Adaptive Neuro-Fuzzy Inference System (ANFIS) with an innovative optimization approach, PSODA as a combination of (PSO) and Dragonfly Algorithm (DA), is introduced for predicting hepatitis disease. The model was based on a publicly available medical dataset and was an end-to-end model, including data pre-processing, feature selection, model formulation, and parameter optimization. In all measured evaluation settings and measures, the model proposed in the current study based on PSODDA showed stable and superior performance. In comparison to the simple ANFIS and other hybrid models including ANFIS-PSO, ANFIS-DA, and ANFIS-GWO, the proposed model achieved the highest classification accuracy rate as well as smaller error readings in performance measures, proved., MSE, RMSE, and SD. These results underscore the model performance trade-off that it achieves between fitting accuracy and generalization, a critical aspect in medical diagnostic applications where this enhances diagnostic by being more precise and stable. Furthermore, the hybrid optimization method adopted by PSODDA effectively avoided the local optima and convergence instability by a real-time balance between exploration and exploitation. The success of this model supports the growing potential of hybrid neuro-fuzzy systems enhanced with bio-inspired optimization for clinical decision support. Future research can explore extending this framework to multi-class classification problems, integrating more diverse medical features, and applying the model to other disease domains where uncertainty and complexity are prevalent.

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