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A Novel Optimization Algorithm: Cascaded Adaptive Neuro-Fuzzy Inference System

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Abstract The adaptive neuro-fuzzy inference system (ANFIS) is employed in a vast range of applications because of its smoothness (by Fuzzy Control (FC)) and adaptability (by Neural Network (NN)). Although ANFIS is better in nonlinear optimization, two major loopholes need to be addressed thoroughly. They are the curse of dimensionality and computational complexity. To overcome these complications, a novel usage of the ANFIS model is proposed as Cascaded ANFIS in this paper. As the primary source of this algorithm, a general two-input one-output ANFIS algorithm is used. The novel algorithm has two main modules called pair selection and training model. Pair selection is responsible for selecting the best match for the inputs, while the training module generates the output. The cascaded behavior of the novel algorithm generates additional iterations to advance the best solution. Even though the number of parameters that need to be adjusted is increasing at each additional iteration, the complexity of the algorithm may stay stable. Two-hybrid state-of-the-art algorithms are used to compare the performance of the novel algorithm, namely, Particle Swarm Optimization-based ANFIS (ANFIS-PSO) and Genetic Algorithm-based ANFIS (ANFIS-GA). Furthermore, individual performance is presented for seven publicly recognized datasets. The results have demonstrated that, for some datasets, the root means square error (RMSE) can be minimum as 0.0001.

Keywords Cascaded-ANFIS · GA · PSO · Pair selection

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1 Introduction

Machine Intelligence (MI), Artificial Intelligence (AI), and Machine Learning (ML) are not the same, but they are distinct from each other. Figuring out the difference in these terms is essential when it comes to implementing systems. For example, if the difference among the above three terms is unknown, the research outcome can become an automation project after all. It is essential to know the potential of MI, AI, and ML. A machine can work as an automation system or as an intelligent system. Automation is simply the work done successfully by a computer, which was assigned by humans. When a machine is programmed to learn trends and patterns, selecting the best option from a collection of possible options is ML. Machine intelligence is a crucial factor in the machine learning process. With the ability of MI, the machine becomes capable of tackling more complex problems. Predicting severe retinopathy of prematurely using machine learning in healthcare [1], underwriting process algorithms [2], and analysis in stock market [3] are some of the complex scenarios. AI can retain all data available in today's world and generate brand new solutions for a set of challenges. AI has become superior to the human brain by producing solutions which humans have never thought of before.

When an algorithm is capable of approximating a solution to a problem, it is called a heuristic. Heuristic algorithms always depend on the problem environment. Hence, it is convenient to say that heuristic algorithms are problem-dependent. Nevertheless, there are methods/algorithms which can be used in many situations called meta-heuristic algorithms. These methods are independent of the problem environment that enables the solution to be used in a broad range of problems. However, meta-heuristic is a descendent of heuristic algorithms [4]. Besides, a higher level of heuristic is meta-heuristic. Because meta-heuristics algorithms are capable enough to select the best solutions by leaning from past solutions and performing sophisticated search moves, meta-heuristic is not a trial and error method [5].

Meta-heuristic shines much better in Computational Intelligence (CI). For many years, CI is an active topic in almost every field of science [6]. Recently, by combining the power of meta-heuristic algorithms, CI has begun to dominate in many fields. [7]. Today, it is considered that AI is potential enough to take care of the knowledge-based systems [8–11]. It is also proven that rather than using proper methods such as Neural Networks (NN) or Fuzzy Logic (FL), combining the methods gives remarkable results in data-driven approaches such as Adaptive Network-Based Fuzzy Inference System (ANFIS) [12–15]. Therefore, the recent researches have been deploying this method in many fields such as control, identification , and prediction [16–18, 18–20]. The best trade-off between NN and FL is ANFIS. Jang in 1993 introduced ANFIS to the world of artificial intelligence [21].

ANFIS is known to have a high degree of accuracy. Hence, it is being used by many fields such as Engineering, medicine, transportation, business, and economics [22]. Many researchers found that ANFIS performs well when there are a small number of inputs. In [23, 24], the authors have used less than five inputs to their ANFIS systems, and authors in [25] have used six inputs for their experiments. In recent years, most of the researches try to expand the ANFIS models to use more input data since this is the era of the Big Data paradigm.

In recent years, a significant contribution to overcome the ANFIS limitations has been made by researchers worldwide. Primarily, reducing input data by selecting the best from the input set and reducing the rule base to overcome the computational complexity can be considered. Some novel implementations of ANFIS methods come with removing layers from the original ANFIS structure. In paper [26], the authors have removed the third layer to save the time of computation and reduce the complexity. Rather than using the raw version of ANFIS models, researchers tend to change the parameters and system variables to find better solutions in complex systems. Although knowledge-based systems are capable of predicting, controlling, and identifying complex systems or models, combining optimization algorithms can result in better solutions to global minimum and computational complexity.

Optimization is one of the primary processes in data learning techniques. The art of making the right decisions is called optimization. Hence, one of the most compelling tasks when dealing with many scientific and engineering problems is optimization [27]. Optimization can minimize costs and maximize efficiency. Generally, these tasks can be solved using traditional analytical methods. When the task is multi-model, multidimensional, and noisy, the general optimization methods find it hard to give the optimum solution. This problem results in more complex methods to be born in the family of optimization. Many researchers in the world give better solutions day by day. Nevertheless, the optimum solution is still out there to be found. Mostly, all the optimization algorithms are meta-heuristic algorithms. Some existing optimization algorithms which give near solutions to the optimum are Genetic Algorithms (GA) [28–30], Particle Swarm Optimization (PSO) [31–34], Artificial Bee Colony (ABC) [35–37], Ant Colony Optimization (ACO) [38], and Bacterial Foraging (BF) [39]. In [40], Cat Swarm Optimization (CSO) is occupied with sharpening ANFIS. It can be observed that these optimization methods were inspired by nature.

There is also a considerable effort in overcoming the limitation of the curse of dimensional of ANFIS. In [41], a wrapper feature selection method is introduced for the Twitter sentiment classification model. With a big data processing platform, a feature selection method is introduced in the paper [42]. Authors in [43] discuss a novel intuitionistic fuzzy clustering algorithm for multiple object tracking based on feature selection. A feature selection that uses a fuzzy boundary area for the nearest neighbor classification is presented in [44].

In recent times, there has been an extensive usage of fuzzy logic due to nonlinear properties, robustness, and easy implementation [45]. Some researches that have been performed to reconstruct the input features using fuzzy sets to reduce the influence of uncertainties [46]. Nonetheless, there is still a qualitative difference between the desired and experimental outputs. Previous research has shown four drawbacks of the existing algorithms as follows [47].

1. Computational burden: It is a common problem in all optimization problems. Though the algorithm's get high in accuracy, the power of computation is way more difficult to obtain.
2. Time consumption: The time consumption has also become a huge obstacle that the researches need to overcome.

3. Application restriction: The state-of-the-art algorithms are not feasible enough to use in every application due to the lack of adaptiveness.
4. Curse of dimensionality: There is always a typical drawback when fuzzy logic is engaged to an algorithm known as the curse of dimensionality. Typically, the use of fuzzy logic is challenging to handle multidimensional data as inputs. Hence, most of the algorithms use the pre-processing stage where they use feature selection steps to determine the best features and reduce the dimension of the inputs.

According to the analysis mentioned above, the novel approach for optimization-Cascaded ANFIS is designed to overcome most of the problems. Consequently,

1. This paper presents a novel optimization algorithm based on ANFIS for classification problems. This method provides computational simplicity due to the usage of two-input ANFIS model as the base.
2. This algorithm is capable of handling a vast amount of input variables.The data reduction is not compulsory for multi-variable data sets. Since the noise data are used in training the model, implementing this algorithm is a promising fact in real-time.
3. Instead of determining the data redundancy, this algorithm presents a novel pair selection method using the same two-input ANFIS model.
4. Detailed results about the comparison of the novel Cascaded ANFIS with state-of-the-art optimization algorithms are presented.

The rest of the paper is organized as follows. In Sect. 2, mathematical theories behind the sources that were taken to develop this novel algorithm are presented. In Sect. 3, the proposed algorithm is presented. Experimental design is discussed in Sect. 4. Section 5 focuses on the experimental study and results and the final section presents the discussion and concludes the paper with future goals.

2 Related Work

2.1 NonLinear Optimization

Within a nonlinear objective function, searching for the largest or smallest value with given constraints is called nonlinear optimization. Consider the following minimization problems. The minimization nonlinear optimization problem can be defined as in equation (1);

$$\begin{aligned}
&\text{Minimize} \quad \mathrm{f(x)} \\
&\text{subjected to :} \\
&g_i(X) \leq 0, \qquad (i = 1,2,3,\ldots,p) \\
&h_j(X) = 0, \qquad (j = 1,2,3,\ldots,q) \\
&x_n \in |\underline{x^r}, \overline{x^r}|, \quad (d = 1,2,3,\ldots,r)
\end{aligned} \tag{1}$$

Here, the optimization function is f where $X = [x^1,\ldots,x^r]^T$ is the solution. The maximum and minimum permissible are $\overline{x^r}$ and $\underline{x^r}$. Moreover, the optimization function is r dimensional and equality and inequality constraints are given by $g_i(X)$ and $h_j(X)$, respectively. At a glance, there can be different methods of reaching the solution space for this specific optimization problem such as PSO, GA, ABC, and ACO. Most of these methods are population-based algorithms.

2.2 ANFIS Algorithm

Jang freshly introduces a versatile and very intelligent hybrid system called ANFIS in 1993. ANFIS is a perfect collaboration between neural networks (NN) and fuzzy inference systems (FIS) [48]. The collaboration of both NN and FIS brings their strengths to the ANFIS system. Moreover, the greatest advantage of this network is the transformation of the system to simple if–then rules [49]. The arrangement of if-then rules of ANFIS provides the ability to deal with nonlinear functions. It is a proven fact that ANFIS has been used in many research areas, and it shows powerful results overall. ANFIS is well known to combine with various range of algorithms to decrease training phase error. For example, to optimize the effectiveness of searching the best parameters, gradient descent and least square method can be combined and used.

ANFIS works similarly to the fuzzy system, which was introduced by Takagi, Sugeno in 1985 [50]. A least-squares approach is used in the step of determining the consequence factors in the forwards' section, and the backward learning phase is based on the gradient least-squares approach. Then, gradient descent in the regressive advance is used to reset the parameters.

Generally, ANFIS consists of five layers called the input layer, the membership function layer, the fuzzification layer, the defuzzification layer, the normalization layer, and the output layer, respectively. Further explanation is based on Figure 1, assuming two inputs into the ANFIS system, namely x and y. The output is f. Following the Sugeno FIS, the if-then rule configuration of ANFIS can be denoted in the following equation.

$$\begin{aligned}
f_1 &= p_1 x + q_1 y + r_1, \qquad \text{assume} \quad \mathrm{x = A_1}, \quad \mathrm{y = B_1} \\
f_2 &= p_2 x + q_2 y + r_2, \qquad \text{assume} \quad \mathrm{x = A_2}, \quad \mathrm{y = B_2}
\end{aligned}$$

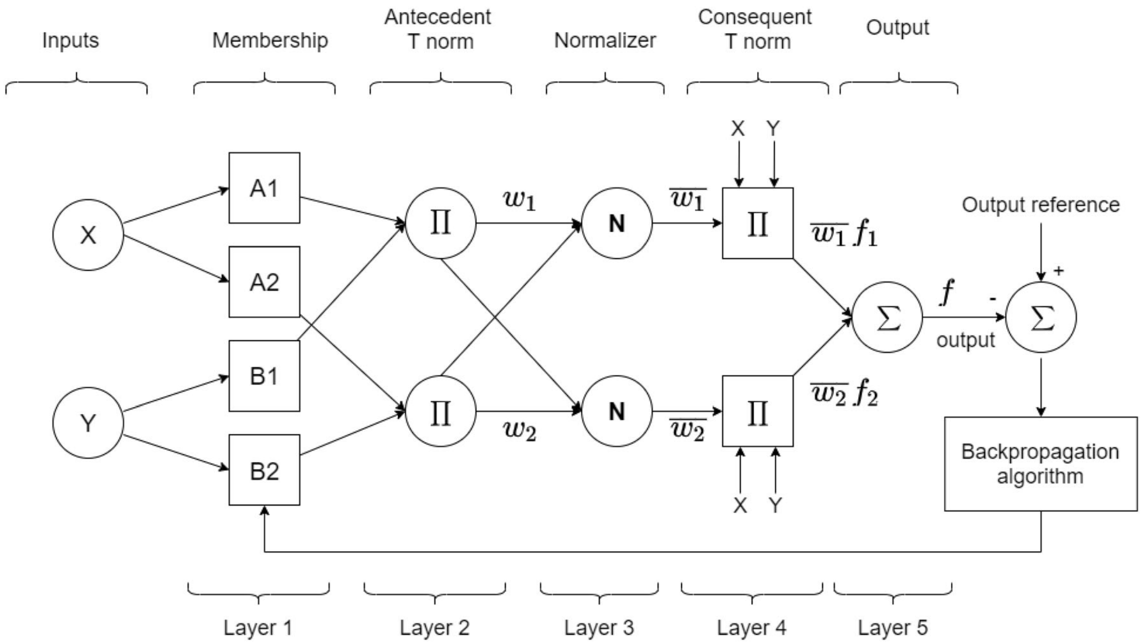

Fig. 1 ANFIS schematic view

Here, A_1 and B_1 are fuzzy sets, and p_i, q_i, and r_i are design parameters where $i = 1, 2$.

The first layer of the ANFIS structure is the membership layer. All the nodes in this layer are adaptive. Membership grades are generated in this layer for each input. The functionality can be expressed as in the following equations:

$$O_{1,i} = \mu_{Ai}(x) \qquad i = 1, 2 \tag{2}$$

$$O_{1,j} = \mu_{Bj}(y) \qquad j = 1, 2 \tag{3}$$

where x and y are the inputs. Linguistic labels for the nodes are denoted as Ai and Bi. $\mu_{Ai}(x)$,and $\mu_{Bj}(y)$ are adaptable and they are the membership grades for a fuzzy set A ($A1$, $A2$, $B1$ and $B2$). For instance, if the membership functions are bell-shaped, the following equation is employed.

$$\mu_{Ai}(x) = \frac{1}{1 + \left\{\left(\frac{x - c_i}{a_i}\right)^2\right\}^{b_i}} \tag{4}$$

Here, bell-shaped function parameters are a_i, b_i, and c_i accordingly.

In the next layer, simple multiplication is performed, and this layer consists of fixed nodes. The mathematical expression of the layer can be presented as follows.

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(x) \qquad i = 1, 2 \tag{5}$$

The next layer is a fixed node normalization layer. The normalization of the output from the second layer is performed in this layer. The following equation shows the operation.

$$O_{3,i} = \overline{w} = \frac{w_i}{w_1 + w_2} \qquad i = 1, 2 \tag{6}$$

Here, the firing strength of node$i$ is presented by w_i.

The fourth layer is capable of simplifying the product of the normalized output from the third layer. This layer is adaptive, and the output can be presented by using the following equation.

$$O_{4,i} = \overline{w}f_i = \overline{w_i}(p_i + q_i + r_i) \qquad i = 1, 2 \tag{7}$$

The final layer has only one node, and it is fixed. This node does the summation of all incoming inputs. Finally, the overall outcome can be presented by using the following equation.

$$O_{5,i} = \sum_{i=1}^{2} \overline{w_i}f_i = \frac{w_if_1 + w_2f_2}{w_1 + w_2} \tag{8}$$

ANFIS has better learning ability because back propagation and least square approaches make the system more precise and faster convergence, as mentioned before; there are six consequent parameters in this system (assuming bell-shaped membership functions are used). To obtain the best cost, tuning these parameters is the main objective in this ANFIS system. Back propagation is determined to change the parameters in the first layer, and the least square approach is responsible for the fourth layer parameter tuning [51].

3 The Proposed Algorithm: Cascaded ANFIS

As mentioned in the above paragraphs, ANFIS has its limitations. Mainly, the curse of dimensionality and the computational complexity [47]. Though some methodologies are proposed by the researchers to overcome this cause, the final result is questionable. Hence, this novel optimization algorithm aims to narrow down the solution space between prediction and reality.

In this section, the novel Cascaded ANFIS method is presented in detail. The overall algorithm can be introduced using Fig. 2. This algorithm can also be introduced as an extension of ANFIS. Because, rather than having five layers for the ANFIS algorithm, there are iterations that can navigate the solution to be more precise.

When compared to the novel algorithm with the traditional ANFIS algorithm, the main difference is the output of the traditional ANFIS algorithm becomes the input of the next usage of the traditional ANFIS algorithm. But, same as in the general ANFIS algorithm, here, fuzzy is used for the fuzzification process in the inner layers of the ANFIS model. Fuzzification is performed using membership functions by converting numerical values into fuzzy members.

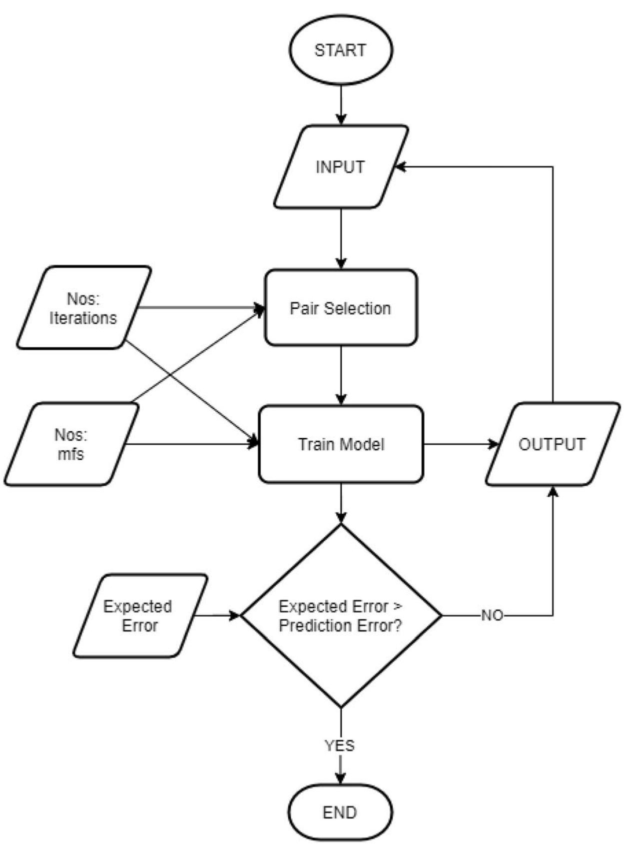

Fig. 2 Overall flow diagram of novel Cascaded ANFIS algorithm

The Cascaded ANFIS algorithm consists of two main modules.

1. Pair Selection Module
2. Training Module

The Pair Selection module gives a solution to the first main limitation of ANFIS. It is a general practice to reduce the input features before using an algorithm. But the novel algorithm uses all the features to build up a robust model, which can also be beneficial for noisy data sets. Computational complexity is handled by the Training Module of the novel Cascaded ANFIS algorithm. Each step can be introduced in detail as follows.

3.1 Input Module

Here, the raw inputs are fed into the Cascaded ANFIS model. Initially, the inputs are paired using the Pair selection module. This particular ANFIS system uses a single module of two-input ANFIS models to calculate all the solution points. The usage of the two-input ANFIS model is explained in the next section.

3.2 Pair Selection Module

The pair Selection module is a Sequential Feature Selection (SFS) process. The complete process of the pair selection module can be demonstrated using the Fig. 3. The novelty of this method uses two-input one-output ANFIS model to determine the best match for each input variable.

As shown in the figure, the final output is the matching pair. Therefore, a nested loop is used to go through every two pair combinations. In the figure, *NI* is the number of input variables. Initially, the first two-input variables are selected and named as $input_i$ and $input_j$. They are used as the input of the two-input ANFIS model, as shown in the figure. The root means square error (RMSE) is calculated and stored, and then the RMSE (E_p) is checked against the previous RMSE (E_{prev}). At the end of the second loop, the matching pair can be extracted by observing the lowest RMSE value. Once the pairs are selected, the training phase can be initialized.

3.3 Train Model Module

Two input ANFIS model is adopted here as well. Since the input variables are paired with the best match form the previous module, the input can be delivered directly to the ANFIS module that can generate contemporary outputs and RMSE for each data pairs. At this point, there is also a predefined target error. Thus, the RMSE is compared with the target error. If the target error is achieved, the process can be terminated. Else, the algorithm advances to the second

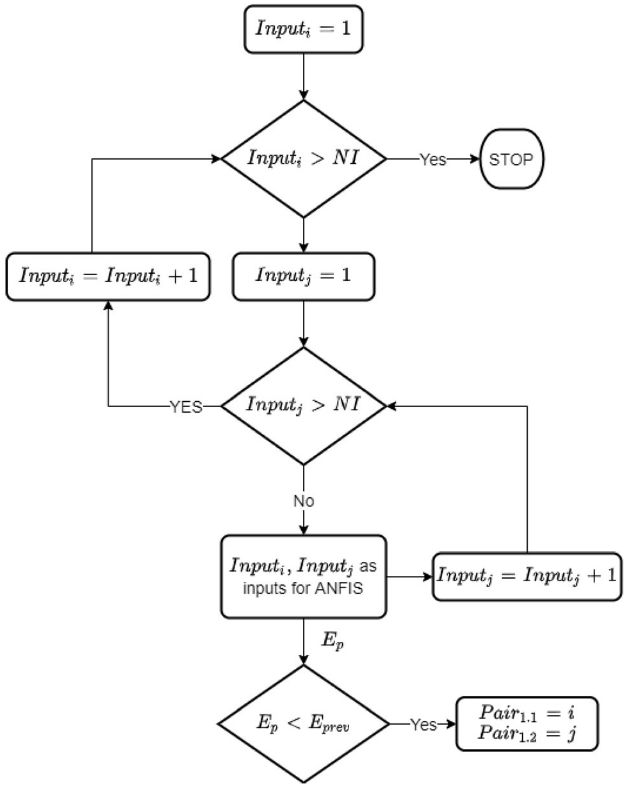

Fig. 3 Pair selection module structure

iteration. The process of the iteration advancement can be explained in detail using Fig. 4.

Figure 4 is an illustration of an example approach of the Cascaded ANFIS model. As shown here, assume that there are four input variables in an optimization problem called X_1,X_2,X_3, and X_4, respectively.

$$input = \{X_1, X_2, X_3, X_4\} \tag{9}$$

As explained in the pair selection section, the input is paired with the best match as shown in equation 10 below.

$$input_{pairs} = \{X_1, X_3\}, \{X_2, X_1\}, \{X_3, X_4\}, \{X_4, X_1\} \tag{10}$$

Then, using two-input ANFIS models for each pair, two outputs are generated namely, $RMSE_i$ and the predicted output (Y_i). They can be obtained by using the following Eqs. 11 and 12.

$$RMSE = \sqrt{\overline{(A-P)^2}}$$
$$RMSE_{A,P} = \left[\sum_{i=1}^{N} \frac{(O_{Ai} - O_{Pi})^2}{N}\right]^{\frac{1}{2}} \tag{11}$$

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 + \frac{w_3}{w_2 + w_3} f_3 + \frac{w_4}{w_3 + w_4} f_4 \tag{12}$$

where A and P are actual results and predicted results, respectively. N is the sample size. Obtaining the results for RMSE and Y completes the initial iteration. The RMSE error now can be compared with the goal error and then proceed to the next iteration accordingly. When moving to

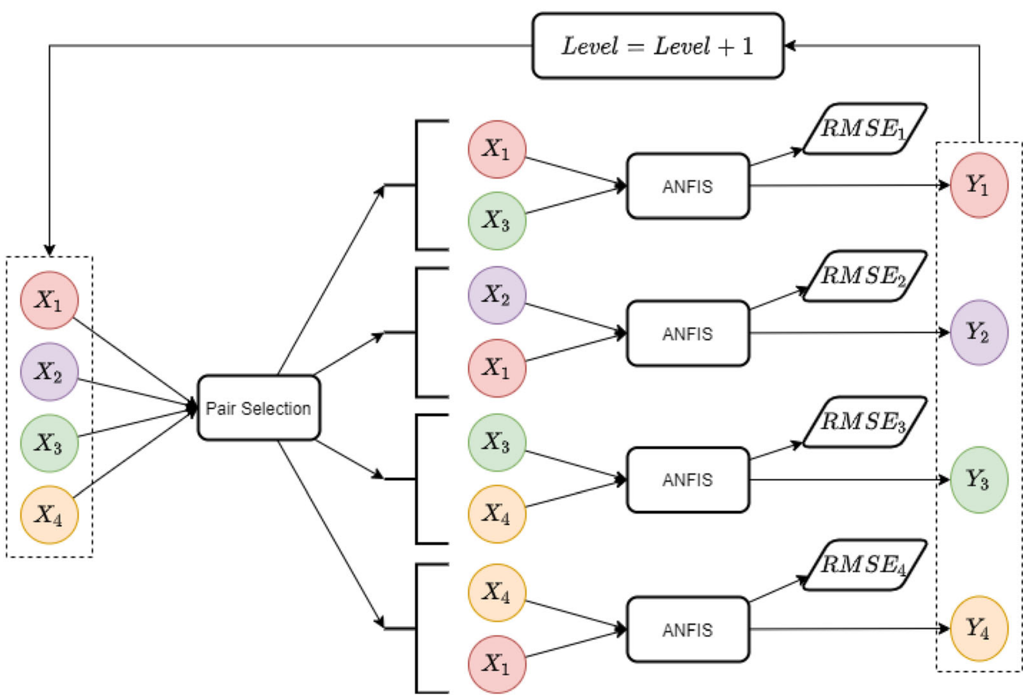

Fig. 4 Example of train module structure

the next iteration, the specialty is that the output from the first iteration, which are Y_1, Y_2, Y_3, and Y_4, will act as inputs for the second iteration.

Note that, the first iteration generated four unique ANFIS network parameter sets. The second iteration also generates four unique ANFIS network parameter sets. ANFIS parameters that are used in this implementation are stated in Table 1. These parameters are used in the testing section of the algorithm.

In each iteration, mainly, six parameters are adjusted to narrow the error between the prediction and the actual results in each ANFIS structure. As shown in the Fig. 4, there are four inputs in the example. Hence, four ANIFS structures have been used to obtain the outputs on the first iteration. In this case, the number of parameters that has been tuned is 24. Because each ANFIS structure has p, q, and r design parameters and membership parameters (if bell-shaped: 3 parameters), the first iteration has 24 parameters (6×4 ANFIS structures) for tuning. If the system advances to the next iteration, again, there will be another 24 unique parameters. Hence, increasing the number of iteration increases the complexity of the novel ANFIS algorithm. But, the algorithm is designed to operate only one ANFIS structure at a time. Hence, the complexity stays stable as two-input ANFIS structure. However, the number of tuned parameters increases the accuracy of the optimization solution. Breast Cancer data set optimization performance in each iteration is shown in Fig 5, which provides a better understanding of the algorithm.

3.4 Pseudo-code Explanation

The pseudo-codes for each section is demonstrated in the below sections.

The above pseudo-code describes how the pair selection operates on the input variables. Here, a two-input ANFIS model is used to obtain the network variables, outputs, and RMSE values. Nested loops are responsible for going through all possible combinations of input variables. After selecting the best pairs for the two-input ANFIS model, the training process can be advanced.

Algorithm 2 presents the pseudo-code for the training model. As shown in the diagram, for each input variable, a

Table 1 ANFIS network parameters

Configuration
Membership parameter
Kalman parameters
Nodes
Number of membership functions
Number of inputs

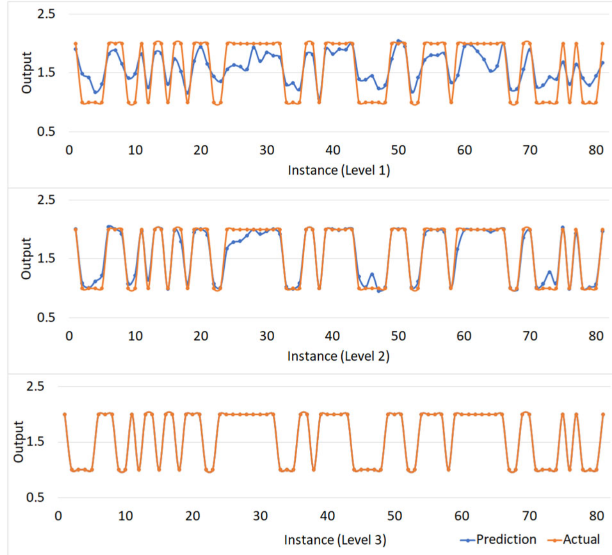

Fig. 5 Performance for breast cancer data set

unique ANFIS model is dedicated to providing the outputs such as networks, outputs, and RMSE. These outputs are stored for later usage of the iteration shifting and training phase.

Testing is performed using the results of the training step. As presented in algorithm 3, the data are imported and used to evaluate the Cascaded ANFIS method. At the end of the testing process, the best cost is calculated using the predicted and actual results.

Algorithm 1: Pseudo-code for Pair selection

```
initialization
MaxIterations = x
(data_input, data_output) = LoadData
ni = size(input variables)
while MaxIterations is not equal to 0 do
    if MaxIterations = 1 then
        input = data_input
    else
        input = output_prev
    end
    for i = 1:ni do
        for j = 1:ni do
            (network,output_prev,RMSE) =
             ANFIS(input(i), input(j),data_output)
            if RMSE ¡ min_error then
                min_error = RMSE
                PairNum1 = i
                PairNum2 = j
            else
        end
        pair = pair + 1
    end
    Iterations = Iterations - 1
end
```

Algorithm 2: Pseudo-code for Train model

```
initialization
MaxIterations = x
(data_input, data_output) = LoadData
ni = size(input variables)
Iterations = 1
while Iteration is not equal to MaxIterations do
    if Iterations = 1 then
        input = data_input
    else
        input = output_prev
    end
    for i = 1:ni do
        (network,output_prev,RMSE) =
          ANFIS(input(pair_1),
          input(pair_2),data_output)
        nets [Iterations][i] = network
        output[i] = output_prev
        error[Iterations][i] = RMSE
    end
    Iterations = Iterations + 1
end
```

Algorithm 3: Pseudo-code for the testing process

```
initialization
MaxIterations = x
Load data from training process
ni = size(input variables)
Iterations = 1
while Iteration is not equal MaxIterations do
    if Iterations != 1 then
        input = output_prev
    end
    for i = 1:ni do
        import ANFIS network
        import pair combination
        output = EVALUATE (network, pair
          combination)
        Calculate the best cost
    end
    Iterations = Iterations + 1
end
```

4 Experimental Design

4.1 Data Sets

The research is conducted for seven publicly recognized data sets from the UCI machine learning repository [52] as follows:

1. IRIS
2. Breast Cancer
3. Statlog (Vehicle Silhouettes)
4. Sports articles for objectivity analysis
5. Superconductivity
6. Musk 1
7. Human Activity Recognition Using Smartphones

Table 2 presents further details of each data set used. These data sets are different in several aspects, such as the number of classes, number of input variables, and the number of example instances. Furthermore, these data sets are also different in the field of usage.

IRIS dataset is a combination of four feature inputs and it contains three classes. These classes are linearly separable. The breast cancer dataset contains 9 attributes. These attributes are a mix of linear and nominal. The data of Statlog (Vehicle Silhouettes) are collected using elevated cameras. 18 features were obtained from the captured images and used as the attributes of the dataset. Sport Activity Objective dataset is constructed using 1000 sport-related articles and this dataset has 59 attributes.The superconductivity dataset contains 81 attributes of superconductors and their relevant features. To predict whether a new molecule to be a musks or nonmusks, Musk 1 data set is introduced. This dataset is rich in 168 distinguish features. Human Activity Recognition Using Smartphones dataset is included with 561 attributes and these features were collected using a waist-mounted smartphone with inertial sensors.

The data sets mentioned above are used in the following manner. Each data set is divided into three parts. Such as 60% of the instances of the data set is used for the training purpose. The remaining instances are divided into two equal parts and used for testing and validation of the algorithm.

4.2 Comparative Study against the Cascaded ANFIS Algorithm

This research is conducted to present the effectiveness and accuracy of the novel Cascaded ANFIS model against three state-of-the-art algorithms:

1. Particle Swarm Optimization-based Adaptive Neuro-Fuzzy Inference System (ANFIS-PSO)
2. Genetic Algorithm-based Adaptive Neuro-Fuzzy Inference System (ANFIS-GA)

As the record from the state-of-the-art methods, the abovementioned hybrid methods outperform most of the other optimization algorithms [24, 25, 27, 29, 31–33]. Parameter adjustments are described in the next subsection.

4.3 Parameter Setting

As for the population, 30 is selected as in [53] for all the above mention algorithms. The number of iterations was

Table 2 Data sets

Dataset	Number of features	Number of classes	Number of instances
IRIS	4	3	150
Breast cancer	9	2	116
Statlog (Vehicle Silhouettes)	18	4	946
Sports articles for objectivity analysis	59	2	1000
Superconductivity	81	7	21263
Musk 1	168	2	6598
Human activity recognition using smartphones	561	6	10299

set to 100, and the membership functions are limited to 4. PSO parameter setting is concluded as follows [54].

- Inertia Weight = 1
- Inertia weight damping ratio = 0.99
- Personal Learning Coefficient = 1
- Global Learning Coefficient = 2

Parameters of the GA are shown below [54].

- Crossover percentage = 0.7
- Mutation percentage = 0.5
- Mutation rate = 0.1
- Selection Pressure = 8
- Gamma = 0.2

5 Experimental Study and Results

In this section, a considerable amount of results is presented. The presented results can be divided into two main categories: the comparison against state-of-the-art algorithms, and the iteration-wise comparison of the Cascaded ANFIS algorithm. As mentioned in the above section, ANFIS-PSO and ANFIS-GA were used for the comparison of the performance for a few data sets. The complexity of the data set is crucial in using state-of-the-art data sets because the size of the input dimensionality is proportional to the computational complexity.

5.1 ANFIS-PSO and ANFIS-GA vs Cascaded ANFIS

The experiments are carried out for few data sets such as IRIS, Breast, and vehicle and the performance is calculated in the following specific ways.

$$MSE = \frac{1}{q}\sum_{t=1}^{q}(\bar{u}(t) - \hat{u}(t))^2 \tag{13}$$

$$RMSE = \sqrt{\frac{1}{q}\sum_{t=1}^{q}(\bar{u}(t) - \hat{u}(t))^2} \tag{14}$$

$$MAPE = \frac{1}{q}\sum_{t=1}^{q}\frac{\|\bar{u}(t) - \hat{u}(t)\|}{\|\hat{u}(t)\|} \times 100 \tag{15}$$

where MSE is the mean squared error and MAPE is the Mean Absolute Percentage Error. q is the size of the population, x_i is the error instance, and μ is the mean error. $\bar{u}(t)$ is the prediction and $\hat{u}(t)$ is the actual output. Moreover, the time consumption is recorded for each training and testing.

The first simulation was performed to present the accuracy of the novel algorithm. As mentioned above, three data sets were occupied for the comparison process. In Fig. 6, RMSE is presented for the corresponding data sets and the algorithms. Here, It is clear that the novel algorithm outperforms the state-of-the-art algorithms in terms of accuracy.

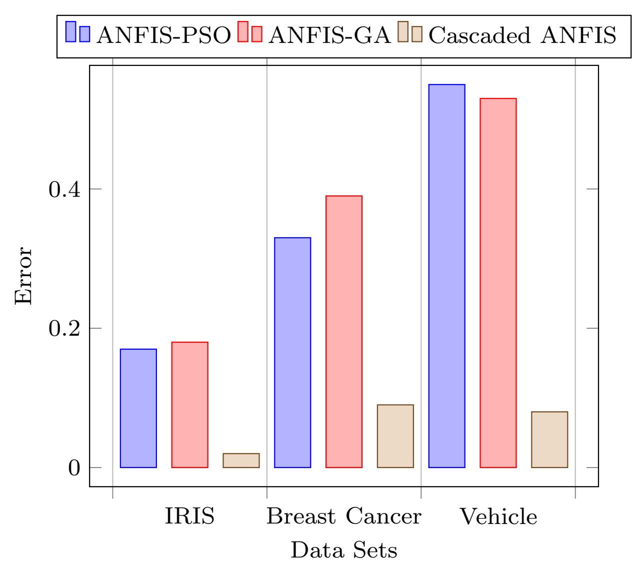

Fig. 6 RMSE comparison

Similarly, Figs. 7, 8, and 10 show the MSE, MAE, and MAPE, respectively. In each of these error measurements, the novel algorithm presents less error amount when compared to ANFIS-PSO and ANFIS-GA. It is worth mentioning that the novel algorithm has used only two iterations to reach these results. When advancing more iterations, better results can be observed. A detailed presentation is given in the next section.

Correlation is another measurement to recognize the performance of an algorithm. Figure 9 shows the correlation for three algorithms for three data sets. It can be observed that the novel algorithm obtained more significant results compared to ANFIS-PSO, and ANFIS-GA. For the IRIS data set, correlations of ANFIS-PSO, ANFIS-GA, and Cascaded ANFIS are 0.977, 0.974, and 0.999, and Vehicle data set correlations are 0.865, 0.878, and 0.997, respectively.

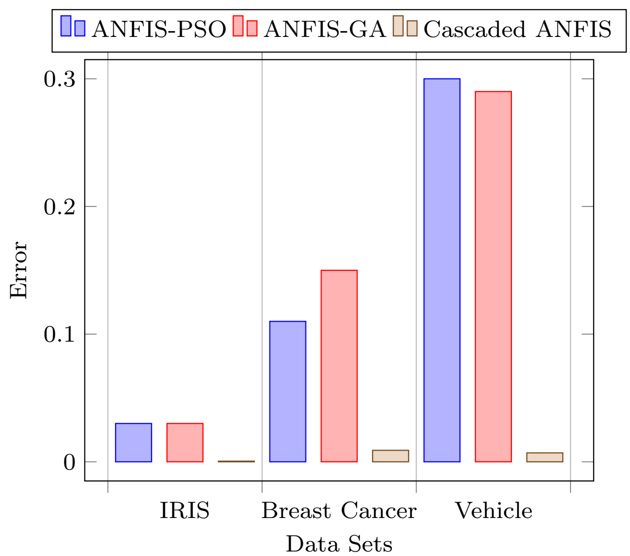

Fig. 7 MSE comparison

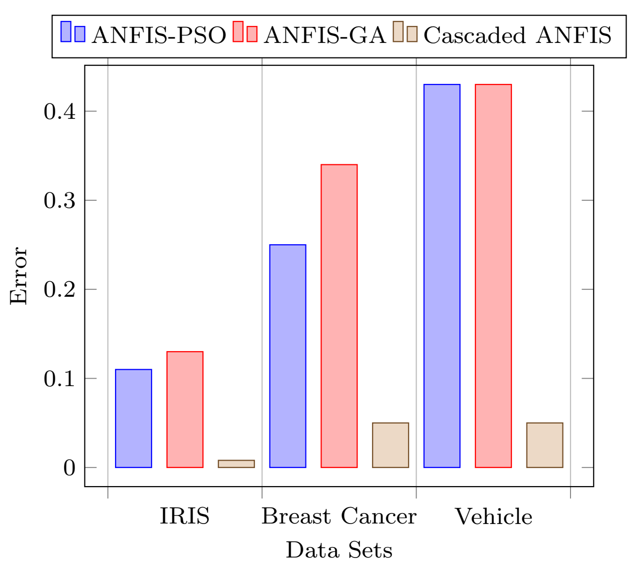

Fig. 8 MAE comparison

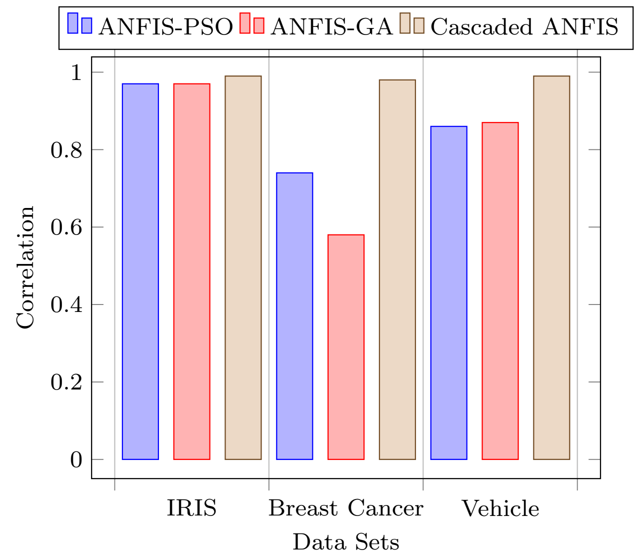

Fig. 9 Correlation comparison

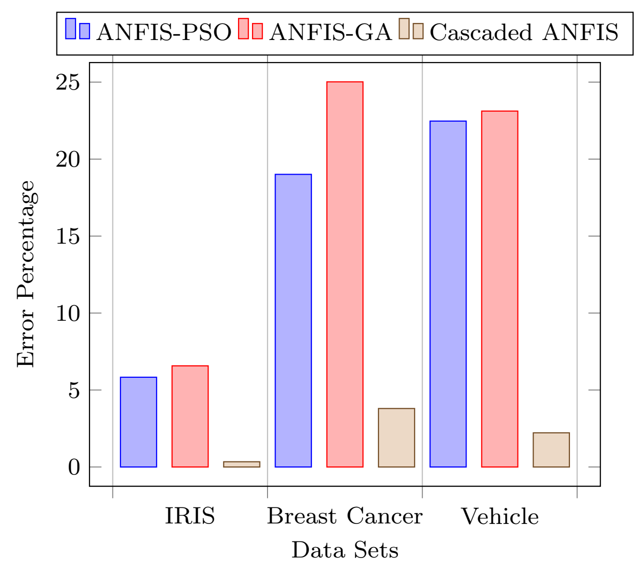

Fig. 10 MAPE comparison

Table 3 IRIS dataset for testing

	ANFIS-PSO	ANFIS-GA	Cascaded ANFIS
RMSE	0.181743	0.174594	0.005674368
MSE	0.033031	0.030483	3.21985E-05
MAE	0.132536	0.128472	0.005674
MAPE	7.825673	7.381097	0.245739
Correlation	0.977487	0.979315	0.999944

Table 4 Breast Cancer dataset for testing

	ANFIS-PSO	ANFIS-GA	Cascaded ANFIS
RMSE	0.497408	0.444374	0.086713
MSE	0.247415	0.197468	0.007519
MAE	0.360477	0.387072	0.050746
MAPE	25.47778	31.24708	3.937956
Correlation	0.557952	0.488011	0.987396

Table 5 Vehicle dataset for testing

	ANFIS-PSO	ANFIS-GA	Cascaded ANFIS
RMSE	0.653112	0.679	0.000324
MSE	0.426556	0.461041	1.05E-07
MAE	0.541745	0.533102	0.000229
MAPE	30.69937	25.08795	0.010369
Correlation	0.821025	0.788542	1

The results mentioned above correspond to the training phase. Table 3 shows the errors and correlation of the IRIS data set at the testing phase. Results show that the RMSE of the novel algorithm for the testing of the IRIS data set is 0.005674, and the correlation is almost equal to 1. Tables 4 and 5 present the testing results for Breast cancer and the vehicle data sets.

The prediction and actual outputs of the considered data sets are given in the following figures. Figure 11 shows the IRIS data set performance for the three algorithms. The smoothness of the outputs can be observed in the novel algorithm compared to the ANFIS-PSO and ANFIS-GA. The prediction curves against the actual output for breast cancer and vehicle data sets are given in Figs. 12 and 13, respectively.

Time consumption of a system is a direct fact to present the computational complexity. Hence, the time consumption is obtained for each dataset training and testing. Tables 6 and 7 present the time consumption for testing and training, respectively.

5.2 The Novel Cascaded ANFIS Performance Evaluation

In this section, a detailed presentation of results is given for the Novel Cascaded ANFIS algorithm. As explained in the methodology section, the novel algorithm has iterations that can obtain far better results by increasing the number of iterations. Since this study considers seven different data sets, the performance is presented in several graphs and plots.

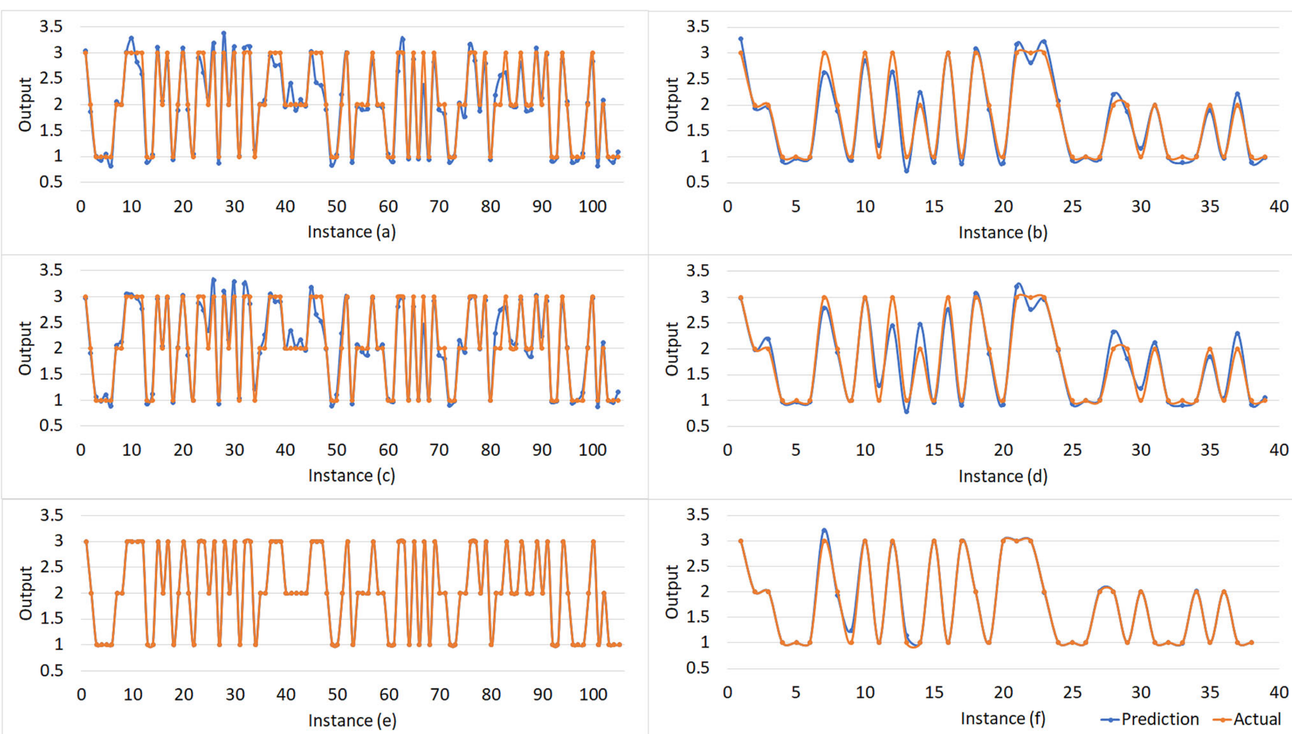

Fig. 11 IRIS data set prediction vs actual outputs for **a** ANFIS-GA Training, **b** ANFIS-GA Testing, **c** ANFIS-PSO Training, **d** ANFIS-PSO Testing, **e** Cascaded ANFIS Training, **and f** Cascaded ANFIS Testing

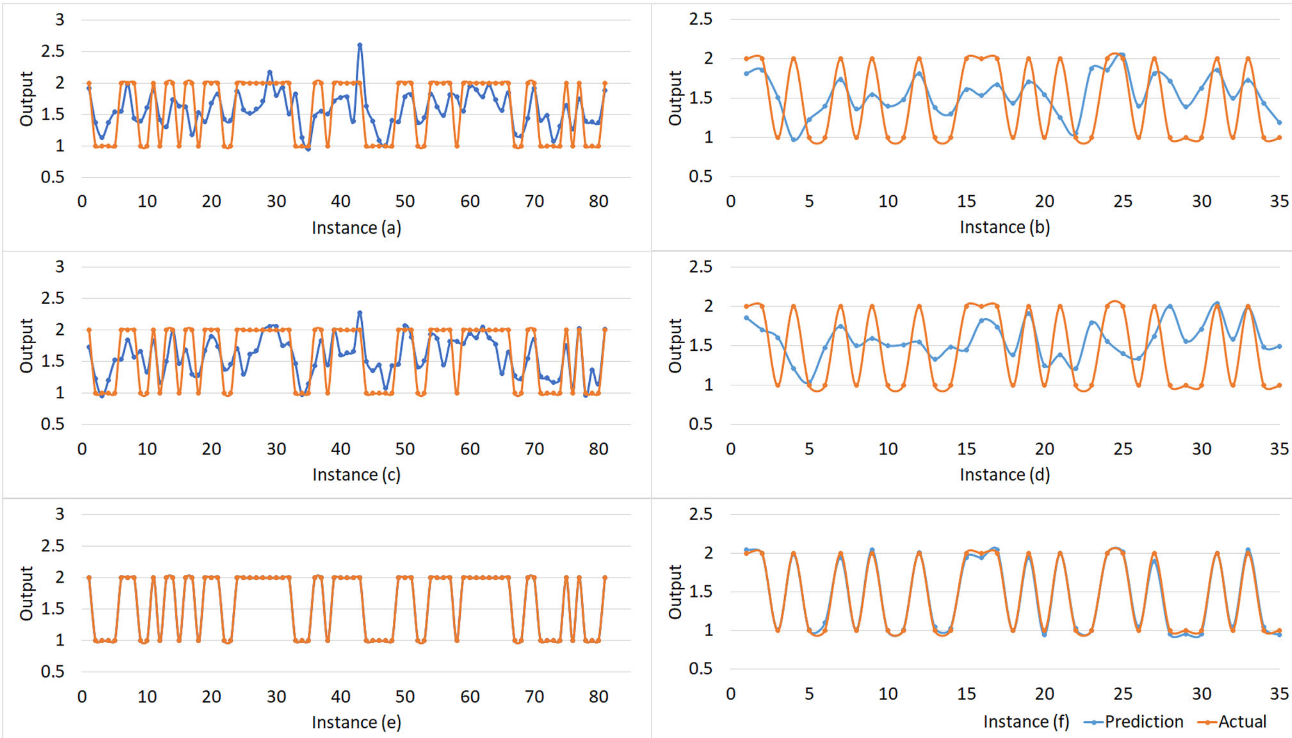

Fig. 12 Breast Cancer data set prediction vs actual outputs for **a** ANFIS-GA Training, **b** ANFIS-GA Testing, **c** ANFIS-PSO Training, **d** ANFIS-PSO Testing, **e** Cascaded ANFIS Training, **and f** Cascaded ANFIS Testing

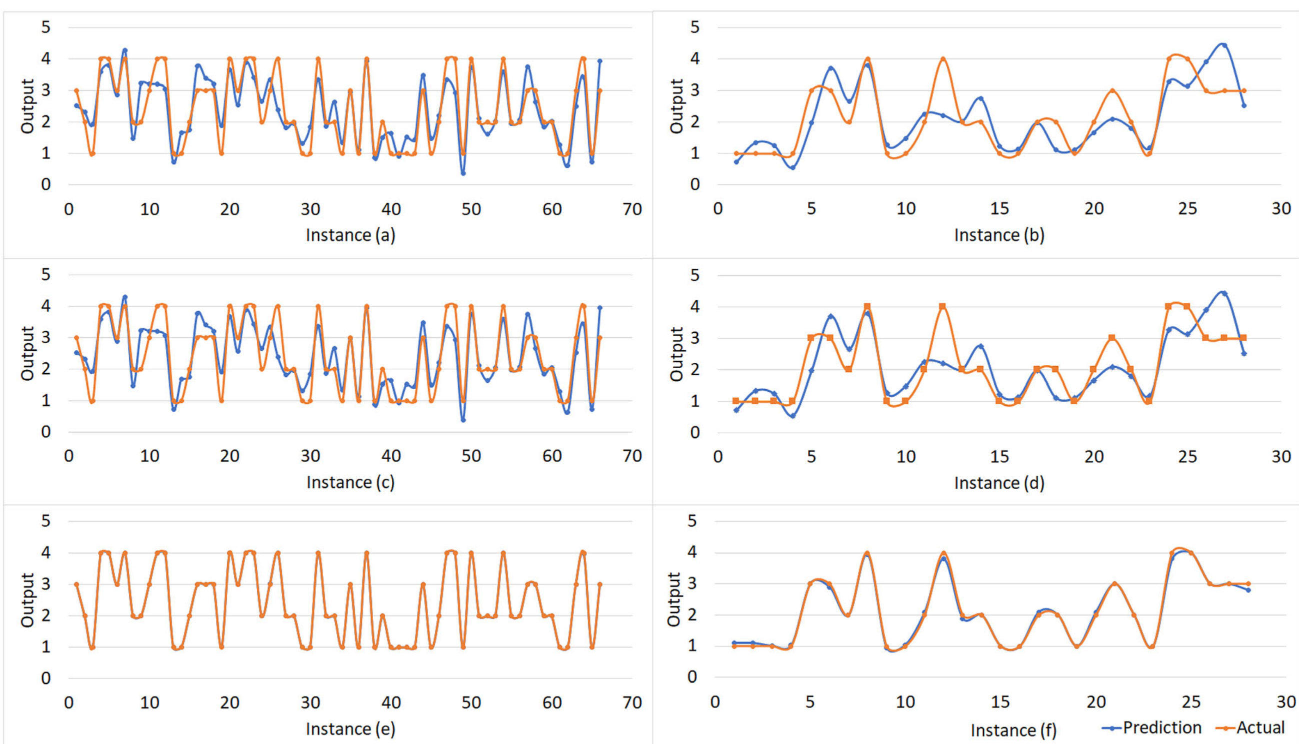

Fig. 13 Vehicle data set prediction vs actual outputs for **a** ANFIS-GA Training, **b** ANFIS-GA Testing, **c** ANFIS-PSO Training, **d** ANFIS-PSO Testing, **e** Cascaded ANFIS Training, **and f** Cascaded ANFIS Testing

Table 6 Testing time comparison (seconds)

Dataset	ANFIS-GA	ANFIS-PSO	Cascaded ANFIS
IRIS	0.184	0.399	0.1442
Breast	0.1824	0.4352	0.1156
Vehicle	0.384	0.8246	0.1697

Table 7 Training time comparison (seconds)

Dataset	ANFIS-GA	ANFIS-PSO	Cascaded ANFIS
IRIS	1697.9	1479.2	743.4052
Breast	5259.807	4278.7	3314.84
Vehicle	15959.39	13055.64	10028.63

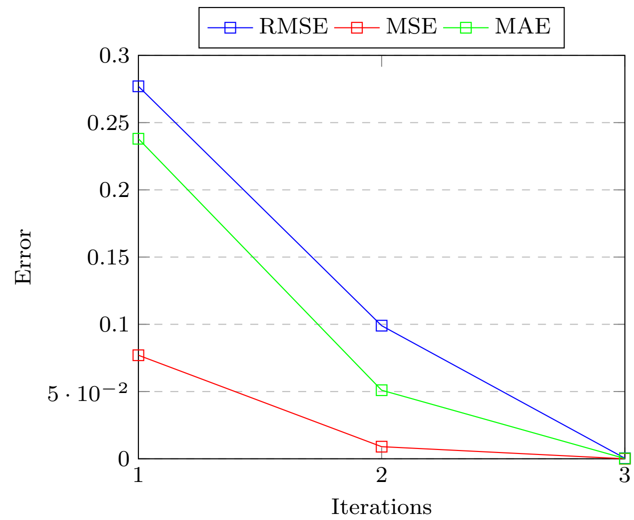

Fig. 15 Breast Cancer data set Error variance by the iterations

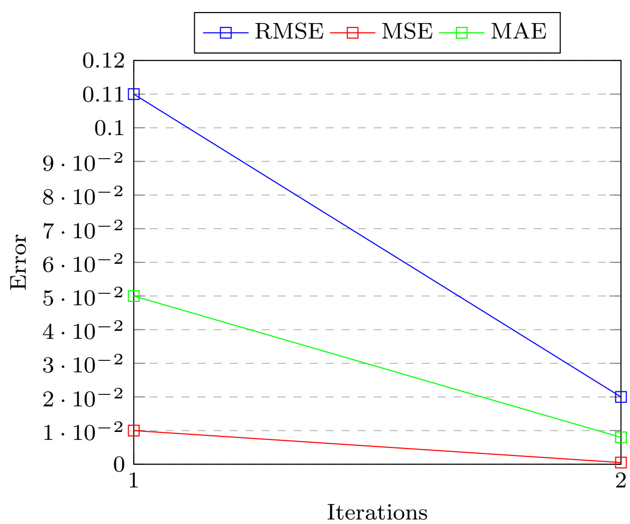

Fig. 14 IRIS data set Error variance by the iterations

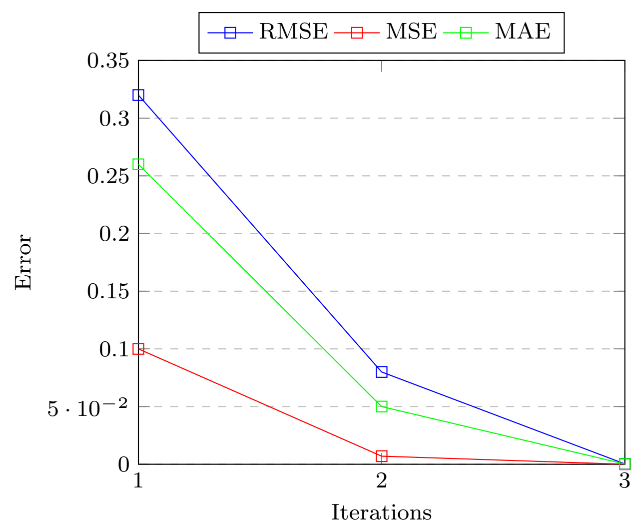

Fig. 16 Vehicle data set Error variance by the iterations

Figure 14 shows the IRIS data set performance by iterations. As in the figure, in the first iteration, the RMSE of the novel algorithm is 0.114778533. Nevertheless, when it reaches iteration 2, the RMSE becomes 0.022531097. In Fig. 15, the breast cancer data set is occupied, and the number of iteration that have has used is 3, and the RMSE decrements are 0.277640323, 0.099419942, and 0.000423648. Here, it can be observed that, at iteration 3, the RMSE is almost zero. Fig. 16 presents the results for Vehicle data sets, and it has also used only three iterations.

The performance results for Sports articles for objectivity analysis data set are shown in Fig. 17. Here ten iterations are used in generating the minimum RMSE. Smart Phone Activities data set is presented in Fig. 18. It has used 20 iterations and achieved 0.234818114 of RMSE.

Super Conductivity data set performance is shown in Fig. 19. Though the number of input variables is higher than that of the Sport Article Objectives and Human Activity Recognition Using Smartphones, the iterations usage is surprisingly less for this data set. Within two iterations, the RMSE has reached 0.000396855. Musk 1 data set performance is presented in Fig. 20. Here the error of 0.224424 is achieved within three iterations.

6 Discussion and Conclusion

This study presents a novel approach to the ANFIS algorithm. The main objective of this implementation is to solve the two main problems in the general ANFIS

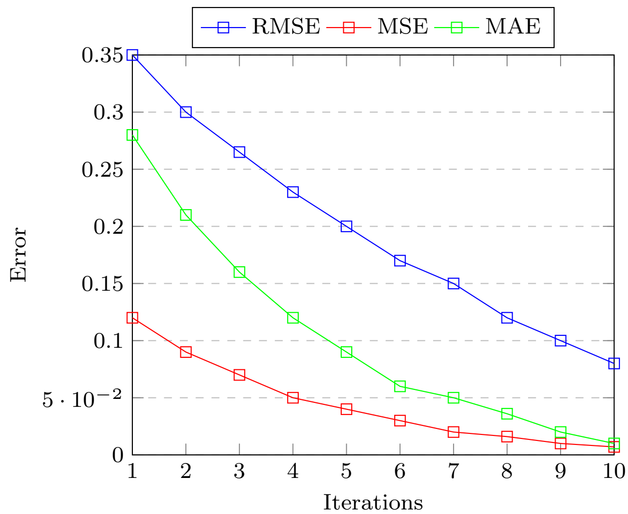

Fig. 17 Sports articles for objectivity analysis data set Error variance by the iterations

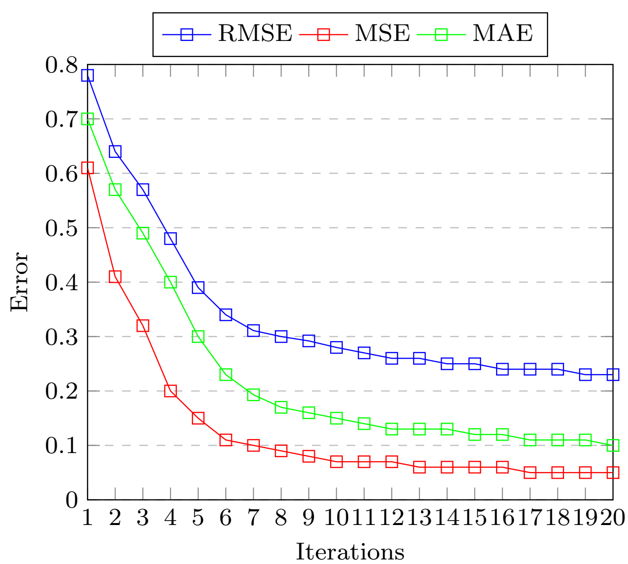

Fig. 18 Human Activity Recognition Using Smartphones data set Error variance by the iterations

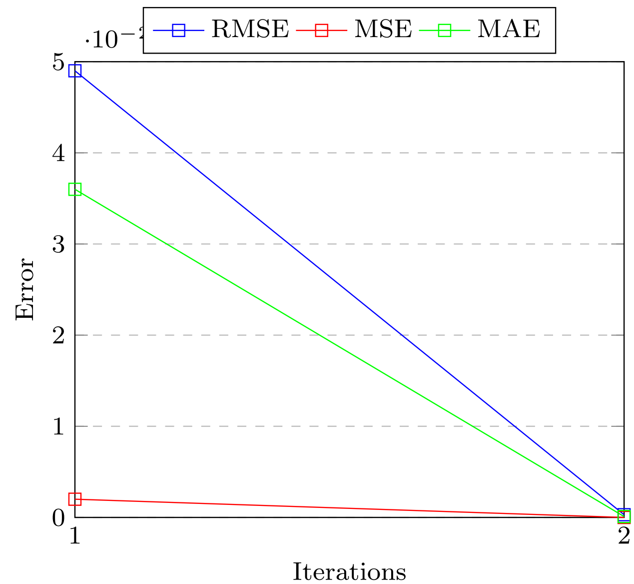

Fig. 19 Super Conductivity data set Error variance by the iterations

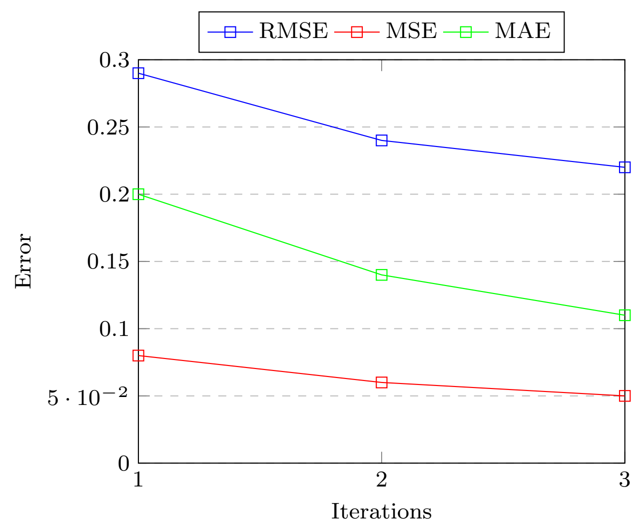

Fig. 20 Musk 1 data set Error variance by the iterations

algorithm, namely, the curse of dimensionality and the computational complexity. ANFIS is a well-known algorithm for the optimization of small input datasets. However, the novel algorithm is tested against leading two state-of-the-art algorithms and with seven publicly available data sets. The input dimension of these data sets varies from 4 to 561. The main difficulty in state-of-the-art algorithms is using a larger number of inputs. Increasing the number of inputs can significantly increase the computational complexity and as a result, state-of-the-art algorithms can fail during the process of optimization. However, the Cascaded ANFIS is capable of using any number of inputs because, at any one time, it uses only two of the inputs. This is the main novelty of the Cascaded ANFIS algorithm. Moreover, the behavior of the novel algorithm generates more accurate results with a lower error percentage.

Demonstration of the effectiveness of the Cascaded ANFIS algorithm was discussed using two parts. The first part is the effectiveness of the proposed algorithm against state-of-the-art algorithms, and the other part is the effectiveness of the proposed algorithms for a vast range of data sets. To evaluate the results, RMSE, MSE, MAE, MAPE, and Correlation are introduced. In each aspect, the novel algorithm outperformed the state-of-the-art algorithms.

The input dimensions of the data sets vary from 4 to 561. As shown in Figs. 14, 15, 16, 17, 18, and 19, the number of iteration usage changes regardless of the input dimension. For example, in figure 14, the IRIS data set has four input variables, and for the Cascaded ANFIS, the number of iteration usage is two. As well as, the superconductivity data set iteration usage is two though it has 81 input variables. Therefore, the discrimination effectiveness of the variables affects the number of iterations. In figure 18, the error has been saturated around 0.25 after 12 iterations.

According to the experimental results, our Cascaded ANFIS algorithm shows significantly improved accuracy, and it is capable of handling any number of inputs. There are few major limitations in implementing the Cascaded ANFIS algorithm on a micro-controller. Since the algorithm generates a large number of variables, it is necessary to have enough storage in the micro-controller to store the data. Furthermore, it is not possible to use the online training method using the novel algorithm, because the time consumption is considerably higher than the online trainable algorithms. As for future work, we will focus on reducing the training time and obtaining a better accuracy using fewer iterations.

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