A Novel Strategy for Improving the Counter Propagation Artificial Neural Networks in Classification Tasks

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***Abstract*—Counter-Propagation-Artificial-Neural-Networks (CP-ANNs) have been applied in several domains due to their learning and classification abilities. Regardless of their strength, the CP-ANNs still have some limitations in pattern recognition tasks when they encounter ambiguities during the learning process, which leads to the inaccurate classification of the Kohonen-Self-Organizing-Map (K-SOM). This problem has an impact on the performance of the CP-ANNs. Therefore, this paper proposes a novel strategy to improve the CP-ANNs by the Gram-Schmidt algorithm (GSHM) as a pre-processing step of the original data without changing their architecture. Three datasets examples from various domains, such as correlation, crop, and fertilizer, were employed for experimental validation. To obtain the results, we relied on two simulations. The first simulation uses CP-ANNs, and the datasets are inputted into the network without any prior pre-processing. The second simulation uses MCP-ANNs, and the datasets are pre-processed through the GSHM block. Experiment results show that the proposed MCP-ANNs recognize all patterns with a classification accuracy of 100% versus 62.5% for CP-ANNs in the Correlation Dataset. Furthermore, the proposed MCP-ANNs reduce the execution time and training parameter values in all datasets versus CP-ANNs. Thus, the proposed approach based on the GSHM algorithm significantly improves the performance of the CP-ANNs.**

***Index Terms*—Counter Propagation Artificial Neural Networks (CP-ANNs), Classification performance, Data Pre-processing, Gram-Schmidt Algorithm (GSHM), Kohonen- Self-Organizing-Map (K-SOM), Modified Counter Propagation Artificial Neural Networks (MCP-ANNs).**

I. Introduction

Artificial Neural Network (ANN) is a distinguished and acknowledgeable field in solving complex problems which are challenging tasks in various issues such as classification, description, prediction, diagnostic, and pattern recognition (PR). The power of the ANN is due to its inspiration from the biological human nervous system that includes intelligent features like self-adapting, learning ability, and generalization of the results. Furthermore, the ANN is among the classification algorithms used in several classification tasks. In the ANN, the classification accuracy depends on pattern recognition performance.

The ANN has been incorporated into numerous areas, including medical data classification [1-3], agriculture prediction [4-6], diagnostic industry [7-9], biometric [10], [11], and face recognition [12]. The performance of the ANN in the previously cited works showed significant results and is considered an effective tool in solving various complex problems. These achievements can be attributed to the effective use of the ANN in PR because this latter has a high weight in the development of research and offers a solution to a variety of challenges. Nevertheless, an improvement step of the ANN is required to avoid some issues faced in pattern recognition systems, which may have a negative impact on the ANN classification performance. Since PR classifies the patterns in a specific class, sometimes the classification results may differ from the results assumed through the lack of recognition of some patterns (unknown class), resulting in a bad decision. For this purpose, many works suggested new strategies for improving the ANN in terms of classification [13-15]. These strategies achieved higher classification accuracy with minimum errors than original neural networks.

Several models of the ANN have been vastly used in pattern recognition, such as Radial Basis Function Network (RBFN), Multi-layer Perceptron (MLP), Counter Propagation Artificial Neural Networks (CP-ANNs), Kohonen Self-Organizing-Map (K-SOM), Convolutional Neural Network (CNN), and so on). In this study, we suggested the CP-ANNs. The purpose of choosing this model is its capability to combine both unsupervised and supervised learning. In Addition, the CP-ANNs are a popular network [16] and are extensively used in numerous areas [17-19] through their abilities to solve the issues of classification, clustering, and recognition tasks. Moreover, pattern recognition comprises two learning modes (Unsupervised and supervised) [20]. Generally, the CP-ANNs are classified as a supervised learning network with two layers: the K-SOM and the Grossberg. The objective of the first layer is to regroup the data into the cluster by making a correct classification of all patterns and the second layer (Grossberg) depends on the classification performance of the

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first layer (K-SOM) to reach some expectations. For the data that suffer linear regularities between their patterns, The K-SOM may fail to increase the number of correct classifications due to the low rate of their patterns recognition. Hence, the Grossberg layer gives incorrect outputs. As a result, the classification accuracy decreases and it is regarded as one of the major inconveniences of the CP-ANNs in all tasks. Therefore, improvement is necessary within the supervised learning. In order to overcome this limitation, there are different approaches to detect and remove the drawbacks encountered during the learning process. For that reason, we must search the appropriate strategy to eliminate them, and this represented a challenging task. Thus, this paper proposes a new strategy for improving the CP-ANNs by adding a pre-processing step of the Gram-Schmidt algorithm. The MCP-ANNs use the GSHM algorithm to remove all the ambiguities and drawbacks detected from data that would improve the rate of pattern recognition and classification accuracy of the classical CP-ANNs. The GSHM algorithm is a linearly orthogonalized algorithm that constructs the (K, R) components from the given (r x c) matrix. This algorithm can enhance the level of the K-SOM pattern recognition. As a consequence, the classification of the CP-ANNs network becomes more accurate.

In this work, three datasets from various domains such as correlation, crop, and fertilizer datasets were used for training and testing the proposed MCP-ANNs approach. The main goal of choosing these datasets is to prove the performance of the proposed MCP-ANNs in data with relation complexes and in data that doesn't have any problems (see Fig. 1). Hence, the effectiveness of the proposed approach will be compared to the CP-ANNs effectiveness.

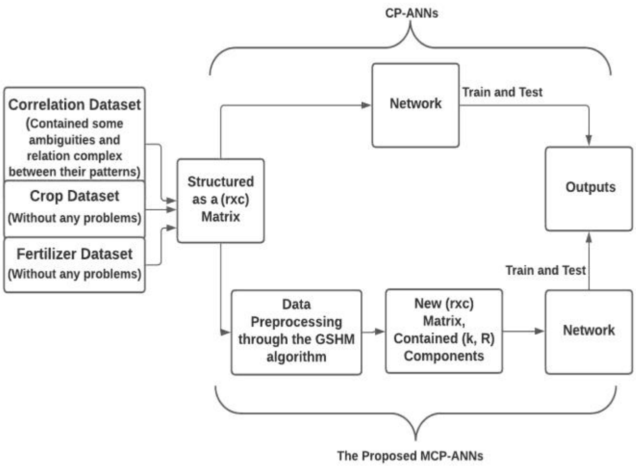

Fig. 1. Process of the dataset implementation used in the CP-ANNs and the proposed MCP-ANNs.

The main contributions of this study are summarized as follows:

- This study contributes by proposing a novel strategy based on a combination of the CP-ANNs and the Gram-Schmidt algorithm (GSHM).
- The GSHM algorithm is employed to increase the rate of pattern recognition by removing all ambiguities detected, which improves the classification accuracy in the supervised learning during the learning process.
- Our proposed MCP-ANNs approach achieves a better classification with high accuracy in the correlation dataset.
- In terms of the ANN, the long training represents a second challenge issue after the classification problem. For that, the proposed MCP-ANNs reduce the execution time in all datasets used. Besides that, the MCP-ANNs minimize some (or all) training parameter values compared to the CP-ANNs.

Furthermore, our paper can provide additional contributions in comparison with previous works on this subject, which are illustrated as follows:

- According to this publication [21], the proposed GSHM algorithm outperforms the PCA in the execution time term since the GSHM algorithm is linear and the PCA algorithm is iterative. Thus, the GSHM is faster than PCA in data pre-processing. Additionally, The GSHM gives more precise values than PCA.
- Based on this publication [15], the linear model based on the Kalman filter improved the classification accuracy of the Neural Network by 94, 93% in the Iris dataset (the example of PR dataset) compared to the proposed MCP-ANNs, which reach an accuracy of 100% in the Correlation dataset (our PR dataset example).
- The authors of this study [22] examined each ANN model in PR, and they obtained the accuracy between 70.11 and 89.97%. Thus, the proposed MCP-ANNs can be added to [22] ANN models by the accuracy of 100% in pattern recognition.

The remainder of the article is structured as follows. Section II gives a few strategies employed for improving the classification accuracy of the Neural Networks. Section III describes the datasets used for experimental validation. Section IV explains the CP-ANNs and the proposed MCP-ANNs. Section V presents and compares the performance results achieved by the CP-ANNs and the proposed MCP-ANNs. Section VI discusses the empirical results. And finally, the conclusion and perspective are determined by Section VII.

II. Related Work

The Principal Component Analysis (PCA) method was proposed in this work [21] to improve the classification accuracy of the K-SOM networks by eliminating the drawbacks encountered during the learning process. In this study, their proposed strategy removed the relation complexes between patterns, resulting in better classification performance when compared to the standard K-SOM. The Gram-Schmidt algorithm was suggested in our first article [23] to increase the classification accuracy of the K-SOM in unsupervised learning. For validation in this study, we used two datasets. The experimental results showed that our proposed approach outperforms the classical K-SOM by removing all ambiguities detected in data that suffer some problems between their patterns. Therefore, the modified K-SOM produced a classification accuracy of 100 % by reducing the execution time and the training parameter values versus the K-SOM. The combination of both Learning Vector Quantization and Self-Organizing Map was employed [24], which was named Weighted-Self Organizing Map (W-SOM). The main objective of their study is to enhance the prediction accuracy of crops and weather for the Mysore region of India. The experimental results demonstrated that their proposed W-SOM improved the accuracy versus the existing methods such as SOM, KNN, and ENN. The linear model based on the Kalman filter was developed to improve the classification performance of the Neural Networks (NN) [15]. Their proposed technique used the Kalman filter to evaluate the linear model parameters, which is considered post-processing of the original Neural Network. For validation, they used five datasets from various domains with different characteristics. Their results demonstrated high classification accuracy than NN. Additionally, their proposed method reduced the error of NN.

III. Dataset Introduction

To evaluate the effectiveness of the proposed MCP-ANNs approach, three examples of the dataset were selected from various domains and with different natures (see Tables I, II, and III). This evaluation aims to study some limitations of the CP-ANNs and improve them. The concise descriptions of each dataset used are portrayed below.

1. The correlation dataset represents our example of a pattern recognition dataset. This latter is one of the datasets that may be encountered during the learning process, and it includes some ambiguities [21]. The correlation dataset consists of two similar input vectors (1 and 5), four input vectors that have linear regularity and dependence between its object components (0, 4, 2, and 6), and finally, two normal input vectors (3 and 7). For desired outputs, we gave them a different number code. And for similar vectors, we gave them the same number code (see Table I).
2. The crop dataset is used to recommend a suitable crop based on specific parameters related to soil and atmosphere, and it was collected from India [25]. This dataset contains seven parameters: Ph, N, P, K, Depth, Temperature, and Rainfall (see Table II). We randomly divided the crop dataset (11 patterns) into training sets (85%), and the remaining 15% was used for testing and validating the models.
3. The fertilizer dataset is employed to recommend the appropriate fertilizer type according to various parameters such as temperature, humidity, moisture, soil type, crop type, nitrogen, potassium, and phosphorus [26] (see Table III). We randomly split the fertilizer dataset (40 patterns) into training sets (95%), testing and validating sets (5%).

Since the CP-ANNs only take numerical values as input and output in the training phase, we offered a number code for each desired output and each parameter related to crop and soil types. The number codes were chosen randomly (see Table V).

TABLE I
THE CORRELATION DATASET

Input Vector Nº	Learning Data	Desired Outputs
0	8,4,6	1
1	5,6,7	2
2	3,5,4	3
3	11,27,39	4
4	4,2,3	5
5	5,6,7	2
6	9,15,12	6
7	13,35,42	7

TABLE II
THE CROP DATASET

The parameters according to atmosphere and soil (Learning Data)							Crop Type (Desired Outputs)
PH	N	P	K	Dep	Temp	Rain	
8.5	100	50	50	30	33	1200	Cotton
7	175	100	100	60	30	750	Sugarcane
8	80	40	40	50	30	1000	Jowar
7	40	20	25	15	28	600	Bajra
7	30	75	15	19	27	800	Soybeans
8	100	25	0	40	20	500	Corn
7	100	50	50	15	22	90	Rice
8.5	100	50	50	30	24	1400	Wheat
6	25	50	30	20	24	1250	Groundnut

TABLE III
THE FERTILIZER DATASET

The specific parameters for recommending the suitable fertilizer (Learning Data)								Fertilizer Name (Desired Outputs)
Temp	H	M	Soil Type	Crop Type	N	Pot	Pho	
26	52	38	Sandy	Maize	37	0	0	Urea
29	52	45	Loamy	Sugar-cane	12	0	36	DAP
28	54	46	Clayey	Paddy	35	0	0	Urea
33	64	50	Loamy	Wheat	41	0	0	Urea
27	54	28	Clayey	Pulses	13	0	40	DAP
25	50	65	Loamy	Cotton	36	0	0	Urea
26	52	31	Red	Grou-ndnuts	14	0	41	DAP
….	…	…	….	……..	…	…	….	…..
36	60	43	Sandy	Millets	15	0	41	DAP

IV. The Proposed ANN Based Systems

A. *Artificial Neural Networks*

The ANNs are based on a biological neural network that can learn, adapt, and generalize results more effectively than other methods [27]. These proprieties allow solving complex problems in various systems [28-30]. In addition, ANNs have been widely employed in nonlinear systems, and they are dominant in numerous application areas [31], [32]. Although to these mentioned capabilities of the ANNs, sometimes they may fail to achieve high classification accuracy due to the lack of pattern recognition. This problem occurs from some detected drawbacks during the learning process. For that reason, we propose a new strategy to improve the ANNs in their performance. The proposed approach makes the ANNs more robust. There are several ANN models; in this study, we suggest the CP-ANNs since they are frequently utilized in pattern classification tasks.

B. Counter Propagation Artificial Neural Networks

The Counter-Propagation Artificial Neural Networks are a popular model of artificial neural networks developed by Hecht Nielsen (1987) [33], [34]. This model serves as a fast network in data classification with high accuracy. The main reason for the CP-ANNs success is their capabilities to solve several problems in clustering and classification tasks [35-37], allowing us to build effective intelligent systems. The CP-ANNs connect the Kohonen-Self-Organizing Map and Grossberg successively. For that reason, the CP-ANNs use two modes of learning; unsupervised and supervised learning. However, the CP-ANNs represent the supervised network model. The architecture of the CP-ANNs is composed of three-layer (i.e., input layer, Kohonen layer, and Grossberg Layer). The input layer aims to distribute the data to the learning processes and is represented by vector X. The second layer is named the Kohonen Self-Organizing Map (K-SOM) and is among the Artificial Neural Network models. Moreover, the K-SOM is the best-known and commonly used in data classification and clustering [38], [39].

In the CP-ANNs, the K-SOM was trained in an unsupervised manner and is based on the values given by the input layer to determine the winning nodes (or neurons), which are the observation situations that we have. The winning neurons are presented by 1 and 0 for all other neighboring neurons (accreditation regime), and for calculating it, there are many methods, but the most used methods are the Euclidean Distance and the Product Scalar. The principle of these techniques is to calculate the distance between all input vectors X and weight vectors W of each neuron, and the shortest distance represent the winning neuron. The outputs values of the K-SOM are the inputs values of the third layer (Named Grossberg). The objective of the Grossberg layer is to achieve the desired outputs that have been classified correctly in the Kohonen layer. Additionally, the Grossberg layer was trained in a supervised mode manner. The CP-ANNs outputs are represented by vector Y. Thus, by linking the Kohonen and the Grossberg layers, we attain the architecture of the CP-ANNs (see Fig. 2).

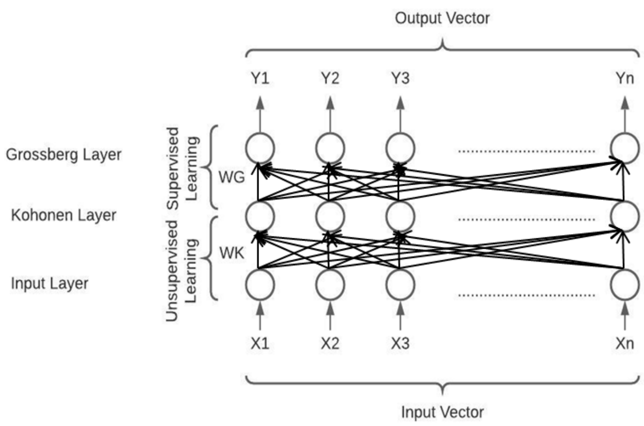

Fig. 2. The architecture of the CP-ANNs.

As can be seen from Fig. 2, the learning Procedure of the Classical Counter-Propagation Artificial Neural Networks begins with the Kohonen Self-organizing map. Thus, we must create the map of the K-SOM that contains the required number of neurons and weights in order to connect the input data with all neurons in the map. The initial weights are initialized randomly between zero and one. For training the patterns, the input data is formed as a (r x c) matrix and must be normalized to speed up the learning time and improve the convergence of the neural network. The equation of the normalization step [40] can be written as follows.

$$X_{\mathrm{i}} = X_{\mathrm{i}} \Big/ \sqrt{\textstyle\sum_{j=0}^{n-1} X_{\mathrm{j}}^{2}} \quad (1)$$

where X_i : is the input vector of i th element.

In the next step, the Euclidean Distance (ED) metric is used in this algorithm to determine the winning neuron by calculating the distance between the input vector X and the weight vector WK_j (of each neuron). The nearest distance between the input vector and weight vector is the winning neuron j and is given by the following equation [21].

$$j: \parallel WK_j - X \parallel \leq \parallel WK_o - X \parallel \quad \forall_o \quad (2)$$

After determining the winning neuron by the Euclidean Distance metric, the weights of the winning neuron and all its neighbors must be corrected and updated using the following equation [23], [41-43].

$$WK_{ij}\ (t+1) = WK_{ij}\ (t) + L(t)\, f(t).\, \lfloor y_{\mathrm{i}} - WK_{ij}\ (t) \rfloor \quad (3)$$

where $WK_{ij}\ (t+1)$ is the updated synaptic weight at iteration t+1, $WK_{ij}\ (t)$ is the synaptic weight before updating at iteration t, $L(t)$ is the learning rate at iteration t, $f\ (t)$ is the neighborhood function. y_{i} is the value of the (i) winning neuron.

In order to complete the Counter Propagation Artificial Neural Networks, we have to create the third layer (Grossberg). Therefore, the values obtained at the output of the K-SOM are transmitted to the input of the Grossberg layer. The equation that calculates the network outputs is as follows.

$$y_k = \textstyle\sum_i^N u_{\mathrm{i}}.\, W_{ik} \quad (4)$$

where y_k : is the output of the network. u_i is the i th output of the K-SOM. And W_{ik} is the synaptic weight within i th neuron of the K-SOM layer and k th neuron of the Grossberg layer.

In the end, the synaptic weight of the Grossberg layer must be updated using the formula below to reach some expectations.

$$WG_{ij}\ (t+1) = WG_{ij}\ (t) + \beta.\, (\, y_d - WG_{ij}\ (t)).\ u_i \quad (5)$$

where β: is the learning rate, and y_d is the desired output.

C. *Modified Counter Propagation Artificial Neural Networks*

The ultimate goal of the supervised CP-ANNs is to train the network to arrive at some expectations. These expectations must be very close to desired outputs. However, when the CP-ANNs encounter drawbacks during the learning, the network is unable to achieve better performance due to its failure in recognizing some patterns by the K-SOM layer, resulting in inaccurate classification. Therefore, to increase the CP-ANNs classification accuracy, the Gram-Schmidt algorithm that generates the new data by removing all drawbacks detected can be considered as a pre-processing step. In the linear algebra, the Gram-Schmidt mathematical algorithm is a technique of orthogonalization to generate the new set of orthogonal vectors in Euclidean space from the original matrix (or original data) [44], [45]. Consequently, we can conclude that the GSHM algorithm is a new technique for pattern recognition, among other algorithms like PCA. By combining the GSHM algorithm and the CP-ANNs, we achieve the MCP-ANNs (see Fig. 3).

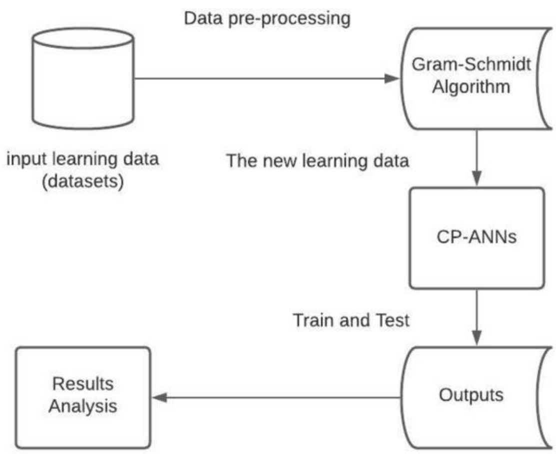

Fig. 3. Flowchart design of the proposed MCP-ANNs approach.

In this work, we use the modified Gram-Schmidt algorithm. To develop the GSHM algorithm, we have to apply all the following steps. We refer to [23].

1. Firstly, the dataset (or learning data) must be organized into a (r x c) matrix in order to facilitate their processing by the GSHM algorithm.
2. Secondly, each matrix row will be represented by a point in 3-dimensional space (see Fig. 4), where the point (1, 2, and m) in 3-dimensional space corresponds to the 1st, 2nd, and mth row of the matrix.
3. Each row of the matrix has (K, R) components. Therefore, to calculate these components of the new matrix generated by the GSHM algorithm, we start choosing the point farthest from the initial coordinates. After that, we draw a vector that starts with the chosen point (l) until the initial coordinates and perpendicular to it, passing through the origin of the coordinate. We draw a plan with the following equation.

$$a_{l1}\, a_1 + a_{l2}\, a_2 + a_{l3}\, a_3 = 0 \qquad (6)$$

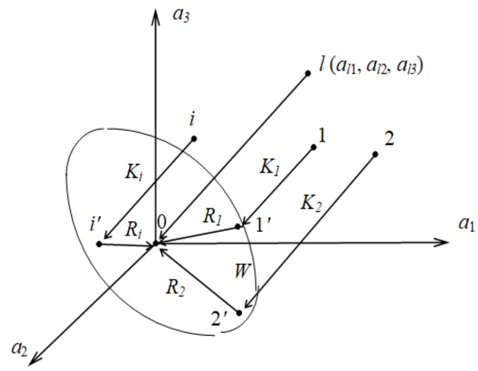

Fig. 4. 3-dimensional space.

4. In a given space, the distances of an arbitrary point regarding the drawn plan are equal to the absolute value of ($Dist$) (see formula below).

$$Dist = \frac{a_{l1} a_1 + a_{l2}\, a_2 + \ldots + a_{l3}\, a_3}{\sqrt{a_{l1}^2 + a_{l2}^2 + \ldots + a_{l3}^2}} \qquad (7)$$

5. The value of the resultant expression for ($Dist$) corresponds to the value of the K_l coefficient calculated by the following function.

$$K_l^{(j)} = \sum_{b=1}^{m} (M_{l,b}^{(j)} \,.\, M_{c,b}^{(j)}) / \sum_{b=1}^{m} (\, M_{c,b}^{(j)})^2 \qquad (8)$$

6. | $Dist$ | is the distance between the base points (l) and the initial coordinates. We can demonstrate that the K_l component is the relative distance between every point and the drawn plan (see formula below).

$$M_{l,i}^{(2)} = M_{l,i}^{(1)} - K_l^{(1)} \,.\, M_{c,i}^{(1)} \qquad (9)$$

After calculation the K_l coefficient, we apply the previous formula only once to calculate the matrix lines, which form the projected points of the initial matrix. The Gram-Schmidt orthogonalization algorithm agrees on the constructed plan.

7. The second component (R_l) that will be calculated is the distances on the plan, i.e., between the points projected on the plan and the point of the initial coordinates.

$$R_l = \sqrt{\sum_{i=1}^{m} (\, M_{l,i}^{(2)})^2} \qquad (10)$$

Finally, we obtain the (K, R) components for each row of the original matrix M^1, as shown below.

$$M^1 = \begin{Vmatrix} x_{11} & x_{12} & \ldots & x_{1m} \\ x_{21} & x_{22} & \ldots & x_{2m} \\ x_{l1} & x_{l2} & \ldots & x_{lm} \\ x_{N1} & x_{N2} & \ldots & x_{Nm} \end{Vmatrix} \begin{Vmatrix} K_1 & R_1 \\ K_2 & R_2 \\ K_l & R_l \\ K_N & R_N \end{Vmatrix} \qquad (11)$$

Thus, the new (K, R) components generated by the Gram-Schmidt algorithm are ready to pass in the training phase.

After that, the MCP-ANNs outputs should be analyzed to show the performance of the combination between GSHM and CP-ANNs and compare them with the original network abilities.

V. Results

A. *Performance of the CP-ANNs Model*

In the training phase of the CP-ANNs, each dataset was run with different training parameter values (see Table IV). The performance of the CP-ANNs during the learning process in all datasets is described below.

1) The Correlation Dataset

The experimental results show that the performance of the CP-ANNs in the Correlation dataset is unqualified enough and unsatisfying due to the inability of the CP-ANNs to reach some desired outputs (see Table V). This limitation comes from the low level of the pattern recognition of the Kohonen-Self-organizing map, which reduces the number of correct classifications. Here, the K-SOM gives five winning nodes for the eight input vectors (i.e., the K-SOM classifies the data into five independent clusters), as shown in Fig.5. The cause of decreasing the classification performance of the K-SOM depends on some input vectors having a linear regularities problem between their components (i.e., inputs 0, 4, 2, and 6), that has an effect on the network performance by giving a single winning node for each pair instead of four, as shown in (Fig. 6 and 7). In this case, the Grossberg layer fails to provide good results. Thus, the CP-ANNs are unable to reach all desired outputs (see Table V). For similar objects (i.e., inputs 1 and 5), the network offers the same winning node, as shown in Fig.9.

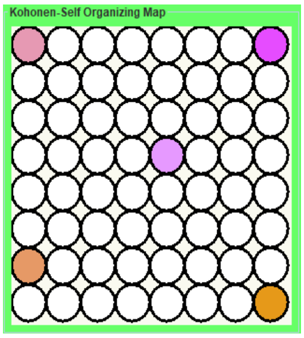

Fig. 5. The capability of the K-SOM in the classification performance of the Correlation Dataset, according to the CP-ANNs.

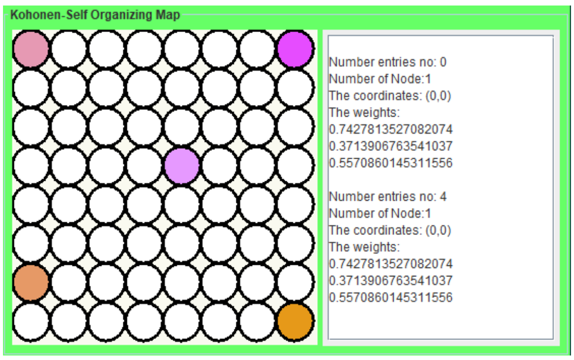

Fig. 6. The winning node of inputs 0 and 4.

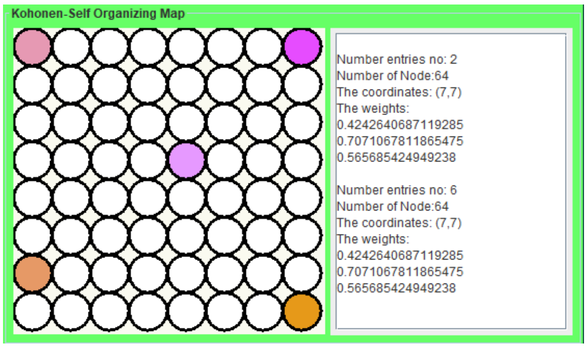

Fig. 7. The winning node of inputs 2 and 6.

From Fig. 6 and 7, the inputs 0 and 4 have the same winning node. In addition, inputs 2 and 6 also get the same winning node. Therefore the network produces two winning nodes from four input vectors instead of four. The coordinates of each winning node are described in Fig.8.

In Table V, the K-SOM classification represents the coordinates (or position (y, x)) of the winning nodes.

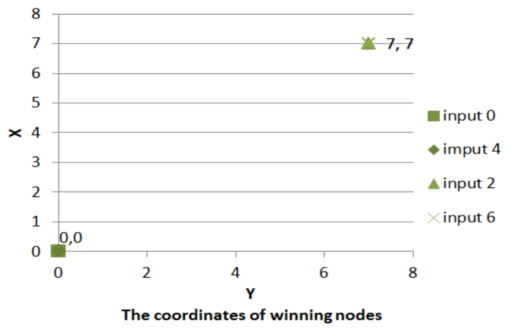

Fig. 8. The performance of the K-SOM in four input vectors that have a linear regularity between their components, according to the CP-ANNs.

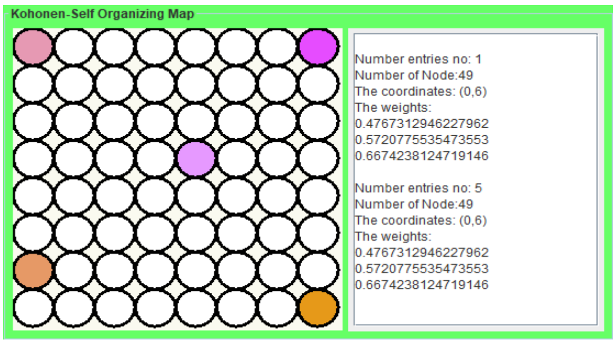

Fig. 9. The winning node of the similar input vectors 1 and 5.

Accordingly to the results obtained, the CP-ANNs achieve a classification accuracy of 62.5% (i.e., 5/8). For training parameter values, the learning process results in the Correlation dataset provide (Max iteration = 523, the mean error of K-SOM = 4.4018 e^{-4}, and mean error of Grossberg = 2.2684 e^{-4}) (see Table IV).

2) The Crop and the Fertilizer Datasets

The experimental tests of the CP-ANNs in the Crop and the Fertilizer datasets show high classification performance due to reaching all desired outputs with an accuracy of 100% (See Table V), but with these training parameter values (i.e., Max iteration = 779, Mean error of the K-SOM = 6.1990 e^{-4}, and mean error of the Grossberg = 8.9907 e^{-4}) for the Crop dataset, and (Max iteration = 3000, mean error of the K-SOM = 1.5712 e^{-4}, and mean error of the Grossberg = 7.9210 e^{-6}) for the Fertilizer dataset (see Table IV).

TABLE IV
THE TRAINING PARAMETER VALUES OF THE CP-ANNS USING THREE EXAMPLES OF DATASETS

Training parameters	Datasets Name		
	Correlation	Crop	Fertilizer
Map Dimension	8	8	15
Iteration rate	1000	1000	3000
Max. iteration	523	779	3000
Learning error	0.001	0.001	0.00001
Mean error of K-SOM	4.4018 e^{-4}	6.1990 e^{-4}	1.5712 e^{-4}
Mean error of Grossberg	2.2684 e^{-4}	8.9907 e^{-4}	7.9210 e^{-6}

TABLE V
THE EXPERIMENTAL PERFORMANCE OF THE CP-ANNS USING THREE EXAMPLES OF DATASETS

	Input vector N°	Desired Output	CP-ANNs Output	K-SOM Classification	Execution Time
Correlation Dataset (Example 1)					
(see Table I)	0	1	5.000241999012946	[0, 0]	119 ms
	1	2	1.99997567993495 75	[0, 6]	
	2	3	6.00013863576897	[7, 7]	
	3	4	4.000265373781499	[4, 3]	
	4	5	5.000241999012946	[0, 0]	
	5	2	1.99997567993495 75	[0, 6]	
	6	6	6.00013863576897	[7, 7]	
	7	7	7.00022684372184	[7, 0]	
Crop Dataset (Example 2)					
(see Table II)	0	5	4.999534540663555	[7, 2]	116 ms
	1	20	19.999712136522206	[3, 5]	
	2	1	0.9995321693464999	[6, 4]	
	3	87	86.99978495693603	[4, 1]	
	4	123	122.99959283025792	[0, 3]	
	5	1234	1233.999291569404	[7, 7]	
	6	67	66.9996038867822	[0, 7]	
	7	250	249.99972761287634	[6, 0]	
	8	90	89.99910092045408	[1, 0]	
Fertilizer Dataset (Example 3)					
(see Table III)	0	1	0.9999946186691387	[0, 10]	232 ms
	1	2	1.9999922567653823	[14, 14]	
	2	1	0.9999961747772984	[3, 14]	
	3	1	0.9999942897648376	[2, 11]	
	4	2	1.999996454285112	[11, 0]	
	5	1	0.9999947559140254	[0, 14]	
	6	2	1.9999931506204915	[8, 0]	
	…	….	……………………..	…….	
	37	2	1.999992078912501	[13, 9]	

In Conclusion, the performance of the CP-ANNs in the Crop and the Fertilizer datasets was high. In addition, the CP-ANNs get an accuracy of 100% in the training, test, and validation sets. However, the CP-ANNs in the Correlation dataset demonstrate the need to add another technique to improve it due to very low classification accuracy (62.5%). For that, our objective is to develop a new approach based on a combination of the Modified Gram-Schmidt algorithm and the CP-ANNs to improve classification accuracy by eliminating the ambiguities detected from the Correlation dataset and reducing the training parameter values and execution time in all datasets used.

B. *Performance of the Proposed MCP-ANNs approach*

In this test, the modified GSHM affords (K, R) components of each row of a given r x c matrix (see Table VI). Hence, these components were transmitted to the training phase.

The proposed MCP-ANNs were trained with the same training parameter values as the CP-ANNs (see Table VIII).

1) The Correlation Dataset

It can be noticed from Table VII that the proposed MCP-ANNs improve the classification accuracy of the classical network by reaching all desired outputs. This improvement is back from the good pattern recognition in the K-SOM layer, which accurately classified the input-vectors as shown in Fig. 10 versus five different clusters for the CP-ANNs, as shown in Fig. 5. In the K-SOM classification, the inputs that have a linear regularities problem between their components (inputs 0, 4, 2, and 6), the network gives a different winning node for each input, as shown in Fig. 11 compared to the CP-ANNs (see Fig. 8).

Thus, the K-SOM correctly classifies all input vectors, which gives the ability for the Grossberg layer to reach good results. These outcomes allow increasing the network classification performance by the accuracy of 100% and with a small mean error of the K-SOM = 3.5632 e^{-4} versus 4.4018 e^{-4} for the CP-ANNs (see Table VIII).

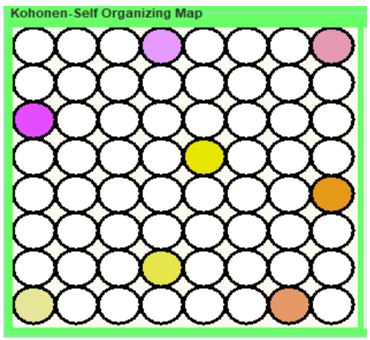

Fig. 10. The capability of the K-SOM in the classification performance of the Correlation Dataset, according to the MCP-ANNs.

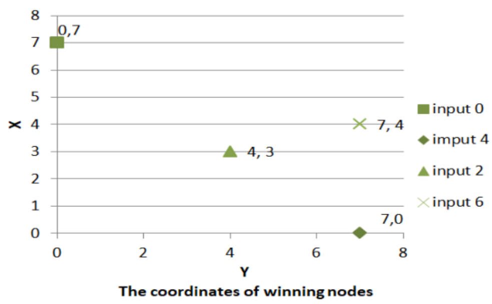

Fig. 11. The performance of the K-SOM in four input vectors that have a linear regularity between their components, according to the MCP-ANNs.

2) *The Crop and the Fertilizer Datasets*

Moreover, the MCP-ANNs are designed to not only aim to solve the classification problem but also to reduce the training parameter values during the learning process, such as max iteration and mean error. In this experimental test, we can observe a significant minimization of the training parameter values of the Crop dataset in terms of max iteration= 656, mean error of the K-SOM= 3.0540 e^{-4} , and mean error of the Grossberg = 3.2211 e^{-5} compared to a max iteration= 779, mean error of the K-SOM = 6.1990 e^{-4} , and mean error of the Grossberg= 8.9907 e^{-4} for the CP-ANNs (see Table VIII). The empirical test of the Fertilizer dataset gave the small mean error of the Grossberg = 4.5406 e^{-6} versus 7.9210 e^{-6} for the CP-ANNs (see Table VIII). Besides that, we obtained a similar classification accuracy of 100% for both of the CP-ANNs and the MCP-ANNs in training, test, and validation sets. The desired outputs and the MCP-ANNs output obtained for the Crop and the Fertilizer datasets during the learning process are described in Table VII.

In addition, the proposed approach reduces the execution time in all datasets during the learning process.

TABLE VI
THE K, R COMPONENTS GENERATING BY THE GSHM ALGORITHM OF EACH DATASET

Input Vector N°		New Learning Data Generating by the GSHM Algorithm	
		K	R
Correlation Dataset	0	0.0	10.7703296
	1	0.9137931	3.6246283
	2	1.2277163	1.0758625
	3	14.5674661	7.0340142 e^{-14}
	4	1.8339636	1.5152288
	5	5.2368931	6.8690373
	6	11.3056469	11.8187847
	7	31.5072648	90.9137290
Crop Dataset	0	0.0	1207.0879214
	1	0.6385109	153.7390552
	2	2.1390526	25.3022920
	3	1.8806842	13.1382881
	4	3.8361564	56.0178076
	5	3.0579054	45.4536858
	6	0.8321133	1.4887561
	7	17.1582981	9.7498510 e^{-11}
	8	15.8635010	3.9076074
Fertilizer Dataset	0	0.0	78.7083223
	1	0.9065375	43.8963008
	2	2.2354967	6.8837815
	3	3.7382374	2.4052783
	4	3.1781479	7.7120735
	5	5.3368075	8.2539199
	6	4.8687976	1.1823540
	….	………	………
	37	29.4138328	120.3985919

C. *Comparison between the MCP-ANNs and the CP-ANNs*

1) *Classification Accuracy*

Figure 12 shows a comparison of classification accuracy between the MCP-ANNs and the CP-ANNs in all datasets. It can be observed from Fig 12 that the proposed MCP-ANNs improve the classification performance of the Correlation dataset with an accuracy of 100% against 62.5% for the CP-ANNs. For this dataset, the best improvement was 37, 5 % on average. This percentage represents an excellent improvement due to the ability of the proposed MCP-ANNs in removing all drawbacks or ambiguities detected from the Correlation dataset.

For the Crop and the Fertilizer datasets, we obtained the same classification performance with an accuracy of 100% of both the MCP-ANNs and the CP-ANNs, as shown in Fig.12.

TABLE VII
THE EXPERIMENTAL PERFORMANCE OF THE MCP-ANNS USING THREE EXAMPLES OF DATASETS

Input Vector N°		Desired Output	MCP-ANNs Output	K-SOM Classification	Execution Time
Correlation Dataset (Example 1)					
(see Table VI)	0	1	1.0009755361207848	[0, 7]	90 ms
	1	2	1.9999355930620624	[3, 6]	
	2	3	2.9999681842404002	[4, 3]	
	3	4	3.9999919233796537	[3, 0]	
	4	5	4.999662299222258	[7, 0]	
	5	2	1.9999949926959124	[6, 7]	
	6	6	5.999910838500265	[7, 4]	
	7	7	6.999754071323308	[0, 2]	
Crop Dataset (Example 2)					
(see Table VI)	0	5	5.000000317521804	[7, 0]	96 ms
	1	20	19.99994836365091	[4, 0]	
	2	1	0.9999099445880586	[6, 6]	
	3	87	86.99998573983048	[3, 6]	
	4	123	122.99991688651545	[5, 3]	
	5	1234	1233.9999692016274	[7, 3]	
	6	67	66.99970701428454	[0, 7]	
	7	250	249.99995884937874	[0, 0]	
	8	90	89.99996778890107	[1, 3]	
Fertilizer Dataset (Example 3)					
(see Table VI)	0	1	0.9999927061766676	[1, 14]	173 ms
	1	2	1.9999903932358885	[0, 13]	
	2	1	0.9999932123688745	[3, 6]	
	3	1	0.9999930307466912	[11, 13]	
	4	2	1.9999959211943152	[6, 6]	
	5	1	0.9999958265352213	[11, 2]	
	6	2	1.999994646884562	[6, 11]	
	…	….	……………………	……..	
	37	2	1.9999954593314826	[2, 9]	

TABLE VIII
THE TRAINING PARAMETER VALUES OF THE MCP-ANNS USING THREE EXAMPLES OF DATASETS

Training parameters	Datasets Name		
	Correlation	Crop	Fertilizer
Map Dimension	8	8	15
Iteration rate	1000	1000	3000
Max. iteration	638	656	3000
Learning error	0.001	0.001	0.00001
Mean error of K-SOM	3.5632 e^{-4}	3.0540 e^{-4}	2.0999 e^{-4}
Mean error of Grossberg	2.4592 e^{-4}	3.2211 e^{-5}	4.5406 e^{-6}

2) *Mean Error*

As shown in Fig. 13 and 14, the proposed MCP-ANNs outperform the CP-ANNs in the mean error of the K-SOM and the Grossberg for the Crop dataset with the best improvement. Moreover, the MCP-ANNs minimize the max iteration number of this dataset against the CP-ANNs (see Table VIII and IV).

For the Correlation dataset, the MCP-ANNs produce a less mean error of the K-SOM versus the CP-ANNs as shown in Fig 13. Additionally, the MCP-ANNs show nearly the mean error of the Grossberg in comparison with the CP-ANNs, as shown in Fig.14.

For the Fertilizer dataset, the MCP-ANNs give the best mean error of the Grossberg in comparison with the CP-ANNs, as shown in Fig 14. Moreover, the MCP-ANNs generate a nearly similar mean error of the K-SOM as the CP-ANNs result (see Fig.13).

3) Execution Time

From the execution time point of view, Fig. 15 shows that the proposed MCP-ANNs also reduce the execution time in all training data (or datasets).

It can be concluded from these experimental tests that the proposed MCP-ANNs have a significant performance in terms of classification accuracy, training parameter values, and execution time.

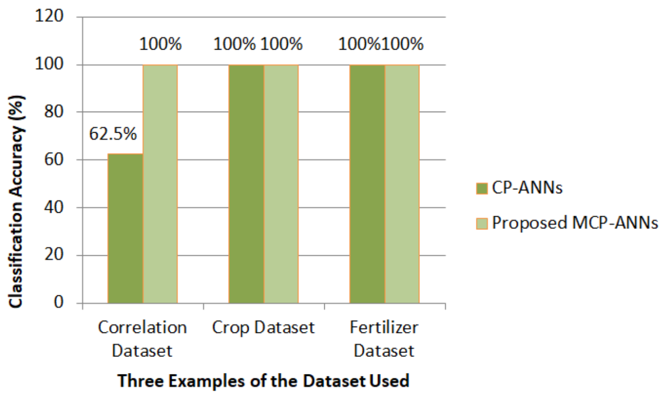

Fig. 12. The MCP-ANNs vs. the CP-ANNs in the classification accuracy.

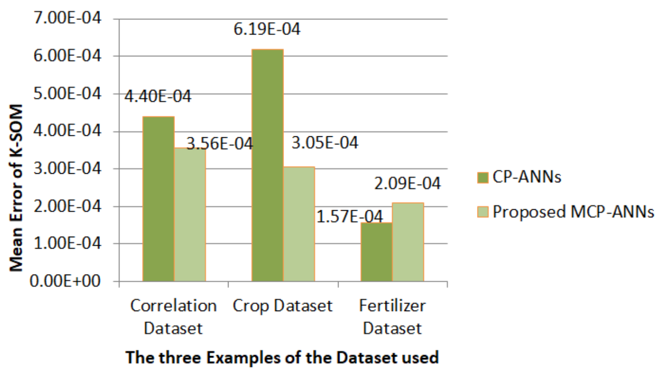

Fig. 13. The MCP-ANNs vs. the CP-ANNs in mean error of K-SOM.

VI. Discussion

Many different strategies have been proposed to improve the performance of the neural network algorithms, such as Kalman filter, particle swarm optimization (PSO), gravitational search algorithms (GSA), fuzzy rules, and recursive data pruning [13-15]. This study presents another new strategy called the Gram-Schmidt algorithm as a pre-processing step of the Counter Propagation Artificial Neural Networks. The CP-ANNs used the GSHM algorithm to eliminate all drawbacks during the learning process. This transformation leads to improving the network performance. Some previous works suggested other approaches to remove the ambiguities detected during the learning process, such as Principal Component Analysis [21]. The problem of the PCA is the execution time because it takes a long time for data pre-processing versus the GSHM algorithm. In addition, the GSHM algorithm produces more accurate values than PCA. Although the high capabilities of the proposed MCP-ANNs in classification accuracy, sometimes they can face some limitations that occur when the new inputs generated by GSHM are very close to each other. Therefore, in this situation, the proposed approach may fail to increase the number of correct classifications.

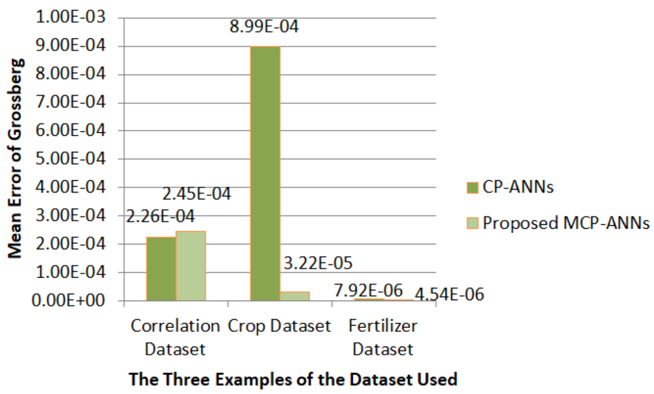

Fig. 14. The MCP-ANNs vs. the CP-ANNs in mean error of Grossberg.

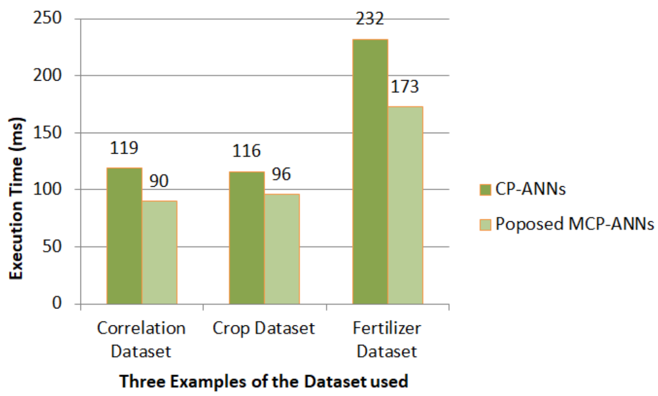

Fig. 15. The MCP-ANNs vs. the CP-ANNs in execution time.

VII. Conclusion

This research presented a lower-cost and accurate Counter Propagation Artificial Neural Network based on the Gram-Schmidt algorithm. The purpose of improving the classical CP-ANNs is the ambiguities and drawbacks that they encountered during the learning process, which influences the first layer (K-SOM) by decreasing the pattern recognition and classification accuracies, resulting in unsatisfying outcomes in the second layer (Grossberg). Thus, this limitation reduces the general network performance. For that, the ultimate goal of the proposed approach is to provide a robust and efficient CP-ANNs model which can be applied in different intelligent systems without worrying about some of its limitations. The proposed MCP-ANNs have been trained and tested using three datasets with different natures. The empirical results show that the proposed MCP-ANNs improve the classification accuracy (100 %) in the Correlation dataset due to good pattern recognition. For the Crop and the Fertilizer datasets, the proposed approach gives an accuracy of 100% in training, test, and validation sets. Furthermore, the proposed MCP-ANNs minimize some (or all) training parameter values and reduce the execution time in all datasets. In future research, we will try to test our proposed approach in various problems, especially in Hybrid and Diagnosis systems in order to show its efficacy.

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