A New Harmony Search Algorithm with Evolving Spiking Neural Network for Classification Problems

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***Abstract*—In this study, a new hybrid harmony search algorithm with evolving spiking neural network (NHS-ESNN) for classification issues has been demonstrated. Harmony search has been used to enhance the standard ESNN model. This new algorithm plays an effective role in improving the flexibility of the ESNN algorithm in creating superior solutions to conquer the disadvantages of ESNN in determining the best number of pre-synaptic neurons which is necessary in constructing the ESNN structure. Various standard data sets from UCI machine learning are utilised for examining the new model performance. It has been detected that the NHS-ESNN give competitive results in classification accuracy and other performance measures compared to the standard ESNN. More argumentation is provided to verify the effectiveness of the new model in classification issues.**

***Index Terms*—Harmony Search; Classification; Spiking Neural Network; Evolving Spiking Neural Networks.**

I. Introduction

Patterns classification becomes very important for various data mining processes. Especially, when it is used for a decision support system [1]. Various fields in existence require classification such as medicine, handwritten character recognition, speech recognition, industry and science, medical diagnoses. Artificial neural networks (ANNs) can be considered as one of the robust classifiers because their ability to deal with noise [2]. ANNs are amongst the most well-known brain computational models and ANN solves problems that are based on standard algorithmic techniques. Spiking neural networks (SNNs), the third generation of ANNs, play a vital role in the processing of biological information [3]. Spiking models give an in-depth explanation of the behavior of biological neuron. More details are utilized with the computations average firing rate with actual neurons. In addition, the difference in firing times could be applied as an alternative of rate coding [4].

As one of the best SNN models, the evolving spiking neural network (ESNN) is utilized extensively in current studies as in [5], [6]. The ESNN has a number of profits [7] as being a competent neural model, simple and trained using a fast one-pass learning algorithm. The treatment of model evolving can be altered at whatever time new data becomes available with no constraint to train again the former existing instances. However, the ESNN has some shortcomings, i.e. finding out the optimal number of pre-synaptic neurons for a specified data set is the mainly essential one [8], [9]. Identifying the pre-synaptic neurons number is vital for the structure of ESNN like the hidden nodes or MLP. More number of pre-synaptic neurons enlarges the time computation whereas fewer of them affect the accuracy of learning. Watts [10] prefers to select the parameters of evolving connectionist systems (ECOS) training automatically. Consequently, choosing an optimization method to carry out this parameter adaptation is significant. Among the various optimization techniques, harmony search (HS) algorithm is utilized in this paper for several reasons summed up as: HS method robustness, less HS results computation and the unnecessary derivative information for HS [11]. Some researchers analyzed the performance of HS compared to the other methods. According to Soltani et al. [12], HS is better than particle swarm optimization (PSO) in convergence rate and time consuming. Moreover, it would be interesting to apply the hybridization of HS with other algorithms. Hence, this paper presents a new method to obtain an accurate and simple ESNN. The new algorithm seeks for the optimal values to achieve better accuracy and better structure of ESNN to enhance performance for classification issues. The rest sections of this study are formed as follows: Section II elaborates the methods utilized in this paper, while Section III elucidates the found results and discussion; as a final point, Section IV presents the conclusion and future works.

II. Methods

This section offers the fundamental basis of evolving spiking neural network (ESNN) and explains the related algorithms that have been used for improvement.

Firstly, ESNN introduction has been presented. The second part concentrates on harmony search (HS) algorithm which is utilized for enhancing the classification performance. Finally, the third part focuses on the proposed method.

A. Evolving Spiking Neural Network (ESNN)

Wysoski enhanced a new model recognized as Evolving Spiking Neural Network (ESNN) [13]. In general, ESNN utilized the evolving connectionist systems (ECOS) principles where neurons are created cumulatively [14, 15]. ESNN used the one-pass propagation of the data to learn data gradually through producing and merging spiking neurons [9]. This method helps ESNN to achieve very fast learning [16]. The ESNN system can learn any new instance by producing new output neurons, mapping them to input neurons and merging with similar ones [9]. This model depends on two vital principles: New classes forming and the Similarities merging. Furthermore, the population is the selected encoding method for ESNN as mentioned in [17]. The original ESNN algorithm has been motivated researchers because of the multiple advantages they offer compared to others models [9, 15, 16, 18-21]. The ESNN algorithm flowchart is demonstrated in Figure 1.

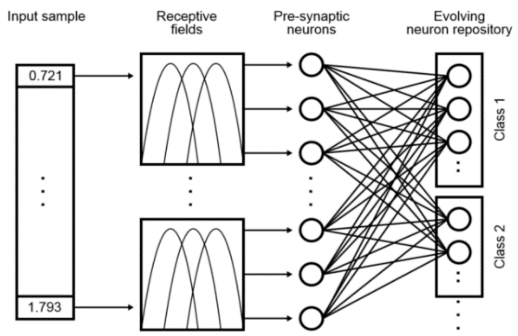

Figure 1: A simplified architecture of ESNN (Hamed *et al.*, 2009)

B. Harmony Search Algorithm

Geem [22] created the HS algorithm benefiting from finding the harmony during the music playing. There are three methods to improve music: playing randomly, keeping the original and playing similar to the original one. For more explanation, Geem indicates set three methods, for instance: pitch adjustment, randomization and harmony memory consideration [23]. The HS algorithm consists of a number of parameters for optimization, i.e.: harmony memory size (HMS), harmony memory considering rate (HMCR), harmony memory (HM), and pitch adjusting rate (PAR). To realize the parameters work, HM mainly stores the available vectors in the space. HMS determines numbers of stored vectors. Accordingly, a new vector is created by selecting the diverse vectors components at random in the HM [24]. The new harmony memory will be affected by the effective harmonies. Moreover, the best value for the harmony memory considering or accepting rate (r_{accept}) parameter must be in the range [0, 1]. Usually parameters values are pinpointed as r_{accep} =0.7 to about 0.95. Wrong solutions could be occurred if some harmonies are not ascertained perfectly [23, 25]. In addition, the pitch adjustment technique can produce better solutions. The parameters like pitch bandwidth (b_{range}) and pitch adjusting rate (r_{pa}) are generally very important for creating new solutions from existing ones. Hypothetically, the pitch can be attuned linearly or non-linearly. However, linear amendment is utilized practically. Therefore the equation can be:

$$X_{new} = X_{old} + b_{range} * \varepsilon \tag{1}$$

where X_{old} is the existing pitch or solution from the HM and X_{new} is the new pitch after the pitch adjusting action. This typically creates a new solution via small random amount addition between [-1,1] [26]. Finally, randomization reflects the ability of the solutions diversity increment compared to global optimality achievement. HS algorithms pseudo-code has been elaborated in detail in [23]. The randomization probability is given by:

$$P_{random} = 1 - r_{accept} \tag{2}$$

and the real probability of pitches adjusting can be indicated as

$$P_{pitch} = r_{accept} * r_{pa} \tag{3}$$

Our previous study investigated the hybridization of HS with ESNN algorithms as in [27]. However, in this paper HS has been applied differently in Section II.C.

C. The proposed algorithm NHS-ESNN

The new algorithm named NHS-ESNN has been explained in this section. Harmony search algorithm is a new HS algorithm for ESNN training. The purpose of this algorithm is to find out the best ESNN structure (pre-synaptic neurons) via dealing with this problem as an optimization issue. In NHS-ESNN, the backpropagation (BP) method is used to enhance the normal algorithm convergence. ESNN pre-synaptic neuron is considered as a candidate. In addition, both HS, BP are integrated with ESNN to find out the fitness evaluation and the schemes of mating selection. Initially, NHS-ESNN collect, normalize and read the dataset. Furthermore, both of candidate size and iteration maximum number are set. Moreover, ESNN pre-synaptic neurons are determined at random. A population of the new proposed algorithm is then created and initialized. After that, for each iteration, each candidate is evaluated based on the enhanced the HS algorithm. The proposed algorithm ends after the maximum iterations are attained. Algorithm 1 elaborates the pseudo-code of NHS-ESNN. In the beginning, the data set has been separated into 10 subgroups of same amount at random. One of these subgroups is utilized as the testing data set, whereas the remaining 9 subgroups are utilized as the training data sets. The processes of training and testing are altered so that all the subgroups are utilized as a testing data set. The algorithms performance is examined by doing analysis on ten evaluations. The abilities of the new hybrid algorithm have been explored via a comparison with some others that have been used for classification problems. For the purpose of evaluating the new hybrid algorithm performance of classification, the comparisons are carried out with the standard ESNN and some other algorithms as differential evolution with evolving spiking neural network (DE-ESNN), DE for parameter tuning with evolving spiking neural network (DEPT-ESNN) HS with evolving spiking neural network (HS-ESNN) and NHS-ESNN methods. The results for all data sets used are examined depending on classification accuracy (ACC), geometric means (GM) and specificity (SPEC) for all data sets. The results of the comparison in terms of all measures are shown in Table 1 and Figure 2. In Table 1, the superlative results are highlighted in bold font. Thus, for each data set, the results of the new hybrid algorithm are examined and elaborated in the next part. The new hybrid algorithm is evaluated by using various standard data sets have been obtained from the repository of machine learning benchmark (http://www.ics.uci.edu/~mlearn/ MLRepository.html).

Algorithm 1: NHS-ESNN Pseudo-code

```
Initialize  algorithm parameters: , HMCR, PAR  and fitness function
Generate the initial harmony population HMS (t) at t=0 where t is the number
          of the actual iteration and  HM as vector represents ESNN
while not reaching NI do    (NI is maximum of iteration)
     for all HM vector do
          use ESNN algorithm to find the HM vector fitness.
          achieve  results of pre-synaptic neurons and ESNN parameters.
          evaluate the HM vector of population HMS (t) according to the fitness value.
          determine the best  HM vector according to the best parents' values.
 improvise a new harmony
                 for j ∈ 1, ..., Nvariables do
                    randomly select any variable-i pitch in HM
                    randomly adjust uj within a small bandwidth alpha α
                    select any pitch within upper UBj and lower bounds LOj
                 end for

                    if vj is better than the worst harmony in HM, xworst, then
                           replace xworst with vj in HM, then sort HM
                    end if
             Applying local search (BP) to each of the harmony
             Perform local search ( BP ) algorithm
             evaluate the harmony HS on the basis of fitness functions
             update pre-synaptic neuron vector and ESNN parameters vector
             sort population HMS (t+1) according to their fitness values.
              t=t+1.
         end for
   end while
```

III. Results and Discussion

This section demonstrates the findings of the new hybrid algorithm NHS-ESNN with other algorithms. The findings of NHS-ESNN are analyzed based on accuracy and other measures. Additionally, the experiments are carried out 10 times in the training and testing for the whole data sets. The findings of the comparison based on accuracy measure, are presented in Table 1. It can be understood that NHS-ESNN achieved the top accuracy results for most data sets. These explorations indicate that NHS-ESNN gives the greatest accuracy in roughly the most data sets, compared to other algorithms. Moreover, the results of new hybrid algorithm comprised to the remaining algorithms depending on GM measure are presented in Table 1. The best GM findings are acquired from the appendicitis data set with 85.10%, 79.39% for the heart data set, 54.47% for the haberman data set and 70.92%for the liver data set. These investigations show the superior of the NH-ESNN algorithm.

From observation (Figure 2), NHS-ESNN is better than other algorithms in the entire data sets. It can be discussed that the new hybrid algorithm gets low specificity for imbalanced data set which appears through increased false positive case. These investigations indicate the poor performance at classifying the majority class by virtue of its lower specificity though they gain higher true positive rate in the process of minority class classification.

An important conclusion can be investigated from these results: the new hybrid algorithm proves superior in most datasets for all measures. Nevertheless, no specific algorithm can achieve the best performance for particular problems as supposed to the 'no free lunch theorem' [28](Wolpert and Macready, 1997).

Table 1
Accuracy and GM analysis for the comparison for ten-fold cross-validation

Data set	ESNN		DE-ESNN		DEPT-ESNN		HS-ESNN		NHS-ESNN	
	ACC	GM	ACC	GM	ACC	GM	ACC	GM	ACC	GM
Appendicitis	48.00	57.50	44.00	47.36	68.00	65.44	70	81.87	77.20	85.10
Haberman	67.32	52.57	73.66	47.67	72.66	18.88	76.40	53.73	78.30	54.47
Heart	53.99	0.00	56.33	60.10	65.57	64.89	50	76.74	60.40	79.39
Hepatitis	52.67	0.00	58.00	78.82	54.67	72.95	46.67	53.44	59.60	67.09
Ionosphere	60.57	31.45	63.43	64.16	62.14	44.33	60	76.19	66.70	72.17
Iris	95.99	100	86.67	100	89.33	87.50	93.33	97.04	94.50	97.15
Liver	48.57	53.88	45.71	53.13	44.00	51.81	45.71	68.87	56.20	70.92

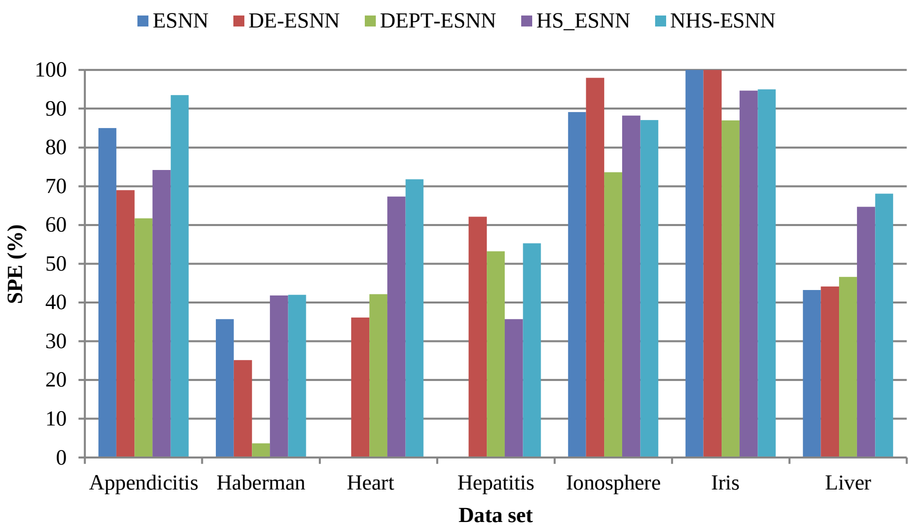

Figure 2: SPE analysis for the comparison for ten-fold cross-validation

IV. Conclusion and Future Works

In this study, a new algorithm NHS-ESNN was presented for the purpose of enhancing ESNN. An extensive research has been carried out linking NHS-ESNN with the standard ESNN and some algorithms to show the performance improvement of ESNN. The findings demonstrate that NHS-ESNN has the ability to give better performance results in accuracy than the other algorithms. Additionally, NHS-ESNN mostly gives superior findings in SPE and GM factors. The new findings of hybridization with ESNN inspire scientists to explore the effectiveness of combination with other new Meta heuristic algorithms for the purpose of improving ESNN. Moreover, it is better to investigate the effectiveness of hybridization with deep learning as one of the future works.

Acknowledgement

This research is supported and funded by RIMC of University Malaysia Sarawak (UNIMAS), under the special Grant Scheme (F04/SpGS/1547/2017).

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