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RESEARCH ARTICLE

Artificial Bee Colony for Logic Mining in Credit Scoring

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Abstract During the SARS-CoV-2 (Covid-19) pandemic, credit applications skyrocketed unimaginably. Thus, creditors or financial entities were burdened with information overload to ensure they provided the proper credit to the right person. The existing methods employed by financial entities were prone to overfitting and did not provide any information regarding the behavior of the creditor. However, the outcome did not consider the attribute of the creditor that led to the default outcome. In this paper, a swarm intelligence-based algorithm named Artificial Bee Colony has been implemented to optimize the learning phase of the Hopfield Neural Network with 2 Satisfiability-based Reverse Analysis Methods. The proposed hybrid model will be used to extract logical information in the credit data with more than 80% accuracy compared to the existing method. The effectiveness of the proposed hybrid model was evaluated and showed superior results compared to other models.

Keywords: Hopfield Neural Network, 2 Satisfiability, Artificial Bee Colony, Logic Mining, Default Credit Card.

Introduction

Credit assessment has been widely applied in various fields such as insurance, education, banking, and other industries. The credit assessment offers the creditor a significant application for loans, employment, and other medical purposes. The unexpected outbreak of COVID-19 at the end of 2019 financially affects more than 200 countries worldwide. This pandemic hammered severe shocks to our monetary system and led to economic instability, leading to a significant credit crisis for various financial institutions. Millions of small and medium-sized businesses have been scrapped during the lockdown due to a lack of capital which led to a high unemployment rate. This pandemic brings detrimental effects to the citizen of the country, where most of the middle class has descended into the bottom 40% in terms of income. Therefore, an efficient credit scoring system is essential for research to support global economic recovery.

One of the main issues in the current credit assessment is that the applicant only can be classified as default or non-default. When the accessor only classifies default/non-default, the assessor will decide based on the correlated attribute. There is no rule to decide or predict whether the existing user will satisfy any given attribute that leads to the said outcome. This will lead to misleading information and cost accessor billions of potential revenues. Thus, a series of artificial intelligence methods are often used to classify the credit outcome. Zhou *et al*. [1] proposed credit risk modeling by proposing a hybrid support vector machine (SVM). The proposed SVM demonstrates remarkable improvement and outperforms another competitive classifier. Kozodoi *et al.* [2] proposed a profit-driven using a non-

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dominated sorting-based genetic algorithm. The proposed method utilizes two objective functions and aid decision-makers in classifying the outcome based on the scoring model that optimizes profitability. Lappas *et al.* [3] recently proposed engaging evolutionary learning and wrapper-based feature selection in classifying final credit outcomes. This paper capitalizes the unsupervised machine learning to group the attributes and analyzes the feature via the analytic hierarchy process. Compared to the existing method, the proposed method demonstrates computational effectiveness in credit scoring. The current research strategy on credit scoring revolves around a hybrid method that does not evaluate the importance of pair of attributes that leads to the final outcomes. In this context, the existing credit scoring methods were observed to pay less attention to another attribute that can act as an outcome for the classification. The creditors will lose the bigger picture of the applicant's behavior, leading to application failure. Building from that point, the current banking system practices default/non-default as an outcome of their candidate's credibility. To makes matters worse, the conventional banking system heavily relies on human intervention that is prone to mistake or misjudgment. Therefore, this raises interest in whether it is possible to propose a model that explicitly shows the relationship of the applicant's attribute that leads to the outcome, which is different from trivial default/non-default. Conventionally, propositional logic can serve as a symbolic rule representing the explicit behavior of the data, which informs the assessor about the credibility of the applicants. More importantly, an optimal Artificial Neural Network (ANN) is required to "host" the logical rule representing personal credit ability.

An artificial neural network (ANN) is a computational model inspired by human biological neural networks [4] consisting of many simple processing units arranged in interconnected layers. ANN contains input and output layers corresponding to the variable of various optimization problems. The task of the ANN is to create an artificial connection among the artificial neuron and fire the final neuron state accordingly, which corresponds to the potential solution of any given problem. Despite several developments in the field of ANN [5-7], the simplest type of ANN is Hopfield Neural Network (HNN). HNN was proposed by Hopfield and Tank [8] to solve the combinatorial problem. HNN consists of a few notable features such as Content Addressable Memory (CAM), no self-connection and no hidden layers. One of the main issues of the HNN is the capacity to store the pattern that leads to the solution of a particular problem. As the number of neurons increases, the capability of the HNN to store pattern reduce dramatically. To overcome the issue, Wan Abdullah [9] proposed logic programming as a symbolic rule for the neuron in HNN. Hence the neuron is connected by synaptic weight, which can be obtained by comparing the cost function of the logical rule with the Lyapunov energy. Since the introduction of logic programming in HNN, Sathasivam and Abdullah have capitalized on this idea by proposing the novel logic mining called Reverse Analysis (RA) method [10]. The RA method is the building block of the other logic mining method. The application of the RA can be seen in Sathasivam and Abdullah [10], whereby the extracted individual logical rule in Horn SAT form has been analyzed to represent the performance of the students. The extracted logical representation from the datasets is according to the number of induced Horn logics generated by HNN. Despite the first application of the RA in real life dataset, the structure of the RA does not assist HNN in arriving at the generalized logical rule. In another development, Kho *et al.* [11] proposed a novel 2 Satisfiability based Reverse Analysis method (2SATRA) by emphasizing 2 Satisfiability as a logical rule representing real-life datasets. The outcome of the 2SATRA is an induced logic that represents the latent information of the dataset. The proposed 2SATRA was implemented into the League of Lagend (LOL), and the extracted logical rule was reported to achieve acceptable accuracy. Alway *et al.* [12] extended the application of logic mining using 2SATRA to extract information related to palm oil prices. In this work, several logical outcomes have been considered, and the proposed induced logic is able to classify the outcome of the dataset. In a recent development, Jamaluddin *et al.* [13] proposed Energy Based logic mining, namely EkSATRA to extract recruitment datasets provided by the insurance company in Malaysia. EkSATRA is reported to outperform the conventional method and can extract the optimal induced logic. Despite the rapid development in the field of logic mining, kSATRA suffers a stability issue as the number of neurons increases. This is due to the limited capacity of the HNN to store the pattern for 2SATRA, which leads to a sub-optimal connection between the attribute of the induced logic. In this context, the metaheuristics method is required to facilitate HNN to learn the logical rule that corresponds to the datasets.

The fundamental development of the 2SAT logical rule in DHNN has been pioneered by Kasihmuddin *et al.* [14], where the logical rule has been optimized via the ABC algorithms in lessening the local minima solutions. However, the work is limited to the implementation of 2SAT using the randomized simulated data only. Mansor *et al.* [15] have extended the capability of 2SAT into the pattern verification in HNN with the ABC algorithm. The work has proven the effectiveness of 2SAT and ABC in facilitating HNN in generating more global P2SAT patterns and minimizing the existence of local patterns. In Alway *et al.* [12], the 2SAT logical representation has been successfully being utilized in logic mining to extract the feasible association between the price trend of palm oil with other commodities. The latest development of 2SAT by Kasihmuddin *et al.* [16] revolves around the effectiveness of the 2SAT logical representation in the supervised learning perspective of logic mining. Despite many developments of other variants of 2SAT, the standard 2SAT logical rule is systematic in 2-dimensional decision-based logic mining.

Metaheuristics algorithms (MA) are computational intelligence paradigms that use an agent to explore the potential near optimal solution without complex mathematical equations. MA is widely utilized in various areas of discipline, such as calibration [17], medical [5], human resources [18], and many more. In theory, logic mining should be able to extract the logical rule from the datasets optimally. One of the essential reasons why logic mining fails to achieve optimal induced logic is the lack of solution diversity. From the perspective of logic mining, MA is no exception in optimizing the learning error of the ANN. Zamri *et al.* [18] proposed Clonal Selection Algorithm (CSA) to reduce the learning error in HNN integrated with 3 SAT logical rules. CSA capitalizes several important operators, such as Somatic Hypermutation and Cloning to obtain a satisfying interpretation for the 3 SAT logical rule. The proposed CSA in logic mining was reported to outperform the conventional method proposed by Mansor *et al.* [19]. In another development, Zamri *et al.* [20] proposed a Modified Imperialistic Competitive Algorithm (ICA) in optimizing logic mining. ICA makes use of several optimization operators such as Assimilation, Revolution, and Imperialist Competition to minimize the cost function of the HNN in logic mining. The proposed ICA is reported to outperform several conventional methods. Despite several successes in 3-dimensional decision making, minimal effort has been made toward optimizing the logic mining integrated with 2 Satisfiability (2SAT).

Artificial Bee Colony (ABC) has been proposed by Karaboga to solve the continuous problem [21]. ABC was inspired by the intelligent behavior of the honeybee that forages food in an optimal pathway. Initially, ABC consisted of 3 groups of bees such as employed bees, onlooker bees and scout bees, where each group was designed to forage the potential solution for any optimization problem. Since then, ABC has been extended into binary ABC that can solve a discrete problem. Kiran and Gunduz [22] proposed binary ABC (BinABC) by introducing XOR modification into the solution update. BinABC modifies the solution update rule by replacing the original equation with several logical operators such as “OR”, “AND” and “NOT”. The proposed method shows the effectiveness of BinABC in solving discrete problems in comparison with other existing state of the art methods. In another study, Jia *et al.* [23] utilizes a similar approach but utilize the bitwise operation (BitABC) for the movement of the employed bees and onlooker bees. The proposed method performs better than, or at least comparable with another algorithm for 13 benchmark functions in terms of various performance metrics. The development of the bitwise operator in ABC inspires Kasihmuddin *et al.* [24] to implement a similar approach for learning logical rules in HNN. The authors proposed bitwise ABC to minimize the cost function corresponding to the logical rule in the work. The proposed method has been reported to outperform the conventional state of the art method in doing simulated datasets. This idea has been extended by Sathasivam *et al.* [25], where the ABC was implemented to minimize the cost function of the Maximum Satisfiability. Interestingly, the proposed ABC minimizes the cost function despite dealing with the non-zero cost function of the logical rule. The ABC and ES are chosen due to the fewer parameters to be controlled as opposed to CSA. Despite the rapid development of the ABC algorithm in learning logical rules, all the proposed work revolves around simulated datasets. In this context, no effort has been made to implement this perspective into real life problems. Motivated by the ability of previous works to reduce the learning error of HNN, ABC integrated with HNN was expected to optimize the existing logic mining.

In the literature, there exist various ANN, machine learning, and ensemble methods for credit scoring with varying strengths and weaknesses. According to the No Free Lunch Theorem (NFL) [26], no algorithm is universally superior for all optimization problems. The novelty of this paper is presenting a logic mining method that harnesses the power ABC via incorporating them in an HNN. The proposed framework aims to increase the exploration capability for the knowledge extraction task. Therefore, the contribution of this paper is as follows:

i. Developing 2 Satisfiability logical rules into Hopfield Neural Network by assigning each neuron in the network as a variable of the whole formulation.
ii. Incorporating Artificial Bee Colony in learning 2 Satisfiability during the learning phase of the Hopfield Neural Network. The incorporation creates a hybrid network that reduces the learning error.
iii. Implementing the hybrid network into specific logic mining named 2 Satisfiability Reverse Based Analysis method. The proposed hybrid network is utilized to extract information for credit default scoring. Several perspectives in terms of extraction have been introduced.

The rest of the paper is structured as follows. Section 2 introduces the formulation of the 2 Satisfiability logical rule to represent the information of the dataset. In Section 3, we will implement 2 Satisfiability logic into Hopfield Neural Network. In Section 4, we will introduce the proposed logic mining that incorporates 2 Satisfiability with Hopfield Neural Network. In Section 5, the binary ABC has been proposed to learn the logical rule in Hopfield Neural Network. In Section 6, the information on the default credit card dataset will be discussed in detail. In Section 7, the detail of the experimental setup will be revealed, and the related performance metric will be discussed. In Section 8, we will further analyze the induced logic produced by logic mining with various performance metrics. The performance of the new logic mining will be compared with the existing method. In Section 9, we summarize the conclusion of this paper and look forward to future work.

2 Satisfiability (2SAT)

2 Satisfiability, abbreviated as 2SAT is defined as a logical rule consisting of two literals per clause [11]. 2SAT is a special case of general Boolean satisfiability. 2SAT logical rule is normally expressed as 2CNF (2 Conjunctive Normal Form). The three components of 2SAT are summarised in the following:

i) A set of m variables, $x_1, x_2, ..., x_m$.

ii) A set of literals. A literal can be variable or negation of a variable.

iii) A set of n distinct clauses: $C_1, C_2, ..., C_n$. Each clause must consist of 2 variables combined by just logical OR $(\vee)$.

The boolean value can take the bipolar value {1, -1}, which indicates the idea of TRUE and FALSE. 2SAT logic has a general formula as the following:

$$P_{2SAT} = \wedge_{i=1}^{n} C_i \tag{1}$$

where $\wedge$ is a logical AND connector and P_{2SAT} is the entire Boolean formula for 2SAT. C_i is a clausal form of DNF with 2 variables. The following form represents each clause in 2SAT:

$$C_i = \vee_{i=1}^{n} \left(x_i, y_i \right) \tag{2}$$

P_{2SAT} is the main point of this paper, considering that the focus of logic programming is to guarantee the logic program considers only two literals per a clause in every execution.

The main impetus for developing logic mining based on the two-dimensional decision-making system requires 2SAT as the optimal logical representation. The other variant of systematic SAT such as 3SAT is suitable for three-dimensional-based decision systems only. On the contrary, kSAT, a non-systematic variant of logic will not be compatible with mapping the data in two-dimensional decisions as well due to the variations of the logical structure.

2 Satisfiability in Hopfield Neural Network (HNN-2SAT)

The architecture of HNN consists of a set of neurons and an equivalent set of unit delays to form a multiple loop feedback system where each feedback loop corresponds to a neuron. In discrete HNN, the units use a bipolar output function where the states of the units are determined by whether the units' input exceeds their threshold. The bipolar units can take values of 1 or -1. The definition for each activated neuron is given as follows:

$$S_i = \begin{cases} 1, & \text{if } \sum_j W_{ij} S_j \geq \theta \\ -1, & \text{Otherwise} \end{cases} \tag{3}$$

where W_{ij} refers to the synaptic weight of the neuron from unit j to i . S_j is the state of the neuron j and θ is the predefined threshold value of HNN. The typically used connections are that the weights must be symmetric where $W_{ij} = W_{ji}$ since this type of connection will ensure that the energy function decreases monotonically while following the activations rules. Hence, the dynamic of HNN (considering all the neurons involved) will asynchronously change according to $S_i \rightarrow \mathrm{sgn}\left[h_i\left(t\right)\right]$, in which denotes the local field of the neuron connection. The equation to satisfy the local field computed by interconnected neurons in a combinatorial problem [10] is shown as the following:

$$h_i(t) = \sum_{j}^{N} W_{ij} S_j(t) + W_i \tag{4}$$

In order to follow the dynamical changes, the final state of neurons will be examined by using the Lyapunov energy function such that:

$$H_P = -\frac{1}{2}\sum_{i}^{N}\sum_{j}^{N} W_{ij} S_i S_j - \sum_{i}^{N} W_i S_i \qquad (5)$$

Note that, Equation (5) was presented to demonstrate the stability of the model which can lead the final state into a stable state [10]. The local minimum of the energy function is with respect to the energy of the stored patterns. In this context, the state in HNN will be updated until the Lyapunov energy function is minimized. Conjointly, each variable of P_{2SAT} will represent the attributes in the credit card datasets. The schematic diagram of P_{2SAT} in DHNN is presented in Figure 1.

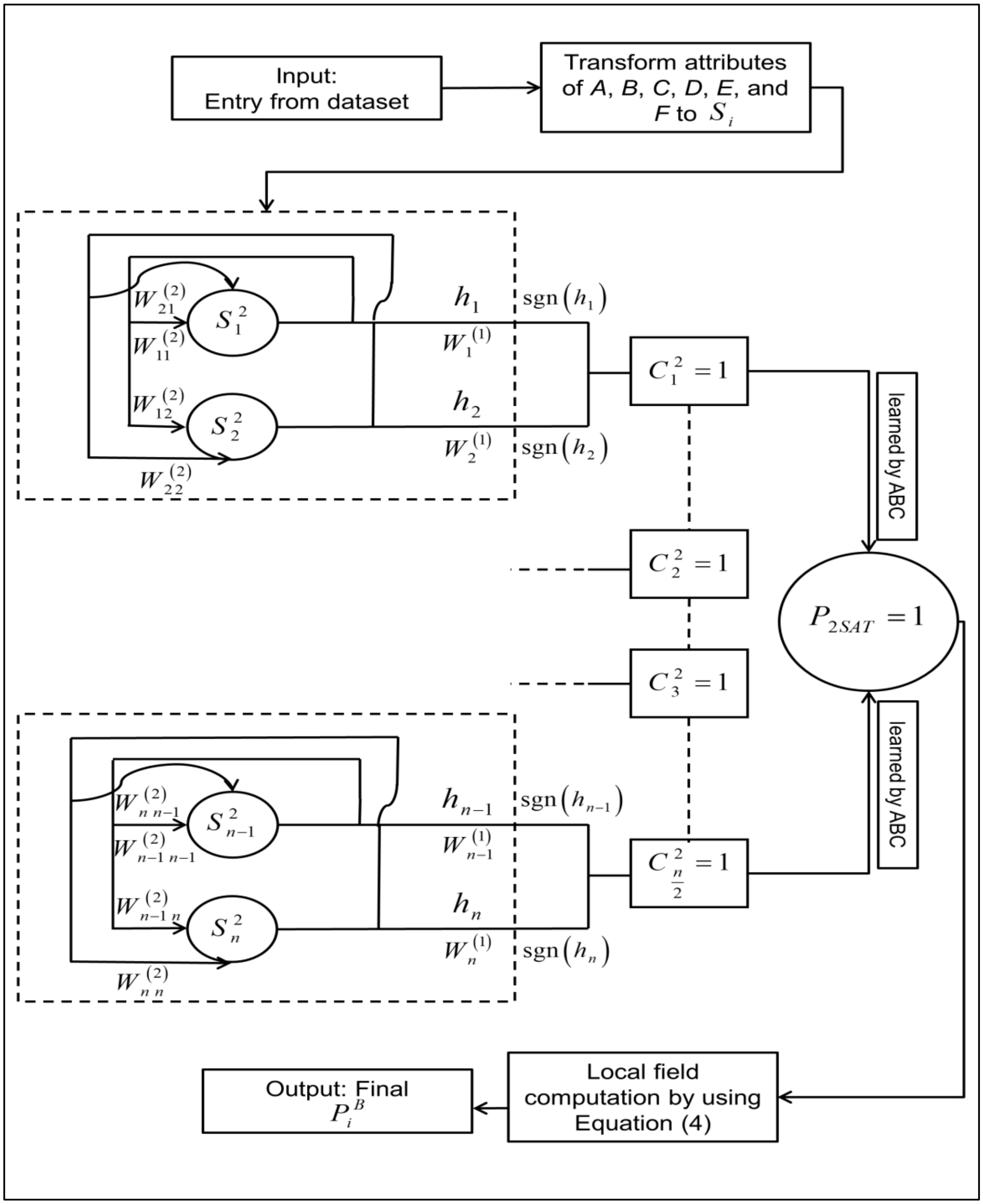

Figure 1. Schematic diagram of P_{2SAT} in HNN.

2 Satisfiability Based Reverse Analysis Method in Hopfield Neural Network (HNN-2SATRA)

The primary goal of integrating logic mining is to extract the behavior of the data set in terms of logical representation. A logic mining approach through 2SATRA has been proposed to effectively extract logical rules that map the attributes that contribute to the decision of a data set [18]. According to work, 2SATRA has proven to successfully extract logical rules of the risk factors of diabetes patients. In addition, another exciting work has successfully applied 2SATRA in extracting the appropriate winning strategies for the League of Legends game [11]. 2SATRA is defined as a logic mining tool that extracts useful logical rules from the data set using HNN-2SAT models. The attributes of the data set can be represented in terms of a 2SAT clause with bipolar representation {-1, 1}. In addition, 2SATRA will reveal the level of connectivity between 2 attributes in the data set by obtaining the corresponding synaptic weight through the WA method. Additionally, Wan Abdullah (WA) method will be employed by 2SATRA during the learning phase to establish the feasible synaptic weight between two attributes in each of the clauses. For instance, consider both attributes A and B where $S_A \in \{-1, 1\}$ and $S_B \in \{-1, 1\}$, the possible 2SAT clause with its corresponding synaptic weight is summarized in Table 1.

Table 1. Possible 2SAT logic with its corresponding Synaptic Weight in 2SATRA.

Synaptic Weight	$P_1 = A \vee B$	$P_2 = \neg A \vee B$	$P_3 = A \vee \neg B$	$P_4 = \neg A \vee \neg B$
W_A	0.25	-0.25	0.25	-0.25
W_B	0.25	0.25	0.25	-0.25
W_{AB}	-0.25	0.25	-0.25	-0.25

Table 1 manifests the possible synaptic weight in 2SATRA. Therefore, if the current neuron (attribute) A and B show -1 and 1 respectively, 2SATRA will select as a current clause representation of the data set. In this paper, 6 attributes chosen from default credit card client dataset will be considered. During the learning phase, the WA method will be implemented by 2SATRA to signify accurate synaptic weight between attributes. 2SATRA will analyze every 2SAT logic in the data set and choose the most frequent 2SAT logic, known as P_{best}. Then, P_{best} obtained from 2SATRA will be embedded in the learning phase of the proposed HNN-2SAT models which are HNN-2SATES and HNN-2SATABC. These models will be utilized to learn from P_{best}. Next, the HNN-2SAT model will restore the induced logic, P_i^B during the retrieval phase by retrieving the state of the neuron. The implementation of 2SATRA in extracting the default credit card data is summarized in Figure 2. In Figure 2, the implementation of 2SATRA starts the conversion of the learning and testing dataset into bipolar representation, followed by the initialization of synaptic weight. Then, P_{best} obtained from 2SATRA via the frequency of the learning data. From that, the optimal synaptic weight will be generated and stored in the CAM. In the learning phase, the proposed 2SATRA will yield the induced logic P_i^B based on the optimal final neuron states. Finally, the outcome of the induced logic, P_i^B will be compared with the P_{test}.

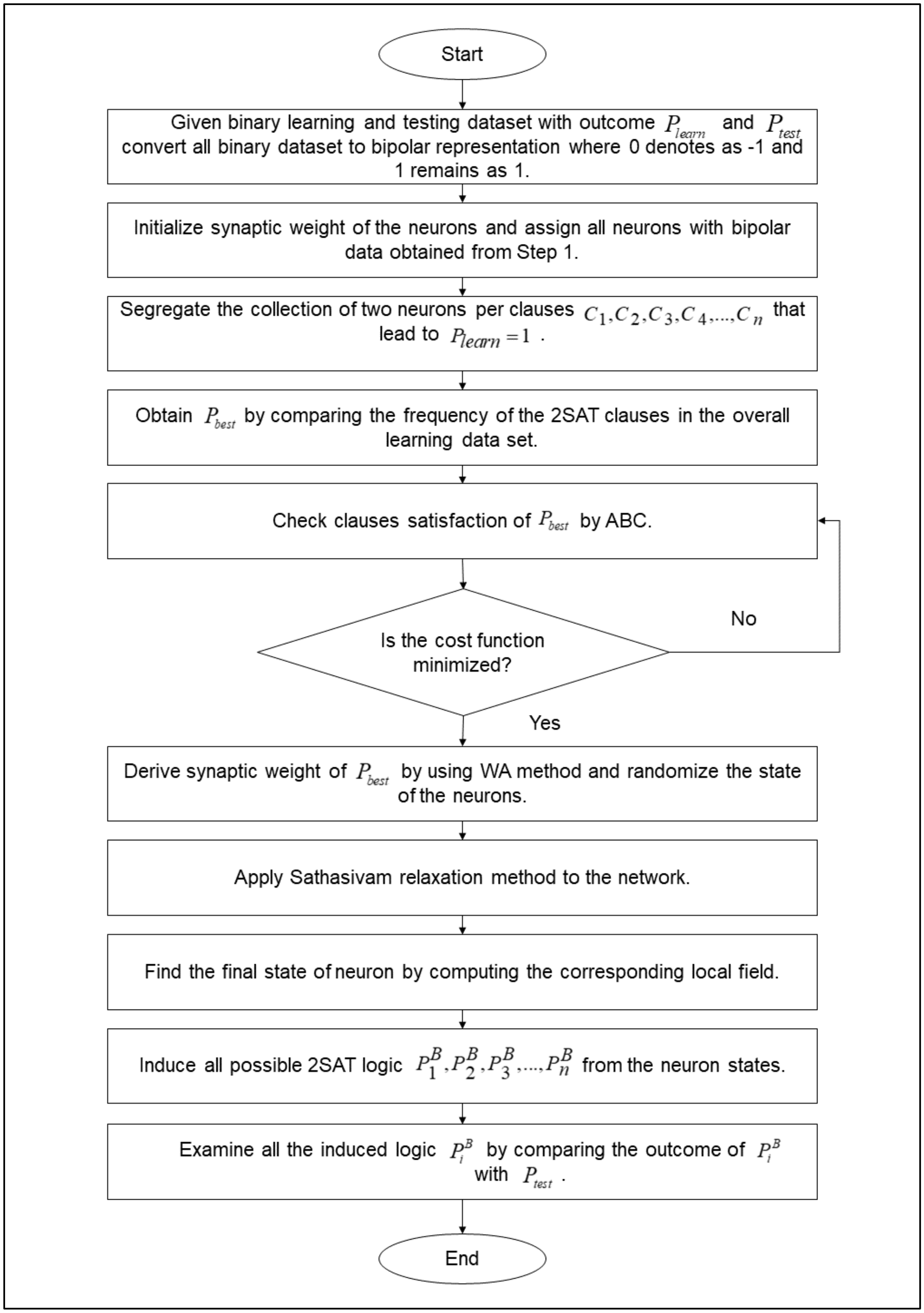

Figure 2. Implementation of 2SATRA in HNN-2SAT models.

Artificial Bee Colony (ABC)

One of the main issues in 2SATRA is the possibility of the method producing non-Satisfiable logic. In this context, an effective method is required to validate all the logical rules learned during the learning phase of HNN. The conventional method proposed by Sathasivam *et al*. [25] was considered ineffective because when the learning in HNN exceeds the threshold number of learning, the synaptic weight will be determined randomly. Thus, the induced logic obtained will not generalize the behavior of the dataset. The artificial bee colony (ABC) algorithm is a swarm-based meta-heuristic algorithm that has been found to optimize numerical problems [21]. Based on the work, this algorithm consists of three essential elements, namely, employed bees, onlooker bees, and scout bees. The solution for a problem is expressed by the food source for each bee in the colony. Employed bees and onlooker bees will hunt for rich food sources. These two elements are vital for self-organizing and collective intelligence. There is only one employed bee for each food source, which corresponds to a number of food sources around the hive. Employed bees allocate their food source information with the onlooker bees while remaining in the hive. In accordance with the information obtained from employed bees, the onlooker bees would decide on their food sources subjected to the probability values determined by using the fitness value given by the employed bees. The unemployed bees that randomly choose their food source are called scouts. The solution that cannot be improved by the employed bees through a pre-determined number of trials is referred to as a “limit”. Their solutions will be abandoned, and these employed bees will be transformed into scout bees that will randomly seek a new set of solutions that will prevent the algorithm from having local maxima (non-improving) solution. Since P_{2SAT} has a discrete structure, we utilize the hybrid ABC proposed by Jia *et al*. [20] where bitwise operator has been used to replace the continuous term in Karaboga [21]. Hence, ABC will be used to search the fittest assignment (highest satisfied clause) for any given P_{2SAT} clause during the learning phase of HNN. For this representation, only bipolar value {1, -1} had been considered where the conventional ABC was refined to develop binary solutions. The fittest assignment will produce the maximum number of satisfied clauses, which can be calculated as follows:

$$f_i(x) = c_1(x) + c_2(x) + c_3(x) + ... + c_{totalNC}(x) \tag{6}$$

where $c_1, c_2, c_3, ..., c_{totalNC}$ is the number of total satisfied clauses. The solution in a search space will be determined by the employed bees. The equation to obtain the food source can be evaluated as follows [23]:

$$v_{ij} = x_{ij} \vee \left(\phi_{ij} \otimes \left(x_{ij} \wedge x_{kj}\right)\right) \tag{7}$$

where $\otimes$ is the ‘XOR’ operator, $\wedge$ is the ‘AND’ operator and $\vee$ is the ‘OR’ operator. ϕ_{ij} is the parameter value where

$$\varphi_{ij} = \begin{cases} 1 \ \ , rand\left(0,1\right) \geq 0.5 \\ -1, rand\left(0,1\right) \geq 0.5 \end{cases} \tag{8}$$

The employed bees will dance once they return to their hive where at this point the transfer of information will occur. Note that, each employed bee has its fitness value which is analyzed based on the number of satisfied clauses. During the dancing, onlooker bees will observe the situation and make a decision of the information based on the probability of roulette wheel selection as follows [27]:

$$p_i = \frac{f_i}{\sum_{i=1}^{SN} f_i} \tag{9}$$

where $\sum_{i=1}^{SN} f_i$ is the total desired fitness and SN is the size of the bee group. Next, the onlooker bees will find the solution according to Equation (8). The optimum solution, which corresponds to the required fitness, is produced until the number of trials equals the limit. However, if the solution from the onlooker bee cannot be refined further, the onlooker bees will transform into scout bees. The scout bees will leave the search space if the solution cannot improve further. Finally, once the algorithm reaches the desired solution, the solution will exit from the algorithm and print as the final solution. Algorithm 1 demonstrates the proposed ABC during the learning phase of HNN for 2SATRA.

Algorithm 1 Proposed Artificial Colony (ABC)
Initialize N, SN, $g_{\max}$, trial limit, all bees X
for $g = 1$; $g \le g_{\max}$
Calculate the fitness for each bee X by using Equation (7);
Evaluate x_i and x_k ;
{Employed bee phase}
for $i \in \{1, 2, 3, \ldots, SN\}$
Produce a new food source v_i by using Equation (8);
Check the fitness of v_i by using Equation (7);
if $v_i > x_i$
$x_i = v_i$;
$trial_i = 0$;
else
$trial_i = trial_i + 1$;
end
Calculate the probability values p_i by using Equation (9);
{Onlooker bee phase}
Initialize $t = 0, i = 1$;
while $t < SN$
if $random < p_i$;
Produce a new food source v_i by using Equation (8);
if $v_i > x_i$
$x_i = v_i$;
$trial_i = 0$;
else
$trial_i = trial_i + 1$;
$BL_{success} = BL$;
end
$t = t + 1; t \le 100$ **;**
end
{Scout bee phase}
if $trial_i >$ limit
Reset x_i ;
end
Record the best fitness;
end
Return Output bee string with maximum $f = totalNC$

Default Credit Card Data Set

The data set has been provided to predict the probability of customers defaulting on their payments in Taiwan [28]. The data set was retrieved from the UCI Machine Learning Repository, which consists of 30 000 instances and six attributes [25]. The attributes can be categorized into clients' details (gender, age, marital status) and financial information (Monthly bill statements, repayment status, and amount paid). The response variable is the default payment. The detailed descriptions of attributes involved in this paper are shown in Table 2. These attributes will help predict the default credit card of a customer in the next month. The personal and financial information will inform the issuers of the credit behavior of the holders. In terms of personal information, these data might be helpful in evaluating new applicants. As for the financial statement, issuers can verify the credit ranking of the client based on the default record history and decide to issue the credit [1]. These two categories have strong relationships in predicting the default and choosing new applicants because if they only rely on personal information to issue new credit, this poses a high risk to the issuers since financial information is also essential to be considered. In comparison, the data set will be compared with the standard German Credit datasets [29]. Therefore, Table 3 shows the attributes of German Credit datasets [29]. By considering all the attributes in Table 2 and Table 3, the attributes associated with the neuron in 2SATRA were assigned based on Table 4.

Table 2. A detailed description of attributes for the Taiwan data set [25].

Name	Description
Sex	Gender (1 = male, 2 = female)
Marriage	Marital status (1 = married, 2 = single, 3 = divorce, 0 = others)
Age	Age (year)
Pay_0	Repayment status in September 2005. The measurement scale for the repayment status is: -1 = pay duly; 1 = payment delay for one month; 2 = payment delay for two months;…..; 8 = payment delay for eight months; 9 = payment delay for nine months and above.
Pay_6	Repayment status in April 2005
Bill_Amt1	Amount of bill statement (NT dollar) in September 2005
Bill_Amt2	Amount of bill statement (NT dollar) in August 2005
Bill_Amt6	Amount of bill statement (NT dollar) in April 2005
Pay_Amt1	Amount paid (NT dollar) in September 2005
Pay_Amt2	Amount paid (NT dollar) in August 2005

Table 3. A detailed description of attributes for the German Credit data set [26].

Name	Description
Savings	The amount of savings accounts/bonds of the customer.
Other debtors/guarantors	Measurement scale of the debtors/guarantors (1 = none, 2 = co-applicant, 3 = guarantors).
Property	Type of property (1 = Real estate, 2 = Building society savings agreement/Life insurance, 3 = Cars/Others, 4 = None).
Other installment plans	The existence of other installment plans (1-Bank, 2-Stores, 3-No).
Existing Credit	The number of existing credits in this bank.
Telephone	Registration of telephone number under customers name (1-None, 2-Yes).

Table 4. List of attributes for each data set [28-29].

Data Set			Details of each attribute	Output P_{2SAT}
Taiwan data set [28]	*A*	:	PAY_5	To classify repayment status in September 2005
	B	:	PAY_6	
	C	:	Bill_AMT1	
	D	:	Bill_AMT2	
	E	:	Default Payment Next Month	
	F	:	Age	
German Credit data set [29]	*A*	:	Savings accounts/bonds	To classify whether the debtor is a foreign worker or not.
	B	:	Other debtors/guarantors	
	C	:	Property	
	D	:	Other installments plans	
	E	:	Number of existing credits at this bank	
	F	:	Telephone	

Performance Evaluation Metrics

The performance of the proposed model in executing logic mining will implement several performance measures such as root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

Root Mean Square Error (RMSE)

RMSE is used to indicate the deviation between the observed value and the target value. This work has modified RMSE stated to imitate HNN models [30] which can be expressed as:

$$RMSE = \sum_{i=1}^{n} \sqrt{\frac{1}{n}(f_{NC} - f_i)^2} \tag{10}$$

Mean Absolute Error (MAE)

MAE could fix the negative trend in RMSE and be simpler compared to RMSE. MAE is commonly associated with the evaluation of the models performance since MAE derives from the consistent magnitude of each difference of $f_{NC} - f_i$ [31]. The equation of MAE is shown as the following:

$$MAE = \sum_{i=1}^{n} \frac{1}{n} \left| f_{NC} - f_i \right| \tag{11}$$

whereby the best HNN model should have the least value of MAE that will prompt the computation to approach the global solution.

Mean Absolute Percentage Error (MAPE)

MAPE showed accuracy in the percentage form of MAE and utilized the correlation of error between the current and global solutions [32]. The equation for MAPE can be expressed as the following:

$$MAPE = \sum_{i=1}^{n} \frac{100}{n} \frac{\left| f_{NC} - f_i \right|}{\left| f_i \right|} \tag{12}$$

However, MAPE is useless if there are zero values for a current solution because it will cause zero division. The lowest percentage of MAPE indicates the best HNN model.

Accuracy

Accuracy will be used to show the precise solutions obtained by the network based on the success of the solutions and the ability of the model to train data set. In this study, the accuracy will portray the successful solutions achieved from the generated induced logic for data set. The equation for accuracy is shown as follows [11]:

$$Accuracy = \frac{Success\_P_{induced}}{Total\_P_{test}} \times 100\% \quad (13)$$

where $P_{induced}$ denotes as induced logic and P_{test}.

The global minima ratio is not included as the work utilized a lower number of neurons. Thus, the differences between the global minima ratio will not be significant due to the less computational burden of the proposed algorithms. Following that, the Hamming Distance is not considered as the formula cannot be modified or mapped with the component of the confusion matrix. Apart from that, the Hamming distance is typically utilized in assessing the similarity of the bipolar structure based on the logical representation. The CPU time is a non-plausible metric due to the lower number of neurons employed and the possibility of bias according to the performance of the computer used during the simulation.

Experimental Setup

The data set used for simulation purposes was retrieved from the UCI machine learning repository. The data set will be divided into two parts (learning and testing), with 60% of the data set will be considered for learning, and the remaining 40% will be considered for testing [33]. The ratio of learning and testing follows the settings of several essential works proposed by Kho *et al*. [11], Alway *et al*. [12] and Jamaluddin *et al*. [13]. In this context, more percentage of testing data will validate the effectiveness of the proposed 2SATRA method in extracting the credit information. To compare with the existing method, we will compare the proposed method with the conventional method proposed by Sathasivam *et al*. [34]. The Exhaustive Search (HNN-2SATES) was implemented in HNN to minimize the cost function associated with the learned logical rule. This comparison is considered critical because HNN-2SATES is a benchmark method representing several logic mining studies [11-13]. Both proposed HNN-2SAT models will be performed in Dev C++ Version 5.11 in Windows 10 Intel Core i7,2.6 GHz processor with 4GB RAM. The implementation code can be found at bit.ly/creditsim2021. The threshold for simulation was set to 24 hours, and any output that exceeds the threshold time will be omitted. Table 5 and Table 6 revealed the list of parameters in HNN for ES and ABC, respectively. Figure 3-7 illustrates the performance of 2SATRA in HNN-2SAT models.

Table 5. List of parameters in HNN-2SATES [11]

Parameter	Parameter Value
Neuron Combination	100
Tolerance Value (Tol)	0.001
Number of Trials	100
Number of Learning (%)	60 [33]
Number of Testing (%)	40 [33]
Activation Function	Hyperbolic Activation Function (HTAF) [25]

Table 6. List of parameters in HNN-2SATABC

Parameter	Parameter Value
Neuron Combination	100
Tolerance Value (Tol)	0.001
Number of Trials	100
Number of Learning (%)	60 [33]
Number of Testing (%)	40 [33]
Employed bees	50 [24]
Onlooker bees	50 [24]
Scout bees	1 [24]
Maximum number of generations	10
Activation Function	Hyperbolic Activation Function (HTAF) [25]

Results and Discussion

The performance of all HNN-2SAT models will be discussed in this section. The result will be divided into two independent simulations. First, the proposed HNN-2SAT model with 2SATRA will be used to extract induced logic that classifies loan repayment after considering the default payment status. The repayment status was chosen as an aim for this status. Second, the proposed HNN-2SAT model with 2SATRA will be used to extract induced logic that classifies the amount paid in the given month. Note that, 2SATRA will provide the outcome in the form of bipolar representation (1 indicates the amount that is above the mean, and -1 represents the amount that is below the mean). Five performance metrics of performance evaluation were analyzed to verify the efficiency and stability of the HNN-2SAT model in doing 2SATRA. In terms of efficiency evaluation, the performance of HNN-2SATABC and HNN-2SATES are represented by analyzing the results obtained for root mean square error (RMSE), mean square error (MAE), and mean absolute percentage error (MAPE) in HNN-2SAT model. A different number of clauses are used to simulate the real data sets.

Simulation of Taiwan Data Set (P_1)

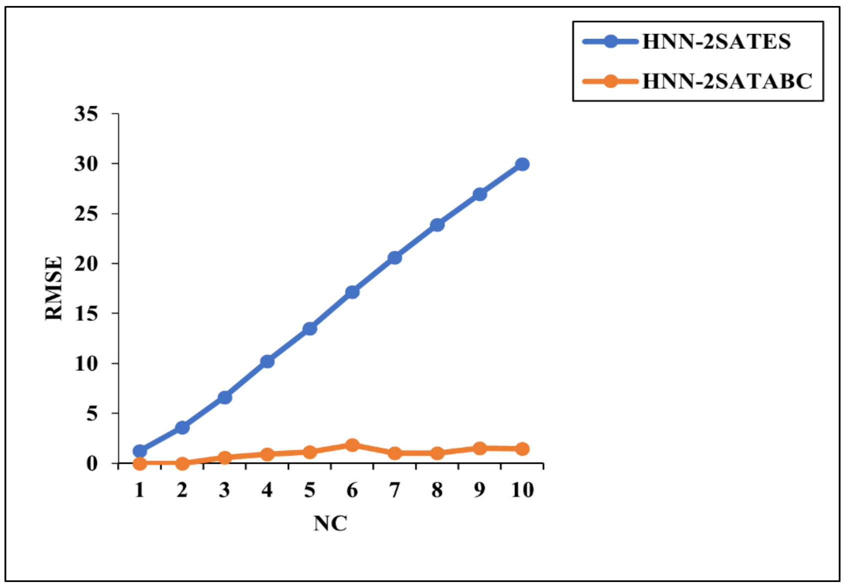

Figure 3. RMSE for both HNN-2SAT models for P_1.

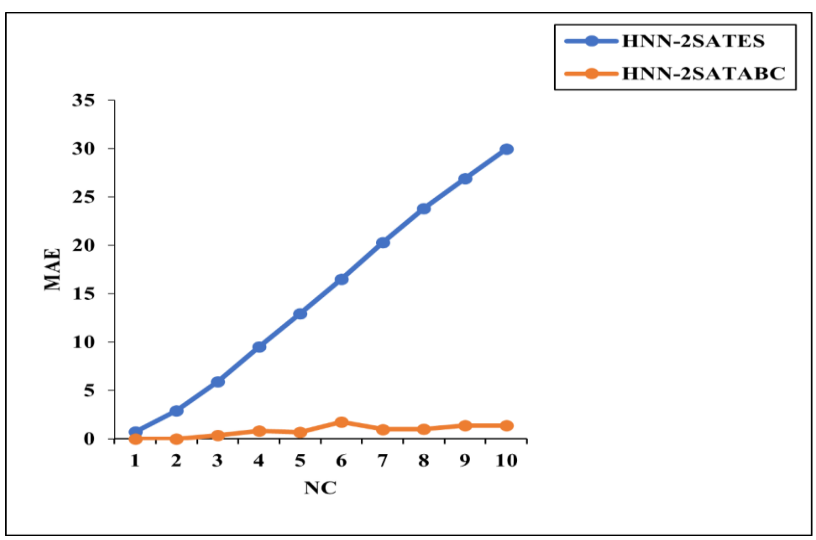

Figure 4. MAE for both HNN-2SAT models for P_1.

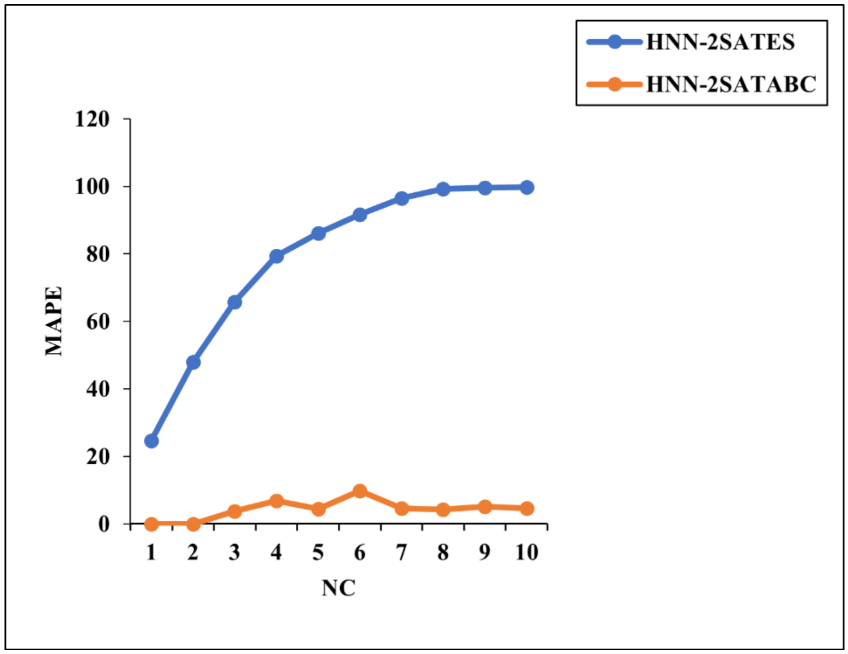

Figure 5. MAPE for both HNN-2SAT models for P_1.

Simulation has been done by implementing various values of NC where a single NC consists of two neurons (NN). In this paper, the value of NC ranges from 1 to 10 to increase the solution diversity. Based on the result obtained, when NC = 9, HNN-2SATES shows a higher RMSE value than HNN-2SATABC. For the case of HNN-2SATES, no results were obtained when NC = 10 (NN = 60), given that this learning model exceeded the threshold CPU time. HNN-2SATABC has reported fewer errors, indicating that the proposed model is more efficient in classifying the outcome of the dataset. Based on Figure 3, HNN-2SATES shows a significant growth trend as the number of clauses increases compared to HNN-2SATABC. This is due to the nature of ES operations that utilize the "generate and test" method to minimize the value of the cost function. A similar trend was shown for MAE in Figure 4, where HNN-2SATES reported higher MAE than HNN-2SATABC. This shows HNN-2SATES is very prone to error, and the linear increase in NC will lead to an exponential increase in error accumulation. On the other hand, HNN-2SATABC utilizes three optimization layers to ensure the possible error can be eliminated before the algorithm arrives at the next iteration. The roulette wheel selection employed by Employed bees and Onlooker bees increases the chance for ABC to locate zero cost function because only high fitness bees are allowed to iterate to the next stage. The optimal balance between exploration and exploitation reduces the chances for optimization via scout bees to occur. Hence, the value of MAPE in HNN-2SATABC portrayed in Figure 5 is significantly lower than in HNN-2SATES. On the other hand, the generate and test employed by HNN-2SATES does not leverage the fitness of the previous string. Thus, the percentage of the unsatisfied clause will be higher than the number of iterations increases. This trend agrees well with the simulation result reported in Sathasivam *et al*. [22] where the number of unsatisfied clauses grows exponentially as the number of clauses increases. This prompts the increase of computational time to satisfy the interpretation. HNN-2SATABC was reported to be more efficient in completing the learning phase of HNN. This is due to a smaller number of iterations required by both employed and onlooker bees to complete the learning phase. Employed bees capitalize RWS in transferring high fitness interpretation to the Onlooker bees reducing the overall computational time. The bitwise operator proposed by Jia *et al*. [20] was observed to be effective in transferring the optimal information that leads to the minimized cost function. Thus, the solution produced by HNN-2SATABC is optimal and faster than the state-of-the-art HNN-2SATES. This study will not consider the final energy obtained in Equation (5) because all the neurons obtained by Equation (4) will be considered. According to the simulation, the best induced logic is given as follows:

$$P_1^{induced} = (A \vee B) \wedge (C \vee \neg D) \wedge (E \vee F) \tag{16}$$

Equation (16) signifies the induced logic that explains the customer's behavior in a given set of attributes. The definition of each attribute can be explained in Table 4. According to Equation (16), $P_1^{induced}$ (the default payment for next month) is greatly affected by the gender of the customer. In other words, if the customer is below the mean age and has paid a lower amount than dues during August and September, they have a higher chance of defaulting on their payment. In this case, the financial institution can strategize its policy to follow up with the customer before the payment defaults. Equation (16) has an accuracy of 92.25%, which is considered acceptable because the number of features used is much lower than the conventional data mining.

Simulation of German Credit Data Set (P_2)

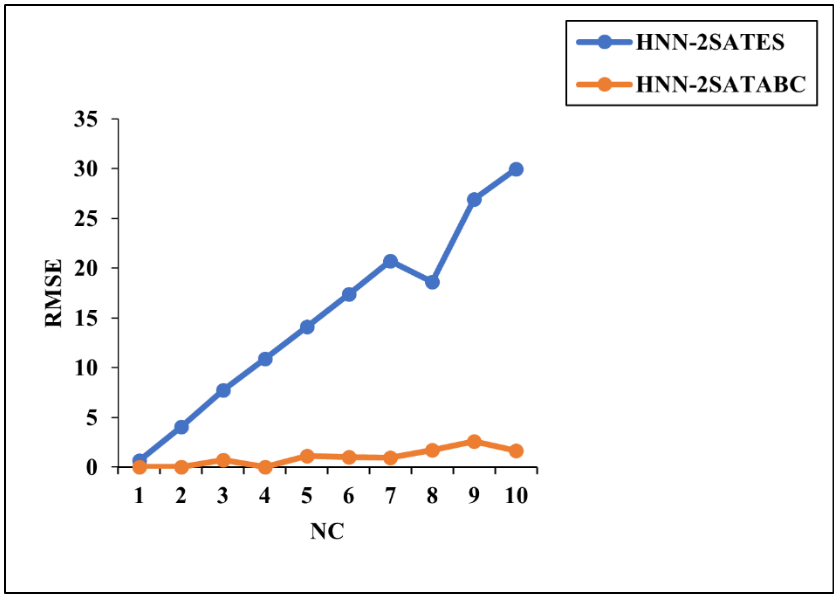

Figure 6. RMSE for both HNN-2SAT models for P_2.

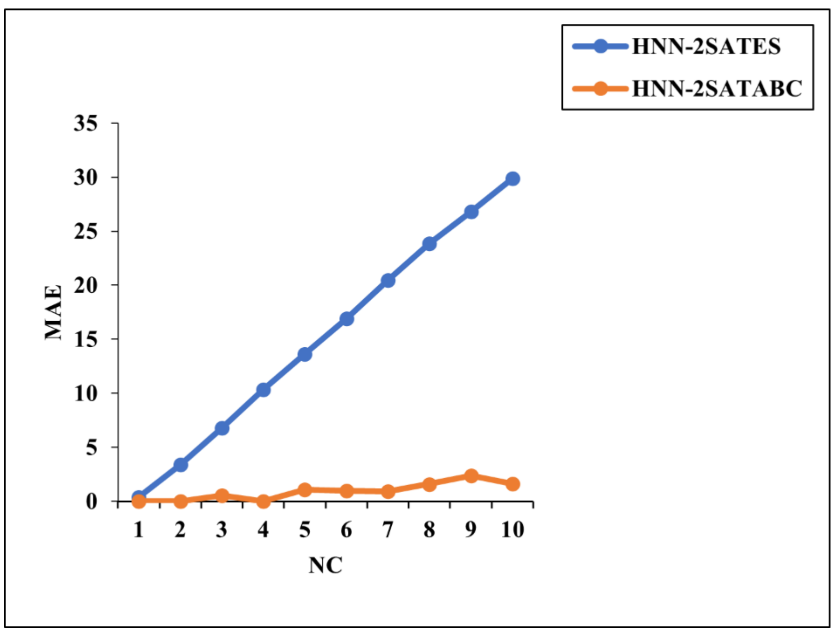

Figure 7. MAE for both HNN-2SAT models for P_2.

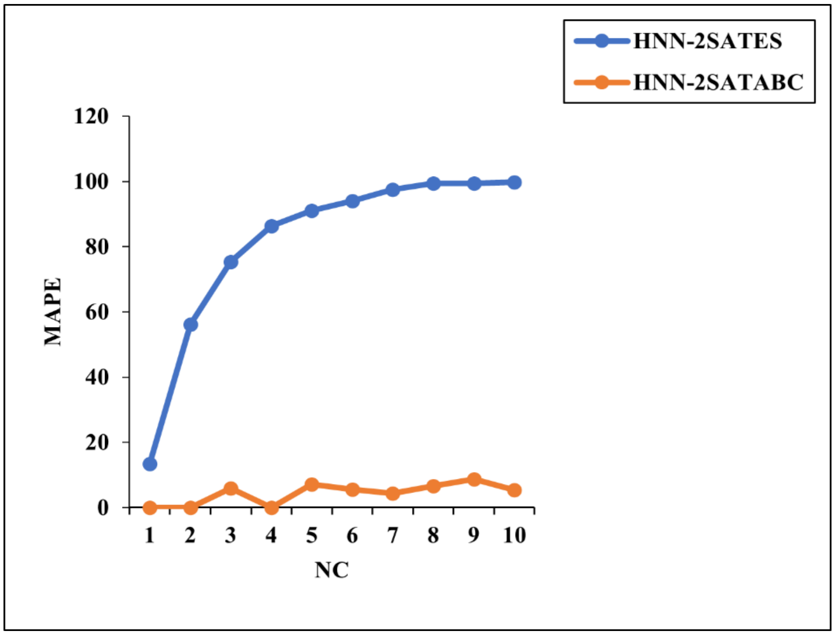

Figure 8. MAPE for both HNN-2SAT model for P_2 .

In comparison with the result analysis of the first simulation, HNN-2SATABC outperformed the conventional method in terms of performance metrics. According to Figure 6, the RMSE value for HNN-2SAT models increases as the number of clause increase. Interestingly, HNN-2SATABC constantly achieved zero RMSE values as the number of clauses increased up to NC = 2. This shows the learning phase of HNN can be completed in a single iteration. This behavior can be observed for all values of MAE and MAPE in Figure 7-8. The interaction among Employed bees using Equation (7) increase the potential solution space, which leads to the minimized cost function. This interaction reduces the distance between the desired fitness and the current fitness of the neurons. If the interaction does not achieve optimal fitness, the interaction via RWS in Equation (9) will improve more fit solutions while exploring other fit solutions. In this case, the value of MAPE will reduce significantly because the process ends at the scout bee phase. In other words, HNN-2SATABC was reported to learn P_{best} effectively and verify the satisfiability of P_{best} with a lower error value. However, during the learning phase, HNN-2SATES shows rapid growth for RMSE, MAE, SSE, and MAPE. This implied that the percentage of the satisfied clause in HNN-2SATABC is higher than the overall 2SAT clause during the learning phase, representing all correct clauses. To summarize, the lack of performance for HNN-2SATES is due to (i) Ineffective solution improvement in every solution iteration. (ii) Lack of solution diversity because the solution tends to oscillate until the cost function is minimized. (iii) Lack of stability as the number of CN increases. Therefore more iteration is required, which results in higher errors. The accuracy obtained from the second simulation was slightly higher compared to the P_1 . The best induced logic generated from the simulation by HNN-2SATABC with 92.25% accuracy is shown in Equation (17) as follows:

$$P_2^{induced} = (E \vee C) \wedge (D \vee A) \wedge (F \vee B) \tag{17}$$

According to Equation (17), the induced logic reflects the customer behavior among the foreign worker based on a set of attributes. Detailed information on the attributes can be found in Table 4, and based on $P_2^{induced}$ (the status of the debtors, whether foreign or local workers) it is significantly affected by all six attributes of German credit data. Thus, the debtor's behavior can be explained in terms of savings amount, other debtors/guarantors, type of property, other installment plans, registered telephone number, and the number of existing credits in that bank. Based on the analysis, the foreign workers have a lower saving amount, no record as other debtors/guarantors, specific property, the existence of other installments plan from other banks, and fewer existing credit records in this bank. Hence, it was found that most of the foreign workers do not have telephone numbers registered under their own names. This measure is essential in assessing the credit risk behavior among foreign workers because a customer's default will damage the bank's profit. Conventional data mining only extracts the surface information that classifies whether a particular customer refers to a foreign or local worker. On the contrary, 2SATRA incorporated with HNN-2SATABC can produce behavioral rules in the form of induced logic, which helps the banker to classify and strategize. Theoretically, the proposed model is reported to give a competitive result where the induced logic in Equation (17) achieved 82.3% compared to the well-established method.

The memetic evolutionary algorithm proposed by Yang *et al*. [35] achieved an accuracy of 87.45% for a similar dataset. This is because: (1) The proposed method utilizes 24 attributes, whereas 2SATRA only uses six attributes but still maintains a high accuracy value. (2) The amount of testing data is significantly small. In this context, only 20% of the data was used as testing data. Hence, comparatively speaking, the accuracy value of the 2SATRA will be lower. (3) Intensive parameter tuning is involved in increasing the classifier's effectiveness. The intensive parameter tuning means more effort is required to optimize the classification if the algorithm with more free parameters is deployed in 2SATRA. Interestingly, the proposed method adopts an intelligent tune-up strategy to reduce the potential validation loss during classification [35]. On the contrary, 2SATRA incorporated with HNN-2SATABC has limited parameters, and there is no need to optimize the assigned parameters.

In summary, our proposed HNN-2SATABC consistently outperforms the conventional method in doing 2SATRA for both simulations. HNN-2SATABC increases the effectiveness of HNN during the learning phase by reducing the iteration error within a shorter period. This view agrees well with all the performance metrics in both simulations. According to the experiment, the optimized 2SATRA is reported to produce optimal induced logic that explains the customer's credit behavior.

Comparison with the existing work

In this section, the performance of the proposed 2SATRA will be tested with the state of the art logic mining models. The state of the art logic mining was chosen based on the type of logic and the feature selection. In this context, logic mining that has a higher order k and different feature selection methods will be disregarded from the comparison. For instance, the proposed 3SATRA proposed by Zamri *et al*. [18] will not be considered due to different k values, which forces logic mining to consider more than six attributes. As for feature selection, supervised learning proposed by [16, 36] will not be considered because this paper only tests the effectiveness of the learning phase of logic mining. Thus, the performance of the HNN-2SATABC will be evaluated based on the Accuracy, Sensitivity and Precision

Energy based logic mining (E2SATRA) was proposed by Jamaludin *et al*. [13], which capitalizes energy analysis during the retrieval phase of the HNN. E2SATRA uses 2SAT as a logical rule to govern the state of the neuron in DHNN. In this model, the final neuron state that achieves a suboptimal energy function will not be considered. According to the study, the suboptimal neuron state will lead to suboptimal induced logic, which reduces the interpretability of the final induced logic.

The reverse Analysis method (RA) was proposed by Sathasivam and Abdullah [10] to extract multiple induced logic from the datasets. Since the value of k in the work can be various, we only implement $k=2$ that exhibit the behavior of the HORNSAT. In other words, the induced logic that is non-HORN will be disregarded during the retrieval phase. Similar to conventional 2SATRA, the RA will utilize ES during the learning phase of the DHNN.

Table 7. The performance of the proposed work in comparison with other existing logic mining methods. The bracket indicates the ratio of improvement and a negative ratio implies the existing method outperforms the proposed method

Taiwan data set [31]			
Model	Accuracy	Sensitivity	Precision
HNN-2SATABC	0.9225	0.9660	0.9535
E2SATRA	0.6725 (0.3717)	0.9604 (0.0058)	0.6899 (0.38208)
RA	0.3925 (1.3503)	0.9615 (0.00468)	0.3876 (1.4600)
+/=/-	2/0/0	2/0/0	2/0/0
German Credit data set [31]			
HNN-2SATABC	0.8230	0.9041	0.8384
E2SATRA	0.8063 (0.0207)	0.8938 (0.0122)	0.8237 (0.0178)
RA	0.6914 (0.1903)	0.7081 (0.2768)	0.9585 (-0.1432)
+/=/-	2/0/0	2/0/0	1/0/1

Based on Table 7, our proposed logic mining (HNN-2SATABC) was reported to outperform all the existing logic mining in almost all performance metrics in the confusion matrix. In terms of all performance metrics, 2SATRA-ABC was observed to produce the highest value of True Positive and True Negative during the retrieval phase. The result demonstrates the effectiveness of the induced logic in 2SATRA-ABC to classify the correct outcome for both datasets. On the other hand, E2SATRA suffers a severe limitation because the induced logic's search space was dramatically reduced. In this context, the induced logic tends to overfit, which reduces the number of unique induced logic during the retrieval phase of the HNN. This study also demonstrates that the optimality of the E2SATRA is specific to a certain field only and tends to overfit, especially when processing financial datasets. In another development, RA proposed by [10] was reported to obtain the worst result in all performance metrics. This is due to the rigid structure of HORNSAT, which cannot represent the datasets' behavior. Although HORNSAT is satisfiable in nature [38], this logic failed to represent the real life problem. This cause the proposed DHNN to obtain suboptimal synaptic weight, which leads to the suboptimal local field. This result has been confirmed by the work of Kasihmuddin *et al*. [16], where RA failed to obtain optimal induced logic to classify the outcome of the datasets. Overall, 2SATRA-ABC was reported to be an optimal logic mining method in extracting the best induced logic for credit datasets. Therefore, using the proposed logic mining, the credit industry can explore the possible outcome before making any critical financial decision.

Conclusions

Effective credit scoring mechanism has benefited financial institution and consumer. The current study on credit scoring heavily emphasizes the black box model, where the only information that matters is the final output. The main issue with this approach is that we fail to see the explicit relationship between the attribute that leads to the final outcome. To extract an explicit symbolic system, 2SATRA has been introduced by incorporating it into HNN. The conventional 2SATRA is prone to learning errors. This paper therefore proposes Swarm Based Metaheuristics algorithm, namely ABC to minimize the cost function during the learning phase of the HNN. The proposed ABC capitalize on the intelligent behavior of the employed and onlooker bees, which act as the verification phase of the logical rule learned in the HNN-2SAT model. Experimental findings show that HNN-2SATABC can optimize HNN's learning phase, which leads to optimal induced logic. The experiment revealed that: (i) Our proposed HNN-2SATABC outperforms the existing method in terms of performance error. The solution obtained from HNN-2SATABC has a higher fitness compared to the state of the art algorithm. (ii) The proposed HNN-2SATABC helps 2SATRA extract optimal induced logic that only utilizes a minimum number of attributes with no additional parameter tuning. (iii) The obtained induced logic shows the relationship of the attributes that leads to two distinctive outcomes: default payment and the payment amount. Thus, the logical rule explains the outcome with respect to the set of attributes defined by the user, which will inform the industrial players and the customers. The accuracy of the induced logic was reported to be competitive compared to conventional data mining. Our future research direction is to take into account multi objective function that leads to the outcome. In this case, the proposed HNN-2SATABC need to consider other fitness function, such as solution diversification which increase the potential search space of HNN-2SATABC. In addition, the work can be extended by using the different optimal logical structures of Weighted Random 2 Satisfiability (r2SAT) [38], PRO2SAT [39], YRAN2SAT [40], Major 2 Satisfiability (MAJ2SAT) [41], Random 3 Satisfiability (RAN3SAT) [42], and GRAN3SAT [43].

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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