The XGBoost Approach Tuned by TLB Metaheuristics for Fraud Detection

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Abstract. The recent pandemic had a major impact on online transactions. With this trend, credit card fraud increased. For the solution to this problem the authors explore existing solutions and propose an optimized solution. The solution is based on an extreme gradient boosting algorithm (XGBoost) and a teaching-learning-based-optimization algorithm. The dataset optimizes the hyperparameters of the XGBoost which is utilized as the main driver for the solution. The evaluation was performed among other similar techniques that have solved this problem successfully in the past. Standard performance metrics were applied which are accuracy, recall, precision, Matthews correlation coefficient, and area under the curve. The result of this research presents a dominant solution that was proposed and successfully outperformed all other compared solutions overall.

Keywords: fraud detection · swarm intelligence · metaheuristics · optimization · teaching-learning-based-optimization lgorithm

1 Introduction

E-commerce as well as online transactions have flourished during the COVID-19 global pandemic. On the other hand, most industries that do not rely on internet shopping suffered during the pandemic and hence have turned to e-commerce to mitigate the newly emerged situation [1]. This market has been expanding rapidly before the pandemic, but not as much. Furthermore, this trend is still on the rise even though the pandemic is on its decline. These predictions are also in the higher margins for credit card fraud, as the projections look grim for the future. The criminal attack of stealing one's credentials is considered a fraud of identity theft. The perpetrator requires private information on the user obtained by malicious attempts. It is only logical that as the usage of credit cards is on the rise for an extensive period of time, the crimes related to this subject also rise. Therefore, a security system that can detect and prevent such attempts is paramount.

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This research introduces a hybrid security system based on extreme gradient boosting (XGBoost) that is capable of detecting malicious activity with transactions performed by credit cards. The method was tested on a public dataset that is built from real-world data of credit card transactions in Europe. To handle the dataset's high imbalance, a swarm intelligence algorithm was implemented called teaching-learning-based-optimization algorithm (TLB) [52]. Other machine learning approaches utilized for comparison in this research are random forest (RF), decision tree (DT), extra tree (ET), support vector machine (SVM), and logistic regression (LR). Every approach was tested independently for the sake of classification and convincingness quality.

Furthermore, the TLB application for controlling highly imbalanced dataset is explored as a possibility. TLB algorithm has been applied for hyperparameter optimization of XGBoost. The experimental setup has been applied as in [33] for the establishment of grounds for comparison. Additionally, the metrics for comparison that were calculated are the precision, accuracy, recall, Matthews correlation coefficient (MCC), and the area under the curve (AUC).

The most notable contributions of this work follow:

– Fraudulent credit card transaction scalable detection framework.
– Extreme gradient boosting hyperparameter optimization by teaching-learning-based-optimization algorithm.
– The increase of performance on the subject dataset with combined XGBoost and TLB techniques followed by a comparative analysis utilizing the following metrics: accuracy, precision, recall, AUC, and MCC.
– The confirmation of effectiveness of the proposed framework through testing on an extremely imbalanced dataset.

The manuscript is organized in the following way: Sect. 2 discusses recent advancements in the field and machine learning application to the problem. Section 3 focuses on the TLB metaheuristics. Section 4 describes the configuration of experiments, the suggested framework implementation on the dataset, as well as the results through comparative analysis. The final Sect. 5 brings this paper to an end.

2 Literature Review and Background

The structure for machine learning model building for credit card fraud detection is available in the work of Tanouz et al. [60]. The European cardholders dataset was utilized for the determination of the chosen methods' performance. The set imbalance was tackled by the implementation of an under-sampling approach. The main measure of performance was the accuracy and random forest and logistic regression were examined. This has resulted in a 95.16% accuracy of the logistic regression, while the efficiency of the random forest came slightly behind with 91.24%. Additionally, the adequacy of the method's performance was measured by a confusion matrix regarding the negative and positive classes.

Propositions of a hybrid method between Adaboost and majority voting are made by Randhawa et al. [51]. The dataset also included information from Europe and besides Adaboost the method utilized different machine learning approaches, like support vector machines. Key measurements of performance were accuracy and Matthew's correlation coefficient. The results of the proposed method were 0.044 for MCC and 99.959% for accuracy.

Parallel investigation of machine learning approaches for the problems of fraudulent activity detection with credit cards was performed by Rajora et al. [50] on the European cardholders dataset. Noteworthy utilized methods from the work are k-nearest neighbors (kNN) and random forest (RF). The performance was measured by accuracy and area under the curve. The conclusion was that the kNN obtained 93.2% accuracy and AUC of 0.93, while the RF obtained 94.9% accuracy and AUC of 0.94. The imbalance of the dataset was not explored in this work.

The dataset used in this research has been put together by a collection of European cardholders' September 2013 transactions. The dataset is available openly on Kaggle. The dataset characteristics include 30 attributes alongside time and amount for 284807 transactions. Valid transactions include 99.828% of the dataset, while the 0.172% are false.

2.1 Extreme Gradient Boosting Algorithm

Regularization terms and second-order derivatives are utilized by XGBoost and introduced to the model of the random forest. The mentioned modifications have been performed due to performance-wise improvements. Consequentially, the XGBoost is an algorithm utilized for the solution of highly complex problems. The objective function optimization is performed by an additive training method of XGBoost. Optimization of each step is performed by considering the previous step's outcome. XGboost t-th objective function equation:

$$F_o{}^i = \sum_{k=1}^{n} l\left(y_k, \hat{y}_k^{i-1} + f_i\left(x_k\right)\right) + R(f_i) + const \tag{1}$$

where the term loss of the t-th round is represented as l, the constants term as $const$, and regularization term R calculated by Eq. (2).

$$R(f_i) = \gamma T_i + \frac{\lambda}{2} \sum_{j=1}^{T} w_j^2 \tag{2}$$

where the increase in customization parameters γ and λ has a positive influence on the tree's simplicity.

The overfitting is addressed by the second-order Taylor expansion application to Eq. (1):

$$obj^{(t)} = \sum_{i=1}^{n} [l(y_i, \hat{y}_i^{t-1}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t) + const \tag{3}$$

The first and second derivatives g and h are given:

$$g_j = \partial_{\hat{y}_k^{i-1}} l\left(y_j, \hat{y}_k^{i-1}\right) \tag{4}$$

$$h_j = \partial^2_{\hat{y}_k^{i-1}} l\left(y_j, \hat{y}_k^{i-1}\right) \tag{5}$$

The Eq. (3 is a combination of Eq. 2, Eq. 4 and Eq. 5 which form the next equations:

$$w_j^* = -\frac{\sum g_t}{\sum h_t + \lambda} \tag{6}$$

$$F_o{}^* = -\frac{1}{2}\sum_{j=1}^{T} \frac{(\sum g)^2}{\sum h + \lambda} + \gamma T \tag{7}$$

where the loss function score is denoted as $F_o{}^*$, while the solution of weights is w_j^*.

2.2 Metaheuristics Optimization

The algorithms from the field of swarm intelligence (SI) are nature inspired by the collective behavior of animals. This translates well to algorithms that have proven excellent optimizers for NP-hard problems. The potential for hybridization should never be overlooked with these solutions as they further push their final potential with said process. The standard swarm algorithms are particle swarm optimization (PSO) [48], ABC [37], elephant herding optimization (EHO) [61], firefly algorithm (FA) [64], and whale optimization algorithm (WOA) [47]. Some of the more novel algorithms are and harris hawk optimization (HHO) [32], salp swarm algorithm (SSA) [40], grasshopper optimization algorithm (GOA) [43], and monarch butterfly optimization (MBO) [62].

Phenomena like mutation, crossover, selection, and reproduction that are observable principles of evolution are applied with evolutionary algorithms (EA). The paradigms for evolutionary calculation are genetic programming, evolutionary strategies, genetic algorithms, and evolutionary programming.

On the other hand, artificial immune systems (AIS) are applied in theoretical immunology and have some similarities to the EA. Antibodies are considered candidate solutions, and their growth depends on the cloning, mutation, and selection operators. The memory cells store good solutions and antigens serve as an objective function. Most of the AIS-based metaheuristics rely on the basis of clonal selection alike clonal selection algorithm [31], B-Cell algorithm, and artificial immune network [30] used for optimizing (opt-AINET) [28], and negative selection algorithms.

As the diversity of metaheuristic algorithms rises, many different phenomena have been exploited and the social behaviors were not skipped. Principles like teaching and followers for the said teacher otherwise regarded as the learners (e.g. TLB), and social networks [59] are exploited in this sub-field. The main inspiration for these algorithms are social interactions. These can be very complex and once more the principles translate well to algorithms that are capable of NP-hard solving.

The informatics field has benefited from the all of the above algorithm types as the improvements to real-world problems can be seen in practice some of which are: medical diagnosis applications [16,22,26,36,49,58], wireless sensor network optimizations [6,11,14,55,67,77], stock price predictions [18], as well as intrusion detection [2,34,45,65,66,70,74,76] and plant classifying task [19], cloud computing scheduling, edge and fog computing [4,7,17,25,54,69], feature selection [10,21,24,35,38,56,71], dropout regularization [13], COVID-19 detection and fake news detection [27,68,72,73,75], tuning artificial neural networks [5,8,9,12,15,20,53,57], text clustering [23], cryptocurrency price prediction as well [46], and list goes on.

3 Teaching-Learning-Based-Optimization Algorithm

The TLB is split into two learning phases which are the teacher and the learner phase. For the duration G population P_G is described as $P_G = [X_{1,G}, X_{2,G}, ..., X_{N_p,G}]$. The N_p shows the size of the population, while the vector of the i-th individual is $X_{i,G}$. Every $X_{i,G}(i = 1, 2, ..., N_p)$ vector possess dimensions D of subjects that are defined by $X_{i,G} = [x_{1i,G}, x_{2i,G}, ..., x_{D_i,G}]^T$.

During the teacher phase, the individual with the best fitness is chosen for the teacher $X_{t,G}$ for the current generation G. According to the teacher phase law, all individuals learn from the teacher which is represented as a vector as $V_{i,G} = [v_{1i,G}, v_{2i,G}, ..., v_{Di,G}]^T$ calculated by the following equation:

$$V_{i,G} = X_{i,G} + r_i(X_{t,G} - T_F M_G) \tag{8}$$

where the mean vector of all individuals is represented as $i = 1, 2, ..., N_p$ and M_G, $r_i \in (0, 1)$ represents a random value, while the learning weight is $T_F = round[1 + rand(0, 1)2 - 1]$. The generation G increases by one upon completion of the teacher phase and P_{G+1} population gets formed with new individuals $X_{i,G+1}(i = 1, 2, ..., N_p)$. The evaluation of the $V_{i,G}$ and $X_{i,G}$ fitness values can update the individual of generation $G + 1$ by the following equation:

$$X_{i,G+1} = \begin{cases} X_{i,G}, & if \;\; f(X_{i,G}) \leq f(V_{i,G}), \\ V_{i,G}, & otherwise \end{cases} \tag{9}$$

where the fitness function is $F(\cdot)$.

The learner phase differentiates from the teaching phase as the individuals mutually teach other. The vector for the learner phase is $U_{i,G} = [u_{1i,G}, u_{2i,G}, ..., u_{Di,G}]^T$ obtained from Eq. 10.

$$U_{i,G} = \begin{cases} X_{m,G}, +r_m(X_{m,G} - X_{n,G}), & if \;\; f(X_{m,G}) < f(X_{n,G}), \\ X_{m,G}, +r_m(X_{m,G} + X_{n,G}), & otherwise \end{cases} \tag{10}$$

in which the random value r_m is between 0 and 1, and $X_{m,G}$ and $X_{n,G}$ represent randomly selected units of the current population while the $m \neq n$.

After the learner phase finishes, the generation G is incremented while the new population $P_G + 1$ is formed with use of $X_{i,G+1}(i = 1, 2, ..., N_p)$ individuals. The fitness values of $V_{i,G}$ and $X_{i,G}$ are evaluated at the generation $G + 1$ can be updated by the following equation:

$$X_{i,G+1} = \begin{cases} X_{i,G}, & if \;\; f(X_{i,G} \leq f(U_{i,G})), \\ U_{i,G}, & otherwise \end{cases} \tag{11}$$

The TLB pseudocode is provided in Algorithm 1. Firstly, the population is initialized, which includes bounds setting and terminal condition setting beside the generation of the population. Afterward, the algorithm switches between the phases for each iteration until the condition for termination is met (eq. $G \geq G_{MAX}$ or Fes_{MAX}).

Algorithm 1. Psuedocode for the TLB algoriithm

```
Initialize population;
Setting the population bounds;
Randomly generate an initial population P_0;
G = 0, Fes = 0;
while G < G_MAX||Fes < Fes_MAX do;
Teacher phase
  for (i = 1; i ≤ N_p; i + +);
   Select the teacher X_{t,G} and calculate the mean vector M_G;
   Implement the teacher learning law according to Eq. 8;
   Check the bounds;
   Update the population according to Eq. 9;
  end for;
  G + +, Fes = Fes + N_p;
  Learner phase
  for (i = 1; i ≤ N_p; i + +);
   Randomly select two individuals X_{m,G} and X_{n,G} where ≠ m ≠ n;
   Implement the learner learning law according to Eq. 10;
   Check the bounds;
   Update the population according to Eq. 11;
  end for;
  G + +, Fes = Fes + N_p;
```

4 Experiments

4.1 Dataset and Experimental Setup

The dataset used for model evaluation is a synthetic credit card dataset obtainable from [3]. The dataset is described in Table 1.

The optimization task for the subject dataset is binary to its entries being labeled as 0 or 1, which represent the legitimate fraudulent data respectively. For this case the main validating metrics of performance are precision (PR), accuracy (AC), and recall (RC), calculated by the next equations:

$$AC = \frac{TN + TP}{TP + TN + FN + FP} \tag{12}$$

Table 1. Description of the dataset key features

Properties	Class
User, Card, Year, Month, Day, Time, Amount, Use Chip, Merchant Name, Merchant City, Merchant State, Zip, MCC, Errors	Is fraud

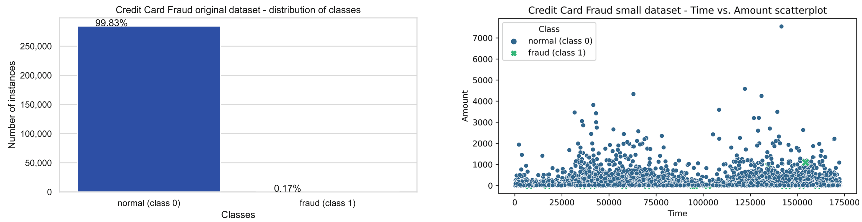

Fig. 1. Class distribution and scatter plot of the observed dataset

$$PR = \frac{TP}{TP + FP} \tag{13}$$

$$RC = \frac{TP}{TP + FN} \tag{14}$$

for which the negative and positives that are true are marked with TN and TP, respectively. The false negatives and positives are respectively FN and FP.

Due to high disproportions with the used dataset (shown on Fig. 1), additional metrics are required. Confusion matrix (CM), the area under the curve (AUC) [44], and the MCC [29] are applied to the comparison process.

The classification quality is measured by the utilization of the MCC for the range of values $[-1, 1]$ for which higher values are better. The same range and value ranking is applied to the AUC measurement as well which is used to test the quality and reliability of the model [44]. The CM is used for observed classifier error highlighting [39].

$$MCC = \frac{(TN \times TP) - (FN \times FP)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{15}$$

For all the implemented metaheuristics eight independent runs of 15 iterations and 6 individual solutions in the populace were performed, and the following six hyperparameters have been optimized by each approach for the XGBoost model:

- learning rate (η), boundaries: $[0.1, 0.9]$, type: continuous,
- *min_child_weight*, boundaries: $[1, 10]$, type: continuous,

- subsample, boundaries: $[0.01, 1]$,type: continuous,
- collsample_bytree, boundaries: $[0.01, 1]$, type: continuous,
- max_depth, boundaries: $[3, 10]$, type: integer and
- γ, boundaries: $[0, 0.5]$, type: continuous.

$L = 6$ is the provided length of the vector of the solution. The boundaries selection was empirical. Only the XGBoost hyperparameters were subjected to tuning by TLB, feature selection was not employed in these experiments. The approach was given the name XGBoost-TLB.

4.2 Experimental Findings

The capabilities of the XGBoost-TLB model have been put into test vs five other superior metaheuristic methods, namely FA [63], ABC [37], HHO [32], WOA [41] and GWO [42], that were verified in equal simulation conditions, with equal number of individuals and iterations, utilizing default metaheuristics' parameters setup. Table 2 gives overview of the simulation outcomes with respect to the achieved error rate over eight runs. The presented XGBoost-TLB method shared the first place with XGBoost-ABC model for all important metrics.

Table 3 brings forward the detailed simulation outcomes on the observed frauds dataset, where it is possible to note that the XGBoost-ILB achieved the

Table 2. Overall Metric

Method	Best	Worst	Mean	Median	Std	Var
XGBoost-TLB	4.39E-04	4.74E-04	4.52E-04	4.48E-04	1.46E-05	2.12E-10
XGBoost-FA	4.56E-04	5.09E-04	4.78E-04	4.74E-04	1.91E-05	3.66E-10
XGBoost-ABC	4.39E-04	4.74E-04	4.52E-04	4.48E-04	1.46E-05	2.12E-10
XGBoost-HHO	4.56E-04	4.92E-04	4.78E-04	4.83E-04	1.46E-05	2.12E-10
XGBoost-WOA	4.74E-04	4.74E-04	4.74E-04	4.74E-04	0	0
XGBoost-GWO	4.56E-04	4.92E-04	4.74E-04	4.74E-04	1.24E-05	1.54E-10

Table 3. Detailed Metric

	XGB-TLB	XGB-FA	XGB-ABC	XGB-HHO	XGB-WOA	XGB-GWO
Accuracy (%)	99.9561	99.9544	99.9561	99.9544	99.9526	99.9544
Precision 0	**0.999613**	0.999578	0.999578	0.999578	0.999578	0.999596
Precision 1	0.962025	0.973684	**0.986667**	0.973684	0.961039	0.961538
M.Avg. Precision	0.999549	0.999534	**0.999556**	0.999534	0.999512	0.999530
Recall 0	0.999947	0.999965	**0.999982**	0.999965	0.999947	0.999947
Recall 1	**0.775510**	0.755102	0.755102	0.755102	0.755102	0.765306
M.Avg. Recall	0.999561	0.999544	0.999561	0.999544	0.999526	0.999544
F1-score 0	0.999780	0.999771	0.999780	0.999771	0.999763	0.999771
F1-score 1	**0.858757**	0.850575	0.855491	0.850575	0.845714	0.852273
M.Avg. F1-score	**0.999538**	0.999515	0.999532	0.999515	0.999498	0.999518

highest accuracy of 99.9561%. XGBoost-ABC also obtained the same accuracy, however, XGBoost-TLB outperformed all other methods when other indicators are observed (the best score is bolded in each row).

Graphical representation of the supremacy of the XGBoost-TLB method against other contending models is depicted on Fig. 2, that gives insight into the convergence diagrams and box plot graphics of the error rate and the obj. function, for all six employed algorithms. It must be noted that the converging speed of the TLB algorithm surpasses significantly other methods.

To provide more insight into the results achieved by XGBoost-IMVO, Figs. 3, and 4 depict precision-recall (PR) and receiver under operating characteristics

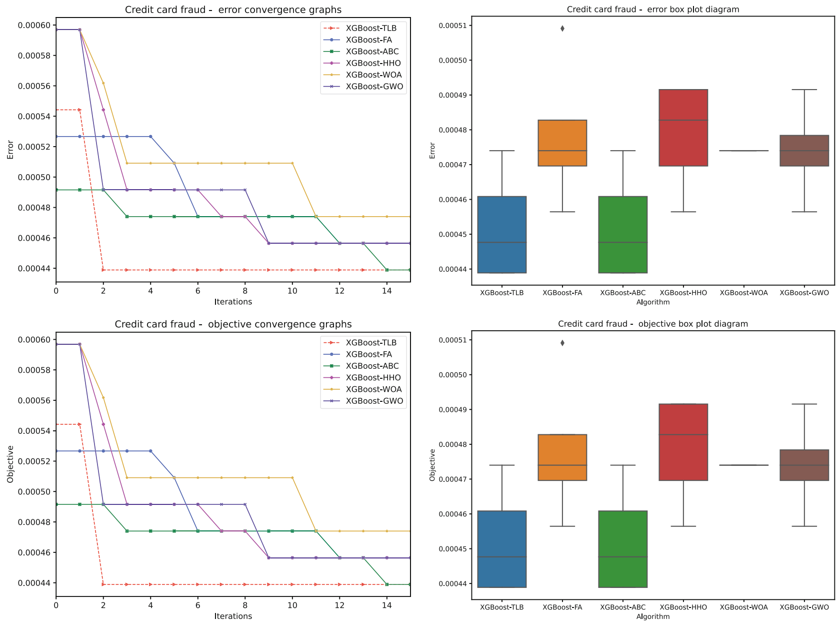

Fig. 2. Convergence and box plot graphics for all contenders

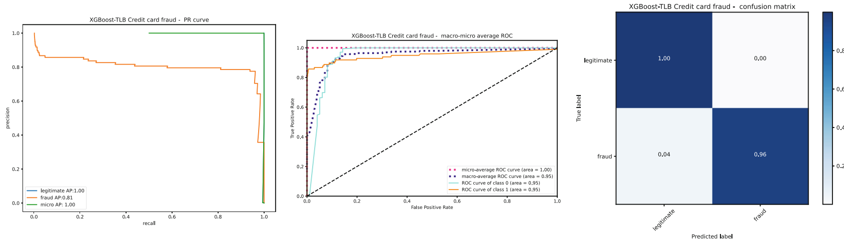

Fig. 3. PR and ROC curves of the proposed XGBoost-TLB model, and confusion matrix over the credit card dataset

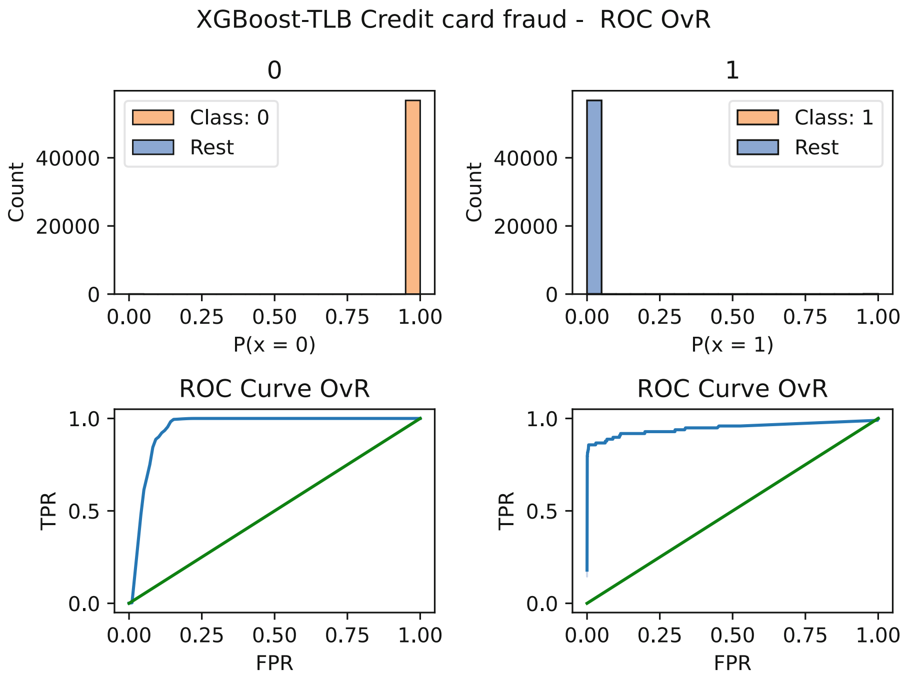

Fig. 4. The XGBoost-TLB one versus rest (OvR) ROC

(ROC), confusion matrix on utilized dataset, and one versus rest (OvR) ROC curves.

5 Conclusion

The focus of this work was on social-inspired metaheuristic algorithms applied to credit card fraud detection problem. The algorithm was compared to other high-end solutions and after a comparative analysis was determined the best solution. The main goal was the improvement of classification accuracy. This was achieved by a hybrid solution between XGBoost and TLB, of which the latter optimized the first. By observing the results there is no doubt that the TLB solution is dominant along with other XGBoost combinations with metaheuristics. The TLB can be further optimized and improved which the authors leave for future research.

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