Bayesian Optimization with Machine Learning Algorithms Towards Anomaly Detection

Mohammad Noor Injadat*, Fadi Salo*, Ali Bou Nassif†*, Aleksander Essex*, Abdallah Shami*
*Department of Electrical and Computer Engineering, University of Western Ontario, London, ON, Canada
Email: {minjadat, fsalo, aessex, abdallah.shami}@uwo.ca
†Department of Computer Engineering, University of Sharjah, Sharjah, UAE
Email: anassif@sharjah.ac.ae

Abstract—Network attacks have been very prevalent as their rate is growing tremendously. Both organization and individuals are now concerned about their confidentiality, integrity and availability of their critical information which are often impacted by network attacks. To that end, several previous machine learning-based intrusion detection methods have been developed to secure network infrastructure from such attacks. In this paper, an effective anomaly detection framework is proposed utilizing Bayesian Optimization technique to tune the parameters of Support Vector Machine with Gaussian Kernel (SVM-RBF), Random Forest (RF), and k-Nearest Neighbor (k-NN) algorithms. The performance of the considered algorithms is evaluated using the ISCX 2012 dataset. Experimental results show the effectiveness of the proposed framework in term of accuracy rate, precision, low-false alarm rate, and recall.

Index Terms—Bayesian Optimization, network anomaly detection, Machine Learning (ML), ISCX 2012.

I. INTRODUCTION

Computer networks and the Internet have become an essential component of any organization in this high-tech world. Organizations heavily depend on their networks to conduct their daily work. Moreover, individuals are also dependent on the Internet as a means to communicate, conduct business, and store their personal information [1]. The topic of Cyber-security has garnered significant attention as it greatly impacts many entities including individuals, organizations, and governmental agencies. Organizations have become more concerned with their network security and are allocating more resources to protect it against potential attacks or anomalous activities. Traditional network protection mechanisms have been proposed such as adopting firewalls, authenticating users, and integrating antivirus and malware programs as a first line of defense [2]. Nonetheless, these mechanisms have not been as efficient in providing complete protection for the organizations’ networks, especially with contemporary attacks [3].

Typical intrusion detection systems (IDSs) can be categorized into two main types, namely signature-based detection systems (misused detection) and anomaly-based detection systems [4]. Signature-based detection systems compare the observed data with pre-defined attack patterns to detect intrusion. Such systems are effective for attacks with well-known signatures and patterns. However, these systems miss new attacks due to the ever-changing nature of intrusion attacks [5]. On the other hand, anomaly-based detection systems rely on the hypothesis that abnormal behavior differs from normal behavior. Therefore, any deviation from what is considered as normal is classified as anomalous or intrusive. Such systems typically build models based on normal patterns and hence are capable of detecting unknown behaviors or intrusions [6]. Although previous work on IDSs has shown promising improvement, intrusion detection problem remains a prime concern, especially given the high volume of network traffic data generated, the continuously changing environments, the plethora of features collected as part of training datasets (high dimensional datasets), and the need for real-time intrusion detection [7]. For instance, high dimensional datasets can have irrelevant, redundant, or highly correlated features. This can have a detrimental impact on the performance of IDSs as it can slow the model training process. Additionally, choosing the most suitable subset of features and optimizing the corresponding parameters of the detection model can help improve its performance significantly [8].

In this paper, we propose an effective intrusion detection framework based on optimized machine learning classifiers including Support Vector Machine with Gaussian kernel (SVM-RBF), Random Forest (RF), and k-Nearest Neighbors (k-NN) using Bayesian Optimization (BO). These techniques have been selected based on the nature of the selected dataset, i.e. SVM-RBF is selected because the data is not linearly separable. Additional details about the utilized techniques are presented in section III. This is done to provide a robust and accurate methodology to detect anomalies. The considered methods are titled BO-SVM, BO-RF, and BO-kNN respectively. The performance is evaluated and compared by conducting different experiments with the ISCX 2012 dataset that was collected from University of New Brunswick [9]. As mentioned in Wu and Banzhaf [5], a robust IDS should have a high detection rate/recall and a low false alarm rate (FAR). Despite the fact that most of intrusion detection methods have high detection rate (DR), they suffer from higher FAR. Thus, this paper utilizes optimized machine learning models to minimize the objective function that will maximize the effectiveness of the considered methods. Totally, the feasibility and efficiency of these optimized methods is compared using various evaluation metrics such as accuracy (acc), precision, recall, and FAR. Furthermore, the performance of the three
optimized methods in parameter setting are compared with the standard approaches. The main contributions of this paper include the following:

- Investigate the performance of the optimized machine learning algorithms using Bayesian Optimization to detect anomalies.
- Enhances the performance of the classification models through the identification of the optimal parameters towards objective-function minimization.
- UNB ISCX 2012, a benchmark intrusion dataset is used for experimentation and validation purposes through the visualization of the optimization process of the objective function of the considered machine learning models to select the best approach that identifies anomalous network traffic. To the best of our knowledge, no previous related work has adopted Bayesian Optimization on the utilized dataset towards anomaly detection.

The remainder of this paper is organized as follows. Section II presents the related work. Section III gives a brief overview of SVM, RF, and k-NN algorithms along with the utilized optimization method. Section IV discusses the research methodology and the experimental results. Finally, Section V concludes the paper and provides future research directions.

II. RELATED WORK

The intrusion detection problem has been addressed as a classification problem by researchers. Different data mining-based methodologies have been posited to tackle this problem including, SVM [10], Decision Trees [11], k-NN [12], and Naive Bayes [13] classifiers as shown in the short review presented in Tsai et al. [1]. Later, noteworthy research have been implemented and acquired promising results through proposing novel approaches based data mining techniques Wu and Banzhaf [5]. Recently, many research adopted optimization techniques to improve the performance of their approach. For instance, a hybrid approach proposed by Chung and Wahid [14] including feature selection and classification with simplified swarm optimization (SSO). The performance of SSO was further improved by using weighted local search (WLS) to obtain better solutions from the neighborhood [14]. Their experimental results yielded accuracy of 93.3% in detecting intrusions. Similarly, Kuang et al. [15] proposed a hybrid method incorporating genetic algorithm (GA) and multi-layered SVM with kernel principal component analysis (KPCA) to enhance the performance of the proposed methodology. Another technique introduced by Zhang et al. [16] combining misuse and anomaly detection using RF. A novel algorithm applied catfish effect named, Catfish-BPSO, had been used to select features and enhance the model performance [17]. Authors used leave-one-out cross-validation (LOOCV) with k-NN for fitness evaluation.

III. THEORETIC ASPECTS OF THE TECHNIQUES

A. A. Support Vector Machines (SVM)

SVM algorithm is a supervised machine learning classification technique that identifies the class positive and negative sample by determining the maximum separation hyperplane between the two classes [18]. Depending on the nature of the dataset, different kernels can be used as part of the SVM technique since the kernel determines the shape of the separating hyperplane. For example, a linear kernel can be used in cases where the data is linearly separable by providing a linear equation to represent the hyperplane. However, other kernels are needed in cases where the data is not linearly separable. One such kernel is the Gaussian Kernel. This kernel maps the data points from their original input space into a high-dimensional feature space. The output of the SVM with Gaussian kernel (also known as SVM-RBF) is [19]:

\[
f(x) = w^T \Phi(x) + b
\]

where \( \Phi(x) \) represents the used kernel. The goal is to determine the weight vector \( w^T \) and intercept \( b \) that minimizes the following objective function:

\[
\min_{w,b} \frac{1}{2} w^T \Phi(x) \sum_{i=1}^{m} \left[ y_i \times \cosf_\alpha(f(x_i)) + (1 - y_i) \times \cosf_\beta(f(x_i)) \right]
\]

where \( C \) is a regularization parameter that penalizes incorrectly classified instances, \( \cosf_\alpha \) is the squared error over the training dataset.

B. k-Nearest Neighbors (k-NN)

k-NN is a simple classification algorithm that determines the class of an instance based on the majority class of its k nearest neighboring points. This is done by first evaluating the distance from the data point to all other points within the training dataset. Different distance measures can be used such as the Euclidean distance or Mahalanobis distance. After determining the distance, the k nearest points are identified and a majority voting-based decision is made on the class of the considered data point [20].

C. Random Forests (RF)

RF classifier is an ensemble learning classifier that combines several decision tree classifiers to predict the class [21]. Each tree is independently and randomly sampled with their results combined using majority rule. The RF classifier sends any new incoming data point to each of its trees and chooses the class that is classified by the most trees. RF algorithm works as follows [22]:

1) Choose \( T \) number of trees to grow.
2) Choose \( m \) number of variables used to split each node. \( m \ll M \), where \( M \) is the number of input variables.
3) Grow trees; While growing each tree, do the following:
   - Construct a sample of size \( N \) from \( N \) training cases with replacement and grow a tree from this new sample.
When growing a tree at each node, select \( m \) variables at random from \( M \) and use them to find the best split.
- Grow tree to maximum size without pruning.

4) To classify point \( X \), collect votes from every tree in the forest and then use majority voting to decide on the class label.

D. Bayesian Optimization (BO)

Bayesian optimization algorithm [23] tries to minimize a scalar objective function \( f(x) \) for \( x \). Depending on whether the function is deterministic or stochastic, the output will be different for the same input \( x \). The minimization process is comprised of three main components: a Gaussian process model for the objective function \( f(x) \), a Bayesian update process that modifies the Gaussian model after each new evaluation of the objective function, and an acquisition function \( a(x) \). This acquisition function is maximized in order to identify the next evaluation point. The role of this function is to measure the expected improvement in the objective function while discarding values that would increase it [23]. Hence, the expected improvement (EI) is calculated as:

\[
EI(x, Q) = EQ[ \max(0, \mu_Q(x_{best}) - f(x))] \tag{3}
\]

where \( x_{best} \) is the location of the lowest posterior mean and \( \mu_Q(x_{best}) \) is the lowest value of the posterior mean.

IV. EXPERIMENTAL SETUP AND RESULT DISCUSSION

A. Dataset Description

In this paper, the Information Security Centre of Excellence (ISCX) 2012 dataset was used to perform the experiments and evaluate the performance of the proposed approach to detect anomalies. The entire dataset comprises nearly 1.5 million network traffic packets, with 20 features and covered seven days of network activity (i.e. normal and intrusion). Additional information about the dataset are available in [9]. A random subset has been extracted from the original dataset. The training data contains 30,814 normal traces and 15,375 attack traces while the testing data contains 13,154 normal traces and 6,580 additional attack traces.

B. Experimental setup and Data Pre-processing

The proposed techniques were implemented using MATLAB 2018a. Experiments were carried out in an Intel® Core™ i7 processor @ 3.40 GHz system with 16GB RAM running Windows 10 operating system. The selected dataset was transformed from their original format into a new dataset consisting of 14 features. We eliminated the payload features which include the actual packet as most of their contents were empty, while start time, and end time features have been replaced by duration feature. In the data normalization stage, attributes were scaled between the range \([0,1]\) by using Min-Max method to eliminate the bias of features with greater values, the mathematical computation is as follows:

\[
x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{4}
\]

As most of the classifiers do not accept categorical features [24], data mapping technique was used to transform the non-numeric values of the features into numeric ones, named categorical in MATLAB.

C. Prediction Performance Measures

To evaluate and compare prediction models quantitatively, the following measurements were utilized:

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{6}
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{7}
\]

where \( TP \) is the true positive rate, \( TN \) is the true negative rate, \( FP \) is the false positive rate, and \( FN \) is the false negative rate [25].

D. Results Discussion

The aim of the work is to discover the optimized models’ parameters of the utilized classifiers to classify the network intrusion data with the selected parameters. The experimental scheme has been done for each technique to reduce the cost function by tuning all possible parameters to obtain the highest classification accuracy and the minimum FAR. To that end, BO technique is used to determine the optimal parameters for the considered machine learning models. For instance, the optimal values of \( C \) and \( \gamma \) (for SVM), the depth of trees and the adopted ensemble method (for RF), and the value of \( k \) and the distance measure method (for k-NN) are determined.

For example, if we have a set of machine learning model parameters \( P^* = P_1, P_2, \ldots, P_n \) where \( P_i \) is a parameter of the parameters subset that needs tuning, then BO tries to minimize the following cost function:

\[
P^* = \min J(P) \tag{8}
\]

where \( J(P) \) is the associated cost function.

To visualize the behavior of the BO technique combined with the machine learning technique on the training dataset, Figures 1 and 2 depict how BO tunes the parameters towards the global minimum value of the SVM cost function with respect to \( C \) and \( \gamma \) as parameters subset. According to the figures, a unique global minimum is obtained for \( C = 433.32 \) and \( \gamma = 1.0586 \). This in turn leads to improving the model’s training accuracy as shown in Table 1 from 99.58% without optimization to 99.95% after optimization. Additionally, the testing accuracy increases from 99.59% to 99.84%. On the other side, the FAR had promising results with a reduction of 0.01 and 0.007 in the training and testing datasets respectively. Table 2 also shows more details about the optimization processing time.
TABLE I

| Classifier | Training | Testing |
|------------|----------|---------|
|            | Acc(%)   | Precision | Recall | FAR | Acc(%)   | Precision | Recall | FAR |
| SVM-RBF    | 99.58    | 0.994     | 0.999  | 0.011 | 99.59    | 0.995     | 0.999  | 0.010 |
| K-NN (k=5) | 99.59    | 0.9965    | 0.998  | 0.008 | 99.36    | 0.994     | 0.996  | 0.012 |
| RF         | 99.96    | 0.999     | 1.00   | 0.001 | 99.88    | 0.998     | 0.999  | 0.002 |
| BO-SVM     | 99.95    | 0.999     | 1.00   | 0.001 | 99.84    | 0.998     | 0.999  | 0.003 |
| BO-k-NN    | 99.98    | 0.999     | 1.00   | 0.001 | 99.93    | 0.999     | 0.999  | 0.001 |
| BO-RF      | 99.98    | 0.999     | 1.00   | 0.001 | 99.92    | 0.999     | 0.999  | 0.001 |

TABLE II

| Best Parameters | BO-SVM | BO-k-NN | BO-RF |
|-----------------|--------|---------|-------|
| BoxConstraint (C) | 433.32 | NumNeighbors | 1 |
| KernelScale (γ) | 1.0586 | Distance | Mahalanobis |
| MaxNumSplits | 1004 | Method | AdaBoost |
| Total function evaluations | 30 | 30 | 30 |
| Total elapsed time in seconds | 6175.78 | 2272.50 | 771.24 |

Fig. 1. Optimized SVM Contour

Similarly, Figures 3 and 4 and Table 2 show how the BO technique is minimizing the cost function \( J(P) \) for k-NN algorithm with respect to the number of neighbors \( k \) and the distance measuring method. A unique global minimum is achieved for the values of \( k = 1 \) and Mahalanobis distance as the distance measuring method. According to Table 1, BO was able to improve the BO performed 30 iterations to evaluate the cost function in the aim to converge toward the optimal \( J(P) \) of each classifier.

Figures 5, 6, and 7 visualize the change in the objective function value vs the number of function evaluations for BO-SVM, BO-RF, and BO-kNN respectively. It can be observed that the objective function reaches its global minimum within 30 iterations at most. This reiterates the efficiency of the BO technique in optimizing the considered algorithms.

By applying BO-RF, a unique global minimum is achieved with 1004 tree splits (Tree Depth) and AdaBoost as a tree method. The BO improves the training accuracy from 99.97% to 99.98% while the testing accuracy improves from 99.88% to 99.92%. The FAR remains steady in the training dataset and is reduced by 0.001 in the testing dataset. Furthermore, Table 2 indicate that the BO find that AdaBoost is the best ensemble method to build the tree.

It is also worth mentioning that Naïve Bayes classifier was utilized at the initial stage of the experiment. However, due to the fact that the dataset’s features are not fully independent, the classifier shows a low accuracy of 87.23% and 87.65% on the training and testing datasets respectively. Hence, the Naïve Bayes classifier was excluded from the experiment.

Based on the previous publications, our results outperform the results of previous experiments conducted using ISCX 2012 such as the results shown in [26] with their model.
acheiving about 95% as overall accuracy using their proposed technique. Additionally, [27] reported the highest accuracy of 99.8% and 99.0% for the training and testing phases respectively.

V. CONCLUSIONS

In this paper, we utilized a Bayesian optimization method to enhance the performance of anomaly detection methodology based on three conventional classifiers: Support Vector Machine with Gaussian kernel (SVM-RBF), Random Forest (RF), and k-Nearest Neighbor (k-NN). The BO optimization method has been applied to set the parameters of these classifiers by finding the global minimum of the corresponding objective function. In order to have an efficient machine learning-based anomaly detection system with high accuracy rate and a low false positive rate, BO was able to improve the utilized classifiers. The experimental results show not only is the proposed optimization method more accurate in detecting
intrusions, but also it can find the global minimum of the objective function which leads to better classification results. Overall, k-NN with Bayesian optimization has achieved the optimum performance on ISCX 2012 dataset in terms of accuracy, precision, recall, and false alarm rate. In order to further improve the performance of the proposed approach, we plan to involve feature selection and parameter setting applied simultaneously in the optimization method. Moreover, the results of the proposed approach will be further improved by combining both supervised and unsupervised machine learning techniques to detect novel attacks with additional datasets such as the new release of the ISCX dataset.

REFERENCES

[1] C.-F. Tsai, Y.-F. Hsu, C.-Y. Lin, and W.-Y. Lin, “Intrusion detection by machine learning: A review,” Expert Systems with Applications, vol. 36, no. 10, pp. 11 994–12 000, 2009.
[2] M. B. Salem, S. Hershkop, and S. J. Stolfo, “A survey of insider attack detection research,” in Insider Attack and Cyber Security. Springer, 2008, pp. 69–90.
[3] W. Bul’ajoul, A. James, and M. Pannu, “Improving network intrusion detection system performance through quality of service configuration and parallel technology,” Journal of Computer and System Sciences, vol. 81, no. 6, pp. 981–990, 2015.
[4] S. M. H. Bamakan, B. Amiri, M. Mirzabagheri, and Y. Shi, “A new intrusion detection approach using pso based multiple criteria linear programming,” Procedia Computer Science, vol. 55, pp. 231–237, 2015.
[5] S. X. Wu and W. Banzhaf, “The use of computational intelligence in intrusion detection systems: A review,” Applied soft computing, vol. 10, no. 1, pp. 1–35, 2010.
[6] H.-J. Liao, C.-H. R. Lin, Y.-C. Lin, and K.-Y. Tung, “Intrusion detection system: A comprehensive review,” Journal of Network and Computer Applications, vol. 36, no. 1, pp. 16–24, 2013.
[7] S. Suthaharan, “Big data classification: Problems and challenges in network intrusion prediction with machine learning,” ACM SIGMETRICS Performance Evaluation Review, vol. 41, no. 4, pp. 70–73, 2014.
[8] J. Zhang and M. Zulkernine, “Anomaly based network intrusion detection with unsupervised outlier detection,” in Communications, 2006. ICC’06. IEEE International Conference on, vol. 5. IEEE, 2006, pp. 2388–2393.
[9] A. Shiravi, H. Shiravi, M. Tavallaee, and A. A. Ghorbani, “Toward developing a systematic approach to generate benchmark datasets for intrusion detection,” Computers & Security, vol. 31, no. 3, pp. 357 – 374, 2012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167404811001672
[10] F. Kuang, W. Xu, and S. Zhang, “A novel hybrid kpca and svm with ga model for intrusion detection,” Applied Soft Computing, vol. 18, pp. 178–184, 2014.
[11] A. S. Eesa, Z. Orman, and A. M. A. Brifcani, “A novel feature-selection approach based on the cuttlefish optimization algorithm for intrusion detection systems,” Expert Systems with Applications, vol. 42, no. 5, pp. 2670–2679, 2015.
[12] W. Li, P. Yi, Y. Wu, L. Pan, and J. Li, “A new intrusion detection system based on knn classification algorithm in wireless sensor network,” Journal of Electrical and Computer Engineering, vol. 2014, 2014.
[13] S. Aljawarneh, M. Aldwairi, and M. B. Yassein, “Anomaly-based intrusion detection system through feature selection analysis and building hybrid efficient model,” Journal of Computational Science, 2017.
[14] Y. Y. Chung and N. Wahid, “A hybrid network intrusion detection system using simplified swarm optimization (ssso),” Applied Soft Computing, vol. 12, no. 9, pp. 3014–3022, 2012.
[15] F. Kuang, W. Xu, and S. Zhang, “A novel hybrid kpca and svm with ga model for intrusion detection,” Applied Soft Computing, vol. 18, pp. 178–184, 2014.
[16] J. Zhang, M. Zulkernine, and A. Haque, “Random-forests-based network intrusion detection systems,” IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 38, no. 5, pp. 649–659, 2008.
[17] A. J. Malik and F. A. Khan, “A hybrid technique using multi-objective particle swarm optimization and random forests for probe attacks detection in a network,” in Systems, Man, and Cybernetics (SMC), 2013 IEEE International Conference on. IEEE, 2013, pp. 2473–2478.
[18] I. S. Taseen and C. A. Kumar, “Intrusion detection model using fusion of chi-square feature selection and multi class svm,” Journal of King Saud University-Computer and Information Sciences, vol. 29, no. 4, pp. 462–472, 2017.
[19] H. Bostani and M. Sheikhan, “Modification of supervised opf-based intrusion detection systems using unsupervised learning and social network concept,” Pattern Recognition, vol. 62, pp. 56–72, 2017.
[20] W. Meng, W. Li, and L.-F. Kwok, “Design of intelligent knn-based alarm filter using knowledge-based alert verification in intrusion detection,” Security and Communication Networks, vol. 8, no. 18, pp. 3883–3895, 2015.
[21] M. Injadt, F. Salo, and A. B. Nassif, “Data mining techniques in social media: A survey,” Neurocomputing, vol. 214, pp. 654 – 670, 2016.
[22] A. J. Malik, W. Shahzad, and F. A. Khan, “Binary pso and random forests algorithm for probe attacks detection in a network,” in 2011 IEEE Congress of Evolutionary Computation (CEC), June 2011, pp. 662–668.
[23] E. Brochu, V. M. Cora, and N. De Freitas, “A tutorial on bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning,” arXiv preprint arXiv:1012.2599, 2010.
[24] M. Salem and U. Buehler, “Mining techniques in network security to enhance intrusion detection systems,” arXiv preprint arXiv:1212.2414, 2012.
[25] M. H. Tang, C. Ching, S. Poon, S. S. Chan, W. Ng, M. Lam, C. Wong, R. Pao, A. Lau, and T. W. Mak, “Evaluation of three rapid oral fluid test devices on the screening of multiple drugs of abuse including ketamine,” Forensic science international, 2018.
[26] H. Huang, R. S. Khalid, W. Liu, and H. Yu, “Work-in-progress: a fast online sequential learning accelerator for iot network intrusion detection,” in HardwareSoftware Codesign and System Synthesis (CODES+ISSS), 2017 International Conference on. IEEE, 2017, pp. 1–2.
[27] W. Yassin, N. I. Udzir, Z. Muda, M. N. Sulaiman et al., “Anomaly-based intrusion detection through k-means clustering and naive bayes classification,” in Proc. 4th Int. Conf. Comput. Informatics, ICOCI, no. 49, 2013, pp. 298–303.