Machine Learning for Detecting Anomalies and Intrusions in Communication Networks

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Abstract—Cyber attacks are becoming more sophisticated and, hence, more difficult to detect. Using efficient and effective machine learning techniques to detect network anomalies and intrusions is an important aspect of cyber security. A variety of machine learning models have been employed to help detect malicious intentions of network users. In this paper, we evaluate performance of recurrent neural networks (Long Short-Term Memory and Gated Recurrent Unit) and Broad Learning System with its extensions to classify known network intrusions. We propose two BLS-based algorithms with and without incremental learning. The algorithms may be used to develop generalized models by using various subsets of input data and expanding the network structure. The models are trained and tested using Border Gateway Protocol routing records as well as network connection records from the NSL-KDD and Canadian Institute of Cybersecurity datasets. Performance of the models is evaluated based on selected features, accuracy, F-Score, and training time.

Index Terms—Intrusion detection, network anomalies, feature selection, machine learning, recurrent neural networks, broad learning system.

I. INTRODUCTION

The Internet has been highly susceptible to failures and attacks that greatly affect its performance. Over the past years, frequent cases of complex and challenging threats have been encountered. Hence, various machine learning algorithms have been considered to enhance cyber security [1]–[3]. Machine learning algorithms [4] have been used to address a variety of engineering and scientific problems. They classify data using a feature matrix where its rows and columns correspond to data points and feature values, respectively. By providing a sufficient number of relevant features, machine learning approaches help build generalized classification models and improve their performance. Supervised machine learning models used to classify network anomalies and intrusions include logistic regression [4], naïve Bayes [5], support vector machine (SVM) [6], decision tree [7], boosting algorithms [8], [9], deep learning networks [10], [11], and the broad learning system (BLS) [12], [13]. In this study, we use training time as one of the measures affecting the generation of a model. Note that a model’s testing time, essential for detecting impending anomalies, is usually rather short. Selecting algorithms that have a short training time is important if they are to be implemented in network intrusion detection systems in order to adequately prevent the onset of malicious attacks. It will enable system administrators to effectively and timely remove affected network elements.

Feature selection algorithms are used to reduce the dimensionality of the dataset matrix by selecting features based on their importance. They enhance performance of machine learning algorithms and classification results. Algorithms such as Fisher, minimum Redundancy Maximum Relevance, mutual information base, and decision tree were used to select relevant features and to achieve better classification performance. In our prior studies [14]–[18], machine learning models were generated using a predefined set of selected features.

Light Gradient Boosting Machine (LightGBM) [9], an optimized gradient boosting decision tree (GBDT) algorithm, utilizes gradient-based one-side sampling and exclusive feature bundling techniques to accelerate the training speed for large datasets. Compared to conventional GBDT models, the LightGBM model achieved comparable performance with shorter training time for ranking and classification using various datasets.

Deep neural networks such as recurrent neural networks (RNNs), including bidirectional RNNs [19], [20], long short-term memory (LSTM) [21], [22], and gated recurrent unit (GRU) [23] are trained to identify important features in the input data by adjusting weights in each iteration. Their significant advantage over logistic regression, naïve Bayes, SVM, and decision tree algorithms is using back-propagation to calculate gradients and update the weights. Furthermore, deep neural networks may achieve desired classification results by adjusting the number of hidden nodes and layers, activation functions, and optimization algorithms. They employ linear or nonlinear activation functions such as rectified linear unit (ReLU), logistic sigmoid, or hyperbolic tangent (tanh). The numbers of hidden nodes and layers are chosen depending on the size of the dataset. An important advantage of RNNs is their ability to use contextual information between input and output sequences. The bidirectional recurrent neural networks (Bi-RNNs) [19], [20] were proposed to enhance handwriting and speech recognition. Bi-RNNs utilize both forward and backward information for prediction: an RNN layer calculates the output by using the sequential input data stream starting from its beginning while another RNN layer uses the sequential input backward starting from its end. The outputs of the two RNN layers are then combined. The LSTM neural network was proposed to address certain deficiencies in RNNs. The GRU structure is a special case of LSTM with a simpler structure. RNNs, convolutional neural networks, deep
belief networks, and autoencoders offer promising results for anomaly detection [24].

BLS [12] and its extensions [13], [25]–[29] are alternatives to deep learning networks. They achieve comparable classification accuracy and require a considerably shorter time for training than the conventional deep learning networks because of a small number of hidden layers. They also use pseudo-inverse or ridge regression approaches rather than back-propagation during the training process. BLS offers desired classification when used for function approximation, time series forecast, and image recognition. Generating a set of mapped features is an important step in BLS and its extensions. Various modifications for creating the set of mapped features have been proposed to improve the generalization of the BLS-based models such as CFBLs, CCFBLS [13], and multi-kernel BLS [28].

Our experimental results indicated that the best BLS models were not often derived by including all features in analyzed datasets. Using a subset of relevant features may enhance the model performance [8], [14], [15], [17], [18], [30], [31]. Reported BLS models that achieved the best performance were trained using a single subset of features extracted from the input data. Existing BLS-based algorithms include a single set of groups of mapped features where each group has a constant number of mapped features. We introduce two new BLS-based algorithms: variable features BLS algorithms without (VFBLs) and with cascades (VCFBLs), which are implemented with and without incremental learning. VFBLs and VCFBLs consist of a variable number of mapped features and groups of mapped features as well as an explicit feature selection algorithm to create subsets of input data thus making the model more generalized compared to BLS algorithms. Models generated using the proposed algorithms with integrated feature selection enable utilizing a variable number of selected features. Each mapped feature in VFBLs is created based on input data while in case of VCFBLs, consequent mapped features are generated based on a previous mapped feature. Training time of the proposed models may be adjusted by allocating a smaller number of mapped features and groups of mapped features to the input data subsets having a larger number of selected features.

Machine learning algorithms have been used to successfully classify network anomalies and intrusions [32]. These algorithms have been evaluated for robustness, high accuracy, and training time when classifying various datasets collected from communication networks. Reliable testing and validation of anomaly and intrusion detection algorithms depend on the quality of datasets such as traffic collected from deployed networks or experimental testbeds. We used the Border Gateway Protocol (BGP) Réseaux IP Européens (RIPE) [33], NSL-KDD [34], CICIDS2017 [35], and CSE-CIC-IDS2018 [36] datasets. CICIDS2017 and CSE-CIC-IDS2018 datasets were collected by the Canadian Institute for Cybersecurity (CIC). (We have not considered in this paper the BGP Route Views datasets [37] because they did not contain a complete record of anomalous events.)

Various intrusion detection systems (IDSs) [2], [38]–[40] are used to identify and classify malicious activities such as anomalies and intrusions in communication networks. They may be host-based or network-based. Host-based systems protect the host (endpoint) by monitoring operating system files and processes. Network-based systems (NIDSs) monitor incoming network traffic (Internet Protocol addresses, service ports, and protocols) by analyzing flows of packets or by inspecting packet headers. Their role is to enhance security by identifying suspicious events in the observed network traffic. Detecting malicious network intrusions may be signature-based or anomaly-based. Signature-based techniques [32] rely on known events that follow certain rules and patterns while anomaly-based intrusion detection techniques [1], [41] rely on detecting deviations from an expected behavior.

This paper is organized as follows: The RNNs (LSTM and GRU), BLS, and proposed BLS-based algorithms are presented in Section II. BGP RIPE, NSL-KDD, CICIDS2017, and CSE-CIC-IDS2018 datasets are described in Section III. The experimental procedure and performance evaluation are given in Section IV. We conclude with Section V.

II. DETECTING NETWORK INTRUSIONS

Machine learning has changed approaches to counter cyber risks. Proposed approaches rely on supervised and unsupervised techniques to identify and classify anomalies in network traffic. Performance of proposed methods, evaluated based on accuracy and F-Score, depends on selected features and their combinations. The main disadvantages of conventional machine learning techniques are long training time and computational complexity. Hence, boosting algorithms (LightGBM) [42], deep learning networks (LSTM and GRU) [15], [17], [43] and the BLS were employed to detect network traffic anomalies [44]–[47].

A. Long Short-Term Memory

LSTM networks are RNNs that are capable of learning long-term dependencies by connecting time intervals to form a continuous memory [21], [22]. Traditional RNN networks perform poorly when they need to bridge segments of information with long time gaps. Hence, LSTM networks were introduced to overcome long-term dependency and vanishing gradient problems.

The LSTM cell is composed of: (a) forget gate \( f_t \), (b) input gate \( i_t \), and (c) output gate \( o_t \). The forget gate discards irrelevant memories based on the cell state, the input gate controls the information that will be updated in the LSTM cell, and the output gate functions as a filter that controls the output. The logistic sigmoid \( \sigma \) and \( \tanh \) are used as cell functions. The output of the LSTM cell is connected to the output layer and the next cell.

The outputs of the \( f_t \), \( i_t \), \( o_t \), and \( h_t \) at time \( t \) are [48]:

\[
\begin{align*}
\hat{f}_t &= \sigma(W_{if}x_t + b_if + U_{hf}h_{t-1} + b_{hf}) \\
\hat{i}_t &= \sigma(W_{ii}x_t + b_i + U_{hi}h_{t-1} + b_{hi}) \\
o_t &= \sigma(W_{io}x_t + b_{io} + U_{ho}h_{t-1} + b_{ho})
\end{align*}
\]

where \( \sigma(\cdot) \) is the logistic sigmoid function, \( x_t \) is the current input, \( h_{t-1} \) is the previous output, \( W_{ij}, U_{hi}, W_{io}, \) and \( U_{ho} \) are the weight matrices.
and $U_{ho}$ are weight matrices, and $b_{if}, b_{hf}, b_{i}, b_{h}, b_{io},$ and $b_{ho}$ are bias vectors. The information is stored in the cell state depending on the output $i_t$ of the input gate. The sigmoid function is used to update the cell state $c_t$ calculated as:

$$c_t = f_t * c_{t-1} + i_t * \tanh(W_{ic}x_t + b_{ic} + U_{hc}c_{t-1} + b_{hc}),$$

(2)

where $*$ denotes element-wise multiplications and the $\tanh$ function is used to calculate the input to the next cell state. The output of the LSTM cell is:

$$h_t = o_t * \tanh(c_t),$$

(3)

**B. Gated Recurrent Unit**

The GRU cell is derived from LSTM and has a simpler structure. To make predictions, it employs gated mechanisms to control input and memory at the current timestep. While an LSTM cell consists of three gates, a GRU cell contains only reset $r_t$ and update $z_t$ gates [23]. The reset gate determines the combination of new input information and previous memory content while the update gate defines the content stored at the current timestep.

The outputs of the reset gate $r_t$ and the update gate $z_t$ at time $t$ are [48]:

$$r_t = \sigma(W_{ir}x_t + b_{ir} + U_{hr}h_{t-1} + b_{hr}),$$

$$z_t = \sigma(W_{iz}x_t + b_{iz} + U_{hz}h_{t-1} + b_{hz}),$$

(4)

where $\sigma(\cdot)$ is the logistic sigmoid function, $x_t$ is the input, $h_{t-1}$ is the previous cell output, $W_{ir}, U_{hr}, W_{iz},$ and $U_{hz}$ are the weight matrices, and $b_{ir}, b_{hr}, b_{iz},$ and $b_{hz}$ are the bias vectors. The output of the GRU cell is:

$$h_t = (1 - z_t) * n_t + z_t * h_{t-1},$$

(5)

where $n_t$ is:

$$n_t = \tanh(W_{in}x_t + b_{in} + r_t * (U_{hn}h_{t-1} + b_{hn})),$$

(6)

$W_{in}$ and $U_{hn}$ are the weight matrices, and $b_{in}$ and $b_{hn}$ are the bias vectors.

**C. Broad Learning System**

Deep learning neural networks may require long training time because of their high computational complexity and a large number of hidden layers. In contrast, boosting algorithms such as LightGBM [9] and BLS [29] offer comparable performance with shorter training time. BLS is based on a single layer feedforward neural network and pseudo-inverse or ridge regression to calculate outputs. Several BLS extensions exploit the algorithm’s flexible structure to include: incremental learning [12], radial basis function network (RBF-BLS) [25] as well as cascades of mapped features (CFBLS), enhancement nodes (CEBLS), and both mapped features and enhancement nodes (CFEBLS) [13].

BLS improves the random vector functional-link neural network [49] by mapping the input data $X$ to a set of groups of mapped features $Z^n \triangleq [Z_1, ..., Z_n]$ that generates enhancement nodes $H^m \triangleq [H_1, ..., H_m]$ using random weights.

Groups of mapped features and enhancement nodes are defined as:

$$Z_i = \phi(XW_{ei} + \beta_{ei}), i = 1, 2, ..., n$$

(7)

$$H_j = \xi(Z^2HW_{hj} + \beta_{hj}), j = 1, 2, ..., m,$$

(8)

where $\phi$ (linear) and $\xi$ (tanh) are the feature and enhancement mappings, respectively, $W_{ei}$ and $W_{hj}$ are weights, and $\beta_{ei}$ and $\beta_{hj}$ are bias parameters. A state matrix $A_n^m$ is constructed by concatenating matrices $Z^n$ and $H^m$ associated with $n$ groups of mapped features and $m$ groups of enhancement nodes, respectively. The Moore-Penrose pseudo-inverse or ridge regression of matrix $A_n^m$ is computed to calculate the weights $W_n^m$ for the given labels $Y$. During testing, data labels are predicted using the calculated weights, mapped features, and enhancement nodes.

The BLS structure may be dynamically expanded by using incremental learning to include additional input data $X_n$, mapped features $Z_{n+1}$, and enhancement nodes $H_{m+1}$. It requires a shorter training time because the weights are updated using only the incremental input data instead of retraining the entire model. RBF-BLS extension employs the Gaussian rather than $\tanh$ function as the enhancement mapping $\xi$. The structure of BLS with cascades is defined by the connections within and between the mapped features and enhancement nodes. In the case of CFBLS, the first group of mapped features is based on input data and weights (7) while subsequent groups $(k)$ of mapped features are created by using the previous group $(k-1)$. The groups of mapped features are formulated as:

$$Z_k = \phi(Z_{k-1}W_{ek} + \beta_{ek})$$

$$\triangleq \phi^k(X; \{W_{ei}, \beta_{ei}\}_{i=1}^k),$$

(9)

for $k = 1, ..., n$.

The cascades of these groups $Z^n \triangleq [Z_1, ..., Z_n]$ are used to generate the enhancement nodes $\{H_j\}_{j=1}^m$. The first CFBLS enhancement node is generated from mapped features while subsequent nodes are generated from previous nodes creating a cascade:

$$H_u = \xi(H_{u-1}W_{eu} + \beta_{eu})$$

$$\triangleq \xi^u(Z^n; \{W_{hi}, \beta_{hi}\}_{i=1}^u),$$

(10)

for $u = 1, ..., m$, where $W_{hi}$ and $\beta_{hi}$ are randomly generated. The CFEBLS architecture is a combination of the two cascading approaches.

**D. Variable Features Broad Learning System**

Mapping the input data to sets of mapped features is an essential step of BLS algorithms. We propose a variable features system (VFBLs) and system with cascades (VCBLS) shown in Fig. 1 that consist of a variable number of mapped features and groups of mapped features. They employ feature selection algorithms that enable models to be trained based on a variable number of features extracted from the input data. The two algorithms also offer variants with incremental learning.

The VFBLs and VCBLS algorithms expand the BLS network by using both original and subsets of input data as well as sets of groups of mapped features. They enable developing more generalized models and, hence, prevent overfitting and enhance the performance. Generating the best
BLS and incremental BLS models is rather time-consuming because they rely on multiple two-stage experiments: selecting features and generating models. In contrast, VFBSLS and VCFBSLS models are developed using a single experiment with integrated stages. A variable number of mapped features is used to reduce training time because the proposed algorithms introduced additional complexity by using the entire input dataset and by incorporating a feature selection algorithm and additional randomness by randomly splitting nodes in order to avoid over-fitting. Features with higher importance are more relevant for a given dataset and capture its properties. They may have better spatial separation and, thus, enhance the model’s performance. The Gini importance is used to compute feature scores in a given dataset [51]:

$$E(W^m_t) = ||A^m_tW^m_t - Y||^2_2 + \lambda||W^m_t||^2_2,$$  

(15)

The output weights are defined as [4]:

$$W^m_t = (\lambda I + (A^m_t)^T A^m_t)^{-1}(A^m_t)^TY.$$  

(16)

Pseudocode for the VFBSLS and VCFBSLS algorithms and their incremental versions are listed in Algorithm 1 and Algorithm 2, respectively.

A variety of feature selection algorithms may be employed. The extremely randomized trees (extra-trees) feature selection algorithm [50] is used in our experiments to rank features based on importance. The algorithm is an improved version of the decision tree and random forests used to select relevant features for generating subsets of the input data. It introduces additional randomness by randomly splitting nodes in order to avoid over-fitting. Features with higher importance are more relevant for a given dataset and better capture its properties. They may have better spatial separation and, thus, enhance the model’s performance. The Gini importance is used to compute feature scores in a given dataset [51]:

$$Importance(X_v) = \frac{1}{N_T} \sum_{t \in T \cap (v(s_t)) \subseteq X_v} p(t) \Delta i(s_t, t),$$  

(17)

where $X_v$ is the subset of $X$ corresponding to one feature, $N_T$ is the number of trees, $t$ is the index of a node in a tree, $s_t$ is the direction of the split, $v(s_t)$ is a randomly generated threshold, $p(t)$ is the weight, and $\Delta i(s_t, t)$ is the decrease of the node impurity equivalent to its importance.

E. Intrusion Detection Systems

An early hybrid intrusion detection system (IDS) was proposed to identify misuse and anomaly intrusions using random forests [52]. Intrusion detection systems [2], [53], [54] have been designed using machine learning and deep neural networks such as stacked non-symmetric deep auto-encoder [55] and recurrent neural networks [43]. Training time is often of concern when employing deep learning algorithms. Hence, a stacked non-symmetric deep auto-encoder (NDAE) that combines deep and shallow learning offered by the random forest classifier has been proposed and implemented using a graphics processing unit (GPU) [55]. Network (NIDS) [56] concatenating input data $X$ and sets of mapped features to create $Z'$ similar to the case of random vector functional-link network [49]:

$$Z' = [X\mid Z'^v].$$  

(13)

The enhancement nodes are:

$$H_j = (X'W^s_{h_j} + b_{h_j}), j = 1, 2, ..., m.$$  

(14)

The state matrix $A'^m_t$ is the concatenation of $Z'$ and $H^m$. The ridge regression algorithm is then employed to compute the weights $W^m_t$ based on $A'^m_t$ and given labels $Y$. The error function, minimized during the training process, is defined as [12]:

$$E(W^m_t) = ||A'^m_tW^m_t - Y||^2_2 + \lambda||W^m_t||^2_2,$$  

(15)

The output weights are defined as [4]:

$$W^m_t = (\lambda I + (A'^m_t)^T A'^m_t)^{-1}(A'^m_t)^TY.$$  

(16)
BGP anomalies are: Slammer [61], [62], Nimda [63], [64], and CIDS2017 [35], and CSE-CIC-IDS2018 [36] datasets.

SwiftIDS employs LightGBM for generating models. Real-time data acquisition and data processing were used prior to classification of anomalies using the proposed parallel intrusion detection mechanism [42].

### III. DESCRIPTION OF DATASETS

We have classified network anomalies and intrusions [16], [17], [44], [47] using BGP RIPE [33], NSL-KDD [34], CI-CIDS2017 [35], and CSE-CIC-IDS2018 [36] datasets.

#### A. Border Gateway Protocol RIPE Datasets

BGP is prone to malicious attacks [60]. Three well-known BGP anomalies are: Slammer [61], [62], Nimda [63], [64], and Code Red I [65], which occurred in January 2003, September 2001, and July 2001, respectively.

BGP RIPE datasets containing anomalies and regular data may be extracted from BGP update messages collected during periods of Internet anomalies [33], [37]. We consider both anomalous (the days of the attack) and regular (two days prior and two days after the attack) data [16], [17], [45], [46]. The duration of anomalies and the number of data points in the BGP RIPE datasets are shown in Table I. We extract 37 numerical features [66] from BGP update messages [33] that originated from AS 513 (route collector rrc04) using a tool written in C# [67]. Slammer and Code Red I datasets contain 7,200 data points consisting of five days of anomalous and regular data while Nimda contains 8,609 data points. Hence, each data point represents one minute of routing records. Training and test datasets for Slammer, Nimda, and Code Red I are shown in Table II.

### Table I: BGP RIPE Datasets: Internet Anomalies

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Beginning of event GMT</th>
<th>End of event GMT</th>
<th>Duration (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slammer</td>
<td>25.01.2003, 05:31</td>
<td>25.01.2003, 19:59</td>
<td>869</td>
</tr>
</tbody>
</table>

### Table II: BGP RIPE Datasets: Number of Data Points

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Regular (training)</th>
<th>Anomaly (training)</th>
<th>Regular (test)</th>
<th>Anomaly (test)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slammer</td>
<td>3,210</td>
<td>330</td>
<td>3,121</td>
<td>339</td>
</tr>
<tr>
<td>Nimda</td>
<td>3,673</td>
<td>827</td>
<td>3,635</td>
<td>474</td>
</tr>
<tr>
<td>Code Red I</td>
<td>3,679</td>
<td>361</td>
<td>2,921</td>
<td>239</td>
</tr>
</tbody>
</table>

Algorithm 1 VFBLS and VCFBLS algorithms: Pseudocode

1: procedure VFBLS and VCFBLS (training dataset X with labels Y)
2: Initialize:
3: Number of subsets v of input data
4: Number f of features to be selected in each subset
5: Sets of input data X_v, v = (1, ..., f)
6: Sets of groups of mapped features Z^m_v, n_v = (n_1, ..., n_f)
7: Groups of mapped features in each set Z_i, i = (k, ..., p)
8: Number of mapped features in each group
9: for each f in v do
10: Calculate feature importance and create F(X) by ranking features using a feature selection algorithm
11: Generate subset X_i = F(X), v = 1, 2, ..., f
12: for each set Z^m_i in Z^m_v do
13: Initialize the set of groups of mapped features Z^m_i
14: for each group Z_i in set Z^m_i do
15: switch Algorithm do
16: case VFBLS
17: Generate Z_i based on X_i and the number of mapped features
18: case VCFBLS
19: Generate Z_i based on X_i and the number of mapped features
20: Generate subsequent groups Z_i based on Z_i-1
21: Insert Z_i into Z^m_v
22: end for
23: Insert Z^m_i into Z^m_v
24: end for
25: end for
26: Construct matrix Z^i = [X | Z^m_v]
27: Generate enhancement nodes H^m = [H_1, ..., H_m] based on Z^i
28: Concatenate Z^i and H^m to create the state matrix A^m_i
29: Compute weights W^m_i based on A^m_i and labels Y using the ridge regression algorithm
30: end procedure

Algorithm 2 Incremental VFBLS and VCFBLS algorithms: Pseudocode

1: procedure Incremental VFBLS and VCFBLS (training dataset X with labels Y)
2: Extract initial input subset X_0 from dataset X
3: Extract initial labels Y_0 from Y
4: Initialize:
5: Number of incremental learning steps: l
6: Number of data points per step: d
7: Number of enhancement nodes per step: e
8: Calculate feature weight vector W_i = [w_0, w_1, ..., w_l]; w_0 = X_0/X_1; w_1,..., w_l = (1 - w_0)/l
9: for each step in l do
10: Generate X_i based on X, X_0, and d
11: Generate Y_i based on Y, Y_0, and d
12: Calculate feature importance and create F(X_i) by ranking features using a feature selection algorithm
13: Generate additional mapped features Z_{i+1} and additional enhancement nodes H_{i+1} using Algorithm 1
14: Update A_{i+1}
15: Update weights W_{i+1}
16: end for
17: Rank and select features to be used in testing based on: selected features and their importance in each step and the weight vector W_i
18: end procedure
For each collected dataset (Slammer, Nimda, Code Red I), we experimented with a number of training and test data points that are selected from periods of anomalies [46]. We partitioned the datasets by selecting 80 %, 70 %, or 60 % of anomalous data for training and the remaining 20 %, 30 %, or 40 % for testing. (We kept the number of data points in the training and test datasets to be divisible by 20 by moving the remaining data points from the training to the test dataset.) Using 60 % of data for training and 40 % for testing generated the best performance results. Another approach was to use concatenations of two datasets for training while the third dataset is used for testing. For example, Slammer and Nimda were concatenated in the training phase and used to test Code Red I dataset. Experiments indicated that the two approaches did not greatly affect performance of the employed algorithms.

B. NSL-KDD Dataset

The NSL-KDD [34] dataset is an improved version of the KDD’99 intrusion dataset based on DARPA 1998 dataset that contains 9 weeks of collected traffic when various intrusions were introduced in a simulated US Air Force base network [68], [69]. Data were captured from an evaluation testbed and included large numbers of virtual hosts and user automata. The KDD’99 dataset [70]–[72] was used in various IDSs [68], [73]–[75]. NSL-KDD is a randomly selected subset of KDD’99 after redundant data were removed [76] and is a widely used benchmark for evaluating anomaly detection techniques. NSL-KDD dataset captures Transport Control Protocol (TCP), User Datagram Protocol (UDP), and Internet Control Message Protocol (ICMP) traffic collected using the tcpdump utility. It contains four types of intrusion attacks: Denial of Service (DoS), User to Root (U2R), Remote to Local (R2L), and Probe.

The NSL-KDD dataset contains one training (KDDTrain+) and two test datasets (KDDTest+ and KDDTest−21). KDDTest−21 is a subset of the KDDTest+ dataset that includes records that could not be correctly classified by 21 models [76]. The number of data points is shown in Table III [34]. Each network connection is represented by 41 features: 38 numerical and 3 categorical (“protocol_type”, “service”, and “flag”) features. Categorical features are converted to numerical features using the dummy coding method to generate 71 additional features.

| TABLE III |
| NSL-KDD DATASET: NUMBER OF DATA POINTS |
| Regular | DoS | U2R | R2L | Probe | Total |
| KDDTrain+ | 67,343 | 45,927 | 52 | 995 | 11,656 | 125,973 |
| KDDTest+ | 9,711 | 7,458 | 200 | 2,754 | 2,421 | 22,544 |
| KDDTest−21 | 2,152 | 4,342 | 200 | 2,754 | 2,402 | 11,850 |

C. CICIDS2017 and CSE-CIC-IDS2018 Datasets

CIC has developed a testbed framework [77], [78] to generate CICIDS2017 [35] and CSE-CIC-IDS2018 [36] traffic data. The CICIDS2017 dataset includes intrusions that rely on various network vulnerabilities [77] executed using tools for malicious attacks: Patator, Slowloris, Heartleech, Damn Vulnerable Web App, Metasploit, Ares, and Low Orbit Ion Cannon. 84 features including duration, size of packets, number of packets, and number of bytes were extracted using an application for generating and analyzing network traffic flows. We consider application-layer DoS attacks data collected on Wednesday 05.07.2017, labeled GoldenEye, Hulk, SlowHTTPTest, and Slowloris having 10,293, 230,124, 5,499, and 5,796 intrusions, respectively.

The CSE-CIC-IDS2018 dataset was captured over ten days between Wednesday 14.02.2018 and Friday 02.03.2018 [36]. It includes attack scenarios, date, and start and end times of the attack(s). Extracted are 83 features including flow duration, maximum/minimum packet size, and packet flow rate. We consider anomalous instances that include slow-rate low-volume application-layer GoldenEye and Slowloris DoS attacks collected on Thursday 15.02.2018 having 41,508 and 10,990 intrusions, respectively.

IV. EXPERIMENTS AND PERFORMANCE EVALUATION

The experimental procedure consists of four steps: (1) Partitioning datasets for training and testing; (2) Processing data: converting categorical to numerical features, selecting features, and normalizing training and test datasets (features selected during training are applied in the test phase); (3) Using 10-fold cross-validation to train and tune parameters; and (4) Testing and evaluating the generated machine learning models based on accuracy, F-Score, and training time. Performance results were obtained using the same division of datasets for testing in all cases except the NSL-KDD dataset. (In the case of the NSL-KDD dataset, the training and test datasets were predefined.)

The BGP RIPE, NSL-KDD, CICIDS2017, and CSE-CIC-IDS2018 datasets were used to create and evaluate performance of various machine learning models: deep learning RNNs (LSTM and GRU); BLS, RBF-BLS, CFBLS, CEBLS, and CFEBLS with and without incremental learning; and the newly proposed VFBLS and VCFBLS algorithms with and without incremental learning. We perform two-way classification to identify regular (0) and anomalous (1) data. The datasets are first sorted based on time stamps and then partitioned. The training and test datasets consist of 60 % and 40 % of anomalous data, respectively. While performance of LSTM and GRU depends on the number of hidden layers and nodes [15], [18], BLS classification performance is affected by BLS architecture as well as the number of mapped features, enhancement nodes, and groups of mapped features [44], [45].

The number of selected features was used to evaluate their effect on BLS performance. (Note that RNNs do not require feature selection.) Features are ranked based on importance using the function sklearn.ensemble.ExtraTreesClassifier() [79] and by tuning and setting parameters n_estimators = 100 and random_state = 1. For cross-validation of LightGBM models, we vary the number of estimators (10–200) and learning rate (0.01–0.1).
We develop deep learning and bidirectional RNN models having various hidden number of layers and input sequence lengths of 10 (Slammer, Code Red I), 100 (Nimda), and 50 (NSL-KDD, CICIDS2017, CSE-CIC-IDS2018) data points. ReLU is used as the RNN activation function. Layers with 0.5 dropout probability are inserted after $FC_2$ and $FC_3$ layers. The optimization algorithm “Adam” is selected to train the RNN models using 30 (BGP RIPE) and 50 (NSL-KDD, CICIDS2017, CSE-CIC-IDS2018) epochs with learning rate $lr = 0.001$. The deep learning neural network model with four hidden layers consists of 37 (BGP RIPE)/109 (NSL-KDD)/78 (CICIDS2017, CSE-CIC-IDS2018) RNNs, 64 FC1, 32 FC2, and 16 FC3 fully connected (FC) hidden nodes.

The CFBLS, CEBLS, and CFEBLS models were implemented by modifying the original BLS functions [45]. For the cross-validation of incremental and non-incremental BLS models, we vary the number of mapped features (10–400), groups of mapped features (1–50), and enhancement nodes (20–700). Parameters of the incremental BLS models are: incremental learning steps $= 2$ (Slammer, Nimda, Code Red I, CICIDS2017, CSE-CIC-IDS2018), 3 (NSL-KDD); enhancement nodes/step $= 50$ (Slammer), 10 (Nimda), 60 (Code Red I, NSL-KDD), 20 (CICIDS2017, CSE-CIC-IDS2018); and data points/step $= 187$ (Slammer), 290 (Nimda), 303 (Code Red I), 3,000 (NSL-KDD), 55,680 (CICIDS2017), 49,320 (CSE-CIC-IDS2018). For the cross-validation of VFBLS and VCFBLS models, we vary mapped features (10–200), groups of mapped features (5–30), and enhancement nodes (40–700). In the case of incremental VFBLS and VCFBLS models, feature weight for initial step $= 0.9$ (BGP RIPE), 0.7 (NSL-KDD, CICIDS2017), 0.85 (CSE-CIC-IDS2018) while the remaining parameters are the same as for incremental BLS. Performance of models was controlled by tuning the parameter $\lambda$ (16) for sparse regularization in the ridge regression algorithm that was used to calculate output weights during the training process.

Training parameters that generate the best performance results are listed in Table IV to Table IX. Performance of LightGBM, RNN and Bi-RNN (LSTM and GRU) with 2 (LSTM2 and GRU2), 3 (LSTM3 and GRU3), 4 (LSTM4 and GRU4) hidden layers, and BLS models are shown in Figs. 2, 3, and 4. Training times for models leading to the best performance are listed in Table X.

### Table IV: LightGBM Parameters: BGP RIPE, NSL-KDD, CICIDS2017, and CSE-CIC-IDS2018 Datasets

<table>
<thead>
<tr>
<th>Number of features</th>
<th>Dataset</th>
<th>Number of estimators</th>
<th>Learning rate</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
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</tr>
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<td>8</td>
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<td>30</td>
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<td>64</td>
<td>NSL-KDD</td>
<td>200</td>
<td>0.01</td>
</tr>
<tr>
<td>32</td>
<td>CICIDS2017</td>
<td>200</td>
<td>0.01</td>
</tr>
<tr>
<td>64</td>
<td>CSE-CIC-IDS2018</td>
<td>100</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Experimental results show that BLS models offer comparable performance to deep learning GRU and LSTM RNN and Bi-RNN models while requiring shorter training time. Introduced VFBLS and VCFBLS models outperform other BLS models in most cases except models based on Slammer dataset. In the case of NSL-KDD datasets, the VFBLS models show 2%–15% improvement in accuracy and 4%–12% improvement in F-Score. Even though the LightGBM models have the fastest training time as shown in Table X, its accuracy and F-Score are in some cases lower than the proposed VFBLS and VCFBLS models, as illustrated in Figs. 2, 3, and 4.

Performance of machine learning models heavily depends on the datasets used for training and test. In the case of BGP RIPE datasets, one of the Bi-GRU models has the best accuracy and F-Score. The proposed VFBLS models have the best accuracy and F-Score for KDDTest+ and KDDTest-21 and the best F-Score for CSE-CIC-IDS2018 datasets. The GRU models have the best accuracy for CICIDS2017 and CSE-CIC-IDS2018 datasets.

Performance results shown in Fig. 2 (top) illustrate that the extra-trees algorithm may not be able to select the top 8 features that better capture properties of the anomalous data. Hence, selecting 8 features is not sufficient for successfully classifying the Slammer dataset. Note that performance of BLS and incremental BLS remains comparable even without feature selection. While performance of incremental VFBLS and VCFBLS is often inferior to other algorithms, their advantage is that the models need not be retrained for new incoming data. These models exhibit poor performance due to inadequate feature selection. Occurrences of long consecutive regular or anomalous data points in the partitioned training datasets lead to low accuracy and F-Score. If a portion of the
TABLE VII  
BLS AND INCREMENTAL BLS PARAMETERS: CICIDS2017 AND CSE-CIC-IDS2018 DATASETS

<table>
<thead>
<tr>
<th>Number of features</th>
<th>Dataset</th>
<th>Model</th>
<th>Mapped features</th>
<th>Groups of mapped features</th>
<th>Enhancement nodes</th>
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</thead>
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<td>CEBLS</td>
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<td>20</td>
<td>80</td>
</tr>
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<td>BLS</td>
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<td>30</td>
<td>20</td>
</tr>
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<td>RBF-BLS</td>
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<td>20</td>
</tr>
<tr>
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<td>CICIDS2017</td>
<td>RBF-BLS</td>
<td>10</td>
<td>20</td>
<td>80</td>
</tr>
<tr>
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<td>Incremental BLS</td>
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</tr>
<tr>
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<td>CICIDS2017</td>
<td>CFEBLS</td>
<td>10</td>
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<td>40</td>
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<tr>
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<td>BLS</td>
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<tr>
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<td>CFEBLS</td>
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<td>CFEBLS</td>
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<td>CFEBLS</td>
<td>10</td>
<td>20</td>
<td>40</td>
</tr>
<tr>
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<td>CSE-CIC-IDS2018</td>
<td>BLS</td>
<td>15</td>
<td>30</td>
<td>20</td>
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TABLE VIII  
VFBLS AND VCFBLS PARAMETERS: BGP RIPE, NSL-KDD, CICIDS2017, AND CSE-CIC-IDS2018 DATASETS

<table>
<thead>
<tr>
<th>Number of features</th>
<th>Dataset</th>
<th>Mapped features</th>
<th>Groups of mapped features</th>
<th>Enhancement nodes</th>
</tr>
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<tbody>
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<td>Slammer</td>
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<td>30, 20, 10</td>
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</tr>
<tr>
<td></td>
<td>Nimda</td>
<td>20, 40, 30</td>
<td>10, 20, 10</td>
<td>50</td>
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<td></td>
<td>Code Red 1</td>
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<td>10, 10, 20</td>
<td>100</td>
</tr>
<tr>
<td>32, 64, 109</td>
<td>NSL-KDD</td>
<td>20, 40, 30</td>
<td>20, 20, 20</td>
<td>40</td>
</tr>
<tr>
<td>32, 64, 78</td>
<td>CICIDS2017</td>
<td>15, 10, 10</td>
<td>5, 10, 5</td>
<td>40</td>
</tr>
<tr>
<td></td>
<td>CSE-CIC-IDS2018</td>
<td>10, 20, 10</td>
<td>5, 10, 5</td>
<td>40</td>
</tr>
<tr>
<td>VCFBLS</td>
<td>Slammer</td>
<td>200, 30, 30</td>
<td>20, 20, 20</td>
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<td>Nimda</td>
<td>20, 30, 30</td>
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<td>10, 20, 10</td>
<td>5, 5, 5</td>
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</table>

training dataset consists of one class only, generated feature importance is 0 and, hence, these features do not contribute to subsequent steps. In the case of BGP RIPE, CICIDS2017, and CSE-CIC-IDS2018 datasets, data points belong to a single class (regular or anomaly) over a long period of time and, hence, features selected during training are not relevant for the test dataset.

BLS and incremental BLS models offer comparable performance to deep learning models and have shorter training time [44] when used with large datasets such as NSL-KDD, CICIDS2017, and CSE-CIC-IDS2018. Introduced VFBLS and VCFBLS models have much shorter training time compared to RNN and Bi-RNN models. The proposed algorithms have an order of magnitude (up to 250 times) shorter training time than Bi-GRU. Their training time is comparable to BLS and its extensions for smaller datasets such as BGP RIPE but it increases for larger datasets because it is mainly spent for selecting features. Incremental variants of VFBLS and VCFBLS require considerably shorter training time. Note that LightGBM models require a much shorter training time than the BLS models.

Note that times reported for training BLS and incremental BLS models do not account for the times spent for selecting features. The overheads for feature selection depend on the size of the training datasets and the number of features. Times spent for selecting features in experiments with the extra-trees algorithm are: 0.13 s (Slammer), 0.22 s (Nimda), 0.24 s (Code Red 1), 10.24 s (KDDTrain\(^+\)), 18.56 s (CICIDS2017), and 13.44 s (CSE-CIC-IDS2018).

Experiments are performed using a Dell Alienware Aurora with 32 GB memory and Intel Core i7 7700K processor. Python 3.6 and libraries [80] NumPy (a scientific computing library), scikit-learn (a machine learning library), LightGBM (a gradient boosting framework), and PyTorch (a Python framework for deep learning) were used to create input matrices and to train and test the machine learning models.
TABLE X

<table>
<thead>
<tr>
<th>Datasets</th>
<th>LightGBM</th>
<th>RNN</th>
<th>Bi-GRU</th>
<th>BLS</th>
<th>CFEBLS</th>
<th>VFBLS</th>
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Fig. 3. Best performance results for LightGBM, RNN and Bi-RNN (LSTM and GRU), BLS, Incremental BLS, VFBLS, and VCFBLS models: KDDTest+ (top) and KDDTest−21 (bottom) datasets.

V. CONCLUSION

In this paper, we evaluated accuracy, F-Score, and training time of LightGBM, RNN, Bi-RNN, and BLS algorithms using BGP RIPE, NSL-KDD, CICIDS2017, and CSE-CIC-IDS2018 datasets. Experiments with BLS models were performed by varying the number of most relevant extracted features. The newly proposed algorithms employed variable number of mapped features and groups of mapped features without (VFBLS) and with (VCFBLS) cascades and a feature selection algorithm. Both algorithms also have incremental learning variants. We also described a procedure for detecting network intrusions.

Performance evaluation indicated that BLS with cascades of enhancement nodes required significantly longer training time. Note that in the case of incremental BLS, the model did not need to be retrained. As expected, larger numbers of mapped features, groups of mapped features, and enhancement nodes required additional memory and longer training time. The advantage of VFBLS and VCFBLS algorithms is their ability to derive generalized models by using various subsets of input data to generate mapped features thus providing an easy process for creating models. Furthermore, VFBLS and VCFBLS models are developed using a single experiment with integrated stages for selecting features and generating models. Training time of these models may be improved by allocating a smaller number of features generated from the input data. In several cases, VFBLS offered the best performance and shorter training time than RNNs and Bi-RNNs and comparable time to other BLS algorithms.

REFERENCES

J-SAC: MACHINE LEARNING IN COMMUNICATIONS AND NETWORKS


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