Soft Computing (2023) 27:6297–6305
https://doi.org/10.1007/s00500-023-07906-6

DATA ANALYTICS AND MACHINE LEARNING

Toward support-vector machine-based ant colony optimization algorithms for intrusion detection

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Received: 25 September 2021 / Revised: 17 January 2022 / Accepted: 27 April 2022 / Published online: 28 February 2023

Abstract
One of the major challenges of network traffic analysis is intrusion detection. Intrusion detection systems (IDSs) are designed to detect malicious activities that attempt to compromise the confidentiality, integrity, and assurance of computer systems. Intrusion detection system has become the most widely employed security technology. The novelty of the proposed research is to develop a system for IDSs. In this research, a support-vector machine (SVM) with ant colony optimization (ACO) is proposed to detect an intrusion. Standard data sets, namely Knowledge Discovery and Data Mining (KDD) Cup '99 and Network Security Laboratory (NSL)-KDD, were utilized to test the results of the proposed system. One of the greatest challenges in a network analysis dataset is dimensionality. To handle dimensionality reduction, the ant colony optimization algorithm was applied. In the ACO method, significant subset features are selected from the entire dataset. These subset features have proceeded the SVM machine learning algorithm for detection intrusion. The empirical results point out that the SVM with ACO has obtained superior accuracy. It is concluded that the SVM-ACO model can more efficiently protect a network system from intrusion.

Keywords Machine learning · Computation algorithms · Network traffic analysis · Cybersecurity

1 Introduction

The Internet has a fundamental part in relentless correspondence; thus, its applicability can lessen the impacts attributed to intrusions. Intrusion is defined as a movement that unfavorably influences the focus on the computer. The intrusion may harm reputability, integrity, privacy, and accessibility to assets during a tagged attack. The security of a computer system will be at risk when an intrusion happens (Alkahtani et al. 2020; Aldhyani and Joshi 2017; Aldhyani et al. 2020).

Intrusions can be aggregated into host-based intrusion and network intrusion, which are considered attempts to access, control, modify, or destroy data, and render a system inconsistent or unusable. These intrusions incorporate and control the system by controlling any alterations to a document system, such as increasing benefits, making unapproved logins and accessing to records and malware (e.g., infections, Trojan stallions, and worms), which can change the condition of the network. Network intrusions are caused by the approaching packets in the network system, which perform behaviors such as a denial-of-service (DoS) attack or even an attempt to split the network into systems (Joshi et al. 2015; Sitalakshm and Alazab 2018).

An IDS consists of software and/or hardware designed to detect malicious behaviors related to accessing, manipulating, and/or disabling a computer system, mainly through a network, such as the Internet. Monitoring the events occurring in a host or network, analyzing the network and system events, detecting malicious activities, and sounding an alarm if an attack is detected are the major tasks of an IDS (Aldhyani et al. 2020; Bassey et al. 2019).

An intrusion detection system is a tool that is used to detect an intrusion on the network and host levels. Generally, the most popular and well-known data for an intrusion detection system is audit data. Audit data record all the activities and actions that occur in a system and saves them in sequential order. As long as the system can

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record all activities, it can correspond to any system call in the system. Thus, it is possible to physically analyze the auditing data and detect any abnormal activity in the system. However, the immense size of the audit data that is available in the system often renders manual analysis impractical. Consequently, an automated audit data analysis tool is the only solution. In recent years, as the second line of defense after a firewall, intrusion detection approaches have rapidly developed (Al-Mughanam et al. 2020). Intrusion detection has an important role in attack detection, security inspection and network checks. With the rapidly growing connectivity of the Internet, network computer systems have increasingly vital roles in the modern community. While the Internet has provided great benefits to society, it has also rendered critical systems vulnerable to malicious attacks, since a preventive approach, such as a firewall, is not adequate for providing sufficient security for a computer system. An intrusion in an information system is an activity that contravenes the security strategy of the system: It is a deliberate unofficial endeavor to access information, manipulate information, and render systems unreliable. Intrusion detection is a process that is employed to identify a malicious intrusion and that is based on the belief that the behavior of an intruder will significantly differ from that of a legitimate user.

Bose et al. (2007) proposed Bayesian and Markov chain algorithms to discover specific rules for an IDS. The results of their proposed system were a detection rate of 94.33% and a false positive rate (FPR) of 0.8%. It is noted that the proposed system achieved satisfactory results compared with existing systems. Mitrokotsa et al. (2013) introduced five classification algorithms, namely the naïve Bayes model, linear model, Gaussian mixture model, multilayer perceptron, and support-vector machine (SVM), for developing an IDS. It observed that the multilayer perceptron classifier has given the best performance compared with other classification algorithms. Azmoodeh and Choo (2018) presented a deep leaning algorithm to detect malware detection in "Internet of (Battlefield) Things Devices". Doshi et al. (2018) presented the K-nearest neighbors, decision tree, SVM, decision tree using Gini impurity scores, random forest using Gini impurity scores and neural network approaches to detect normal IoT packets from denial service attacks packets. It is concluded that the random forest tree has attained the best results.

Li et al. (2012) used the SVM classification algorithm to detect the denial of service attack (DoS), Probe or Scan, user to root (U2R), remote to local (R2L) attacks and normal packets. The standard dataset Knowledge Discovery and Data Mining (KDD) Cup '99 was employed to test the proposed system. In Amiri et al. (2011) presented a least-squared SVM algorithm for classification of big data. In Hu et al. (2003) applied a SVM algorithm to classify the anomalies. Wagner et al. (2011) presented a one-class SVM classifier to detect anomaly detection by using different types of attacks in dataset. The SVM classifier was proposed for detecting unknown computer attacks (Moskovitch et al. 2007). Kotpalliwar et al. (2015), Saxena et al. (2014), Pervez et al. (2014), Shon et al. (2005), and Kokila et al. (2014) presented a SVM algorithm to build a cybersecurity system for detecting intrusion.

2 Materials and methods

Framework of proposed system shown in Fig. 1.

2.1 Data sets

As the experiments have been conducted, two standard IDS data sets are applied. A detailed description of these datasets is presented as follows:

2.1.1 KDD Cup'99 data set

The KDD Cup data set[1] is employed in three international KDD tools to develop intrusion detection and robust data mining algorithm discovery and distinguish between normal packets and attack packets. This contains three major intrusions, namely DOS, Probe, User to Root (U2R) and Remote to Local (U2R). KDD Cup is represented by 41 attributes. Table 1 shows the features of KDD Cup dataset.

2.1.2 NSL-KDD data set

The NSL-KDD is an advanced version of KDD Cup data for analyzing and detecting intrusion in a network. The NSL-KDD data set has been proposed by McHugh. Furthermore, each record consists of 41 features, and these features can be described as either normal or attacks. The NSL-KDD dataset contains three major intrusions, namely (DOS), Probe, and (U2R) & (U2R). The attacks of the data are illustrated in Table 2.

2.2 Pre-processing techniques

Pre-processing has a vital role in analyzing patterns from network data to achieve accurate results. Therefore, the pre-processing steps are an essential part of the intrusion detection system to improve the SVM algorithm for detection intrusion. The ant colony optimization (ACO) algorithm was proposed as a pre-processing stage to select

[1] KDD Cup 1999 Data (http://kdd.ics.uci.edu/databases/kddcup99/kddcup99.html).

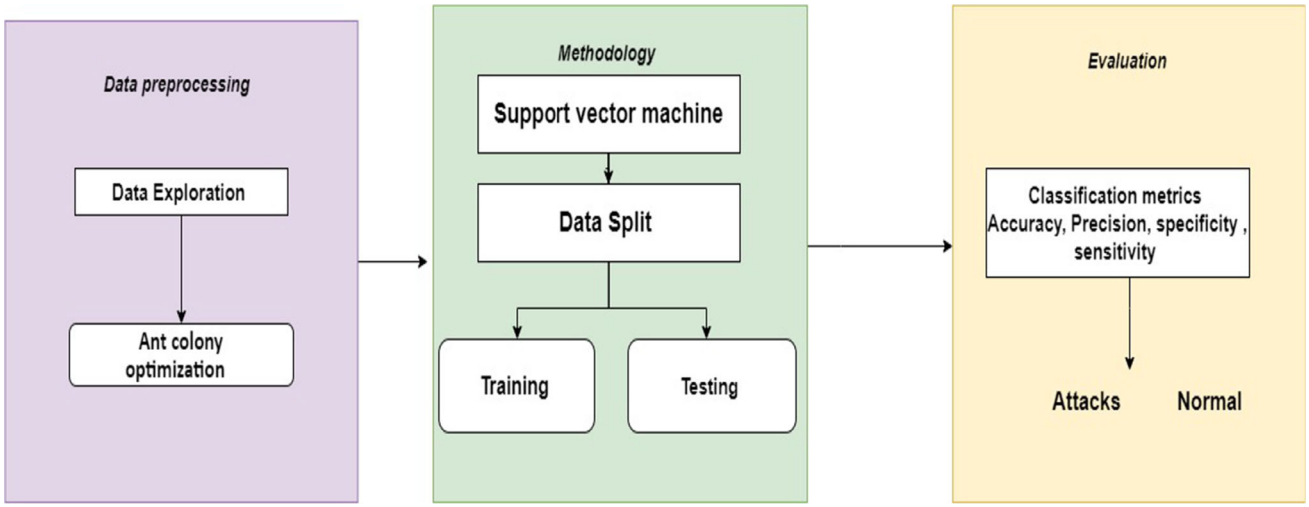


Fig. 1 Methodology of the proposed system

the irrelevant features from network traffic datasets. These features can help to develop a cybersecurity system.

2.2.1 Ant colony optimization (ACO)

The ACO algorithm is one of the most important probabilities techniques for resolving a computation problem. ACO is applied to determine the best approach for solving this problem based on the rules of real ants. The ACO algorithm is developed by Marco Dorigo in 1992, as mentioned in his Ph.D. thesis (Vishwakarma et al. 2017a). The algorithm has focused on determining the best path in the graph using the behaviors of ants for seeking the best path between their colony and a source of food. Ants pass through the graph where fewer nodes are found, and the graph nodes are fully connected to allow for features. The main object of the ACO algorithm is transition between the pheromone rules and the modernized rules; thus, the pheromone and heuristics values are connected instead of each having a separate value. Primarily, the portrayal of the heuristic value is the engaging quality of a beacon; the essential element of any ACO algorithm is a helpful heuristic for developing probabilistic features (Kanaka Vardhini and Sitamahalakshmi 2017). A constructive heuristic process assembles arrangements as successions of highlights from the limited arrangement of highlights. A subset construction begins with an unfilled subset. Furthermore, each construction step of the subset is reached by including the main feature from the set of features. An appropriate heuristic attractive quality of crossing between two features could be any subset assessment (Vishwakarma et al. 2017b).

$$P_i^K(t) = \frac{[T_i(t)]^{\alpha}.[\eta_i]^{\beta}}{\sum_{u \in j^k}[T_u(t)]^{\alpha}.[\eta_u]^{\beta}} \text{ifi} \in j^k \quad (1)$$

The feasible feature set is j^k, where ant k can be added to its subset; the pheromone value and heuristic value are η_i and T_i, respectively, which are connected with features i. α and β are parameters that are utilized to identify the weight of the pheromone and heuristics value. The selection of the parameter values is very important for balancing between exploitation and exploration. The pheromone update is the main part of the ACO algorithm. After ants completed their task of identifying the best path for solving a problem, the pheromone update is used to help the next ants follow the same path for completing their task. To distribute the pheromone in all nodes, Eqs. (2) and (3) is considered.

$$T_i(t) = (1-p)T_i(t) \quad (2)$$

$$T_i(t+1) = T_i(t) + \Delta T_i \quad (3)$$

$$\Delta T_i(t) = \sum_{k=1}^{m} \Delta T_i^k(t) \quad (4)$$

where M is the number of ants at each repetition and $p \in (0, 1)$ denotes the decomposition factor of the pheromone trail. The essential objective of using the pheromone is to evaporate other ants along the same path. The ants can update the pheromone according to Eqs. 4 and 5.

$$\Delta T_i^k(t) = w \cdot \gamma\left(s^k(t)\right) + \emptyset \cdot \left(\frac{n}{|s^k(t)|}\right) \text{ifi} \in S^k \quad (5)$$

where s^k (t) is the features, subset obtained by ant k at iteration t and $|s^k\ (t)|$ is the length of the pheromone. w and $\varnothing$ are parameters that govern the performance of the classifier. We have applied the ACO algorithm to choose the significant features from the different datasets that have been utilized. Eight of the most significant features selected from the KDD CUP dataset is illustrated in Table 3.

Table 1 Eight Most significant selected features from KDD Cup 99 by using the ACO algorithm

Attacks	Number of features	Name of feature
Probe	34	dst_host_same_srv_rate
	4	Flag
	14	num_file_creations
	20	Count
	41	dst_host_srv_rerror_rate
	19	num_access_files' real
	9	logged_in
	21	is_host_login
DOS	9	logged_in
	21	is_host_login
	31	dst_host_same_srv_rate
	12	su_attempted
	40	Service
	18	is_host_login
	3	dst_bytes
	14	num_file_creations
U2R and R2L	40	dst_host_rerror_rate
	39	dst_host_srv_serror_rate
	10	Hot
	34	dst_host_srv_diff_host_rate
	10	num_compromised
	40	Service
	14	num_file_creations
	20	Count

Table 4 shows the subset features selected from the NSL-KDD data set. Figure 2 displays the ACO algorithm process for selecting subset features from the original dataset. The ACO algorithm is applied to detect the space of subsets from among all features. These significant features are fed into the classification algorithms to build a robust IDS system. It is observed that the time processing for selecting the features is more suitable.

2.3 Support-vector machine (SVM) algorithm

The SVM was proposed by Vapnik (Cortes 1995) in 1963. It is a significant supervised machine learning algorithm that is employed for large databases and provides more accurate results. The SVM is designed for the dichotomist classification problem, such as binary classification with two classes or with multiclasses. The SVM works to determine the optimal dichotomist hyperplane that can maximize the margin, which can achieve the largest separation of two or more classes. To classify two classes, two parallel hyperplanes are constructed. The SVM tries to separate the hyperplane and increase the distance between these two hyperplanes. Hence, the hyperplane has the largest distance, which is considered a reasonable separation. The SVM has obtained a lower error when the margin is large.

Table 2 All types of attacks in KDD Cup and NSL-KDD

Major attack	Types of major attacks
Dos	Back,
	Land,
	Neptune,
	Pod,
	Smurf,
	Teardrop,
	Mailbomb,
	Processtable,
	Udpstor m,
	Apache2,
	Worm
Probe	Satan,
	IPsweep,
	Nmap,
	Portsweep,
	Mscan,
	Sa int
R2L	Guess
	_password,
	Ftp_write
	, Imap,
	Phf,Multihop,
	Warezmaster,
	Xlock,
	Xsnoop,
	Snmpgue,
	ss,
	Snmpgetattack,
	Httptunnel,
	Sendmail,
	Named
U2R	Buffer_ overflow,
	Loadmodule Rootkit,
	Perl,
	Sqlattack,
	Xterm,
	Ps

3 Experimental results

In this section, the results of the proposed methodology for the IDS are presented.

Table 3 Eight most significant selected features from NSL-KDD by using ACO algorithm

Attacks	Number of features	Name of feature
DOS	4	Flag
	37	dst_host_rerror_rate
	34	dst_host_srv_diff_host_rate
	21	is_host_login
	12	su_attempted
	41	Flag
	40	dst_host_rerror_rate
	39	dst_host_srv_serror_rate
Probe	39	protocol_type
	9	logged_in
	8	num_failed_logins
	31	dst_host_same_srv_rate
	8	num_failed_logins
	40	Service
	10	num_compromised
	4	Land
U2R and R2L	31	dst_host_same_srv_rate
	41	Flag
	8	num_failed_logins
	32	dst_host_diff_srv_rate
	14	num_file_creations
	33	dst_host_same_src_port_rate
	4	Land
	40	Service

Table 4 Experiment environment setup

Hardware	Environment
Operation system	Windows 7
CPU	I3
Memory	4
Development environment	Jupyter Python 3.6

3.1 Experiment environment setup

This research has been conducted by employing different environments, such as hardware and software. Table 4 displays the requirements employed to develop the proposed system.

3.2 Evaluation metrics

The performance measures were proposed to evaluate the proposed methodology for the IDS. The Accuracy, False Positive, Precision, True Positive and Time were presented. The equation performance measures are presented as follows:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{FP} + \text{FN} + \text{TP} + \text{TN}} \tag{6}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \tag{7}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{8}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{9}$$

$$F1\ \text{score} = 2 * \frac{\text{precision} * \text{Recall}}{\text{precision} * \ \text{Recall}} \times 100\% \tag{10}$$

where TP is True Positive, FP is False Positive, TN is True Negative, and FN is False Negative.

3.3 Results and discussion

The proposed methodology was designed by using real network data, which contains normal and attacks labels. The ACO method was employed to handle dimensionality reduction, and the ACO method was utilized to select the significant features from the big network data. We have selected eight significant features, which were the more important features from the entire the dataset. These eight features were processed by using the SVM machine learning algorithm. The dataset was divided into 70% for training and 30% for testing. Tables 5 and 6 show the division of the data for KDD Cup'99 and NSL-KDD, respectively. Figures 3 and 4 display the size of the total KDD Cup '99 and NSL-KDD datasets.

Table 7 indicates that the results obtained by using the SVM classifier and the ACO method for the KDD Cup '99 dataset. The KDD Cup '99 dataset has 41 features, and eight important features were selected for the ACO method. The hybrid model was applied for each major attack in KDD Cup'99 with a normal class. The empirical results reveal that the hybrid mode has obtained suitable performance with DOS and U2R & R2L attack and normal, 100% with respect to accuracy metric.Table 8 summarizes the results of the hybrid model by using the NSL-KDD dataset. It is observed that the hybrid model has obtained the best accuracy with DOS and Probe attacks and the normal class. The accuracy for a DOS attack is 99.90%, and the accuracy for a Probe attack is 99.62%. It is observed that the proposed methodology has achieved the highest accuracy, due to the proposed obtained these results with minimal time. The performance of the hybrid model, which utilizes the KDD Cup'99 dataset and NSL-KDD dataset, is shown in Figs. 5 and 6.

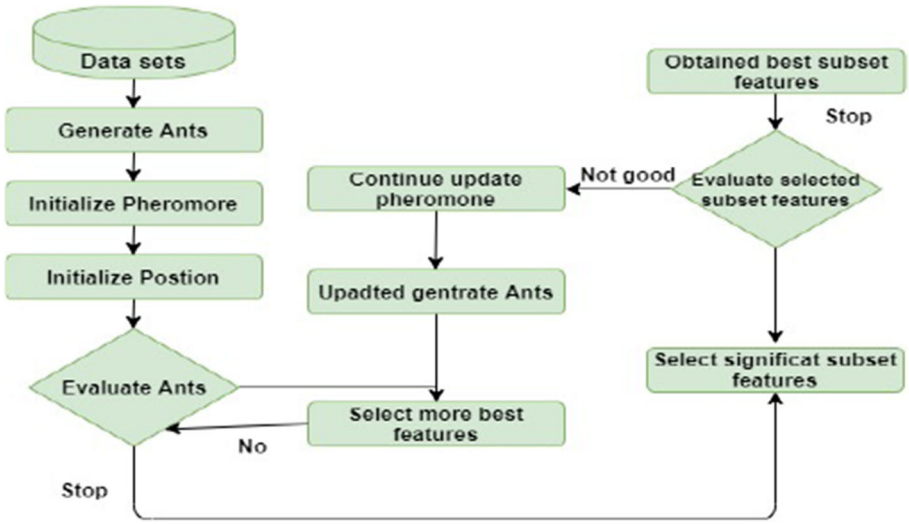


Fig. 2 Algorithm steps of ACO for feature selection from network datasets

Table 5 Splitting KDD Cup'99 dataset

Attacks	Total data	Training data	Testing dataset
DOS	13,500	9450	4051
Probe	10,252	7176	3076
U2R & R2L	18,252	12,776	5476

Table 6 Splitting NSL-KDD dataset

Attacks	Total data	Training data	Testing dataset
DOS	308,966	216,276	92,690
Probe	22,635	15,844	6791
U2R & R2L	32,568	22,797	9771

4 Conclusion

Taking into account the notion that digital marketing and online business have access to highly private information that is communicated with the Internet, it is very important to develop a security system to protect this information from threats. In this methodology, a hybrid system, ACO with a SVM, is proposed to detect intrusions. The system was tested by using a real standard dataset. The ACO method was applied to select subset features from an entire dataset to enhance the proposed system. The subset features were considered significant features for developing the system, and the SVM system was employed as a classification process for detecting attacks. The proposed system has the capability of improving cyber-security system for detection attacks. The overall results show that the proposed system can efficiently detect various intrusions. In the future, we will use our real dataset and the deep learning method to improve the cybersecurity system.

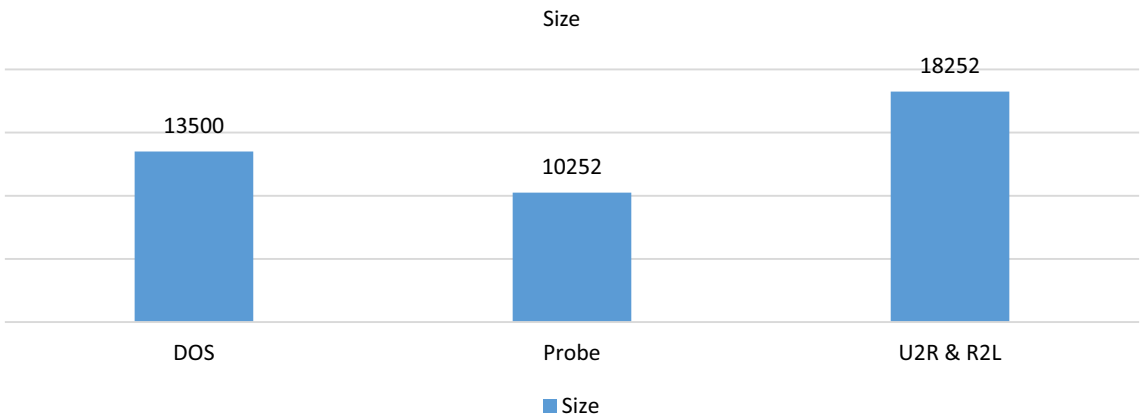


Fig. 3 Size of simple for KDD Cup'99 dataset

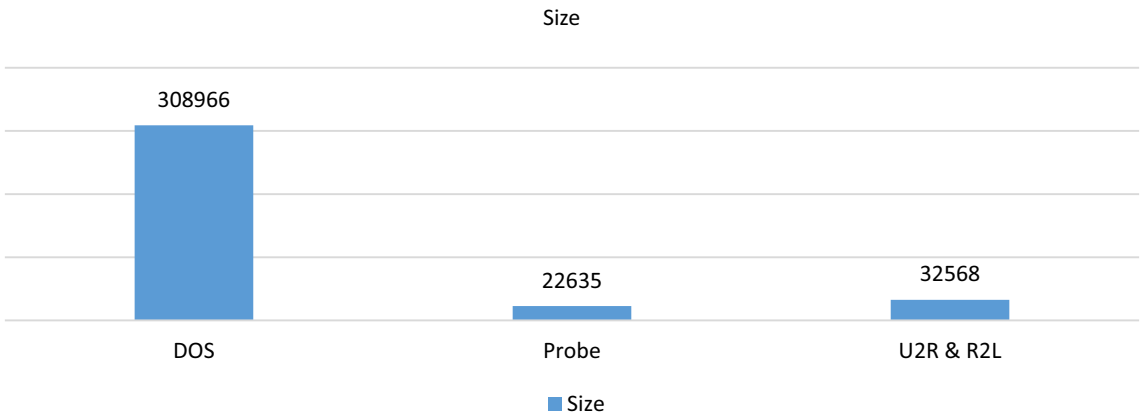


Fig. 4 Size of simple NSL-KDD dataset

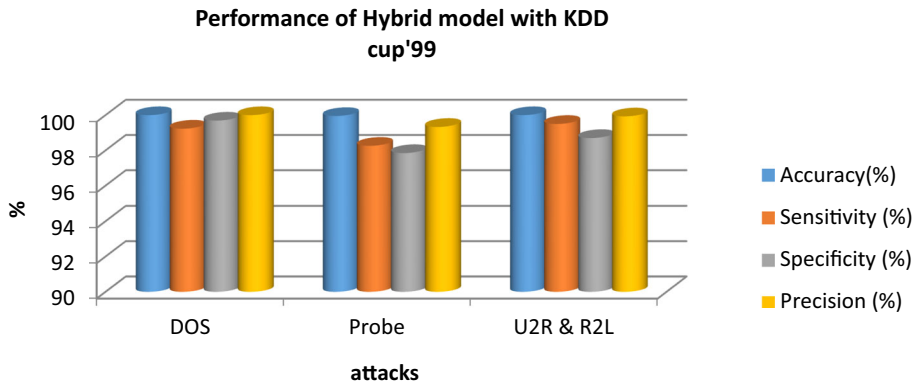
Table 7 Performance of hybrid model of KDD Cup '99 dataset

Attack	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Time (seconds)
DOS	100	99.23	99.69	100	0.92
Probe	99.95	98.26	97.85	99.33	0.035
U2R & R2L	100	99.50	98.70	99.93	0.025

Table 8 Performance of hybrid model of NSL-KDD dataset

Attack	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Time (seconds)
DOS	99.90	99.60	98.89	99.63	0.85
Probe	99.62	99.02	98.25	99.65	0.72
U2R & R2L	99.23	99.11	99.22	99.62	0.95

Fig. 5 Performance of proposed model in KDD Cup '99 dataset



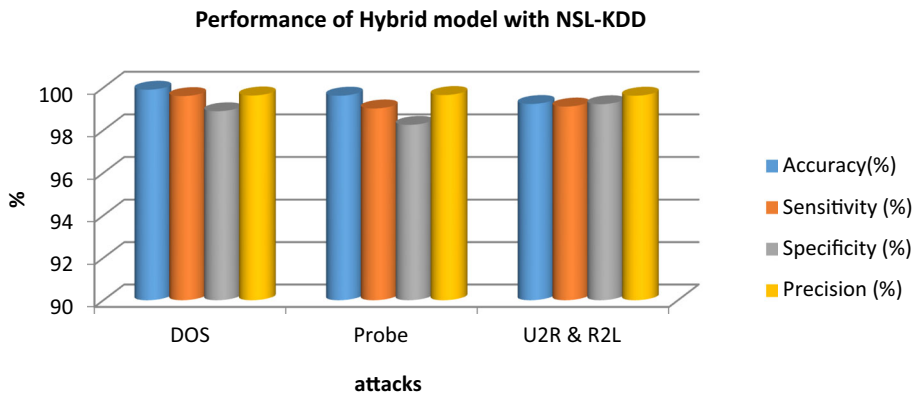


Fig. 6 Performance of proposed model in NSL-KDD dataset

Funding The authors have not disclosed any funding.

Data availability Enquiries about data availability should be directed to the authors.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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