# A Pragmatic Optimal Approach for Detection of Cyber Attacks using Genetic Programming

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***Abstract*—Cyber-attacks are becoming an increasing threat to people and daily businesses regularly. Attackers have also been evolving their strategies and methods with time. Every attack carried out has the potential to exploit the system on a large scale. Various Artificial Intelligence (AI) algorithms are used to defend such vulnerabilities. This paper analyzes a novel attack and extracts attackers' intrusion scenarios. Evolutionary Computation Techniques have been remarkably used in the field of cybersecurity. This paper particularly discusses the Distributed Denial Of Service (DDoS) attack. The effect of this attack ranges from a disturbance of an elementary service to causing major threats to critical services. In recent times these attacks have become more intricate and carry a significant threat. Therefore, there is a necessity for an intelligent Intrusion Detection System (IDS) to recognize attacks. In this study, work is carried on the latest dataset called Modern DDoS. This paper comprises of comparing the results of six established classification techniques: Random Forest, Naive Bayes, Stochastic Gradient Descent, Decision Trees, Logistic Regression, and K-Nearest Neighbour (KNN) with the proposed Genetic Programming model. The results show that the proposed Genetic Programming model has better accuracy when compared to various existing methods.**

***Keywords*—Intrusion Detection System (IDS), Distributed Denial of Service (DDoS), Modern DDoS dataset, Evolutionary Computation (EC), Genetic programming (GP), Principal Component Analysis (PCA).**

## I. Introduction

Cybersecurity is becoming a regular struggle for organization asset's and businesses. The effort to hinder the integrity, confidentiality, or availability of the system is called Intrusions. [3] "Intrusion Detection is the process of investigating and monitoring the events occurring in the network or computer system which are violations or impeding threats of computer security policies" [5]. An Intrusion detection system (IDS) is an application that defends your network from suspicious activities, threats, and vulnerabilities when detected [7]. However, IDS faces several issues such as unbalanced data distributions, large traffic volumes, continuously changing environments, and the need to recognize normal and abnormal behavior [14].

A Cyber attack is a deliberate attempt that targets one or more computers against multiple computers or networks. The Cyber Attacks such as Denial-of-service (DoS) and Distributed Denial-of-service (DDoS), Man-in-the-Middle (MitM) attack, Phishing, and Spear-Phishing attacks, Cross-site Scripting (XSS) attack, Malware attack, etc have attracted the attention of researchers over the years [16]. The primary focus of this study is particularly restricted to DDoS attacks which will be extended to various attacks in the future and thus coming up with a model capable of detecting attacks of various kinds and providing an immediate remedy of the attack in case attack happens. A DDoS attack is a pernicious attack on a network wherein the targeted system (a server or website or any other network resources) gets affected by causing the denial of services to the user of the targeted system (or resources) [23]. Hackers make use of botnets to flood an IP address with thousands of messages and connection requests thereby denying services to legitimate users.

Advances in Machine Learning (ML) and Deep Learning (DL) [24], [25] have a profound impact on science and technology. These technologies have many recent successes in the field of Cyber-security. The study focuses on the usage of ML and Evolutionary Computation (EC) algorithms specifically Genetic Programming to investigate the IDS building process more effectively than the existing methods [26]. "Genetic programming (GP) is an evolutionary approach towards computing that focuses on optimal classification. GP is a metaheuristic approach that is capable of using complex pattern representations such as trees" [27]. This paper demonstrates a comprehensive analysis of detecting DDoS attacks using various classification models as well as the proposed method using genetic programming. Within this evaluation, six ML models namely Random Forest, Naive Bayes, Stochastic Gradient Descent, Decision Trees, Logistic Regression, K-Nearest Neighbour (KNN), [28] and genetic programming model are explored for detecting DDoS attacks and their performances are evaluated based on experiments on Modern DDoS dataset.

The rest of the paper is organized as follows: Section II encapsulates the available literature. Section III sums up the genetic programming fundamentals and explanation. In section IV, the proposed method is reported in detail. Section V furnishes the experiments and results. Section VI bestows the conclusions and future scope of the work.

## II. Related Work

Espejo et.al [1] have surveyed how Genetic Programming can be used for classification. They have spoken of different methods of constructing a classifier which can be more accurate and dependable. The main aim was at upgrading the quality of classification by using GP. The distinctive elements of GP make it a dependable technique for classification. It was concluded from this paper that different classification models such as Decision trees, Random Forest, etc can be used as individuals of a population. Drawbacks of GP were also highlighted.

A literature survey of Machine Learning (ML) and Data Mining (DM) methods used for intrusion detection is portrayed by authors Buczakk and Erhan Guven [2]. Though they have discussed different ML/DL techniques, it is difficult to conclude which method is most efficient. There are various parameters from which the effectiveness of a model can be calculated since it depends on the particular IDS. They have discussed how datasets play a major role in training and testing models in cyber intrusion.

Since there were no common datasets that contained new types of DDoS attacks, hence a new dataset was collected by Alkasassbeh et.al [4]. The collected dataset was named as Modern DDoS. It comprised of five DDoS traffic classes. No redundant or duplicate records were found. Various methods such as collection and audition, preprocessing, feature extraction, and statistical measurements were performed before obtaining the dataset. Three established classification techniques were used for example Naïve Bayes, Random Forest, and Multilayer Perceptron (MLP). Improved results over this paper have been discussed ahead in the comparative study.

Alyasiri et.al [5] have discussed a graph-based optimal approach for Genetic Programming called Cartesian Genetic Programming. Rules are constructed for the detection of different kinds of cyber attacks using this technique. The Modern DDoS dataset was used for experimentation. The Java Evolutionary Computation Toolkit (ECJ) was used for implementation. Suitable parameters such as population size, generations, mutation rate, etc were used while performing the experiments. The results of this approach are compared to the proposed GP model.

Mukkamala S.et.al [8] explored the feasibility of the Linear Genetic Programming (LGP) technique to model systematic IDS. Through a variety of experiments, they have discussed appropriate parameters such as program size, population size crossover rate, and mutation rate and proved in terms of accuracy that LGP programs can outrange Support Vector Machine and Artificial Neural Networks.

In [10] Ahvanooey et.al provided a comprehensive review of various aspects of Genetic Programming including key steps, selection strategies like a tournament, rank-based, exponential, and truncation selection, crossover operators like single-point,n-point, uniform and flat crossover and mutation operators, and its applications in different scientific fields. It also aimed at providing an easy understanding of various types of GP including linear, grammatical evolution, cartesian, extended compact, probabilistic incremental program evolution, and strongly-typed genetic programming along with their advantages and disadvantages.

Husák et.al [11] surveyed attack prediction, intention identification, intrusion prediction, and network security forecasting. Three important conclusions from the survey were: The use of discrete models were used for attack projection and continuous models was used for forecasting. The dependence on artificial prediction models was resolved by Data mining. Problems were encountered relating to the analysis of forecasting in cybersecurity.

Al Najada et.al [12] presented a taxonomy for different types of attacks using Deep Learning. Forecasting models were created for each attack independently and then a forecasting model was created for all the attacks using deep learning and distributed random forest considering only a set of attributes to improve the accuracy. The class imbalance case was resolved using the oversampling technique. Their developed model could accurately forecast the type of attack or menace.

Yusof et.al [17] have presented a comprehensive systematic literature review on DDoS impact, which includes the definition of DDoS attack, various types of DDoS attacks, the existing DDoS detecting techniques, and different kinds of prediction techniques. The result of their observation showed that the machine learning technique was significantly used in the prediction and detection of DDoS attacks.

## III. Genetic Programming

Genetic Programming (GP) can be considered as an extension of Genetic algorithms where one of the major differences lies in consideration of the initial population. The initial population in the genetic programming are computer programs which undergo selection and fitness function evaluation and further crossover operators and mutation are applied. GP was introduced by John Koza [22] as a type of Evolutionary Algorithm (EA) which evolves over time and hence solution becomes better over generations [22]. It is a method that procreates a population that consists of computer programs that solve a particular problem. They can be enhanced by using certain naturally occurring genetic operations. These programs are constructed using functions and there are a certain set of rules according to which they are executed [29]. These operations are performed iteratively until a better result is obtained. GP has the capability to evolve its problem space and problem representation to perceive regularity in different domains [29] [15] .

The execution steps of GP are shown in Fig. 1.

Initial Population is considered, it consists of various programs or strategies depending on the problem. Not all the programs are optimal, hence each individual has a value given to it which is called as a fitness measure. This value can be in a numerical form which tells us how well the particular program performs. After applying suitable fitness measures, selection of these individuals is done using various methods which include Select Random, Select Best, Select Worst, Select Tournament,

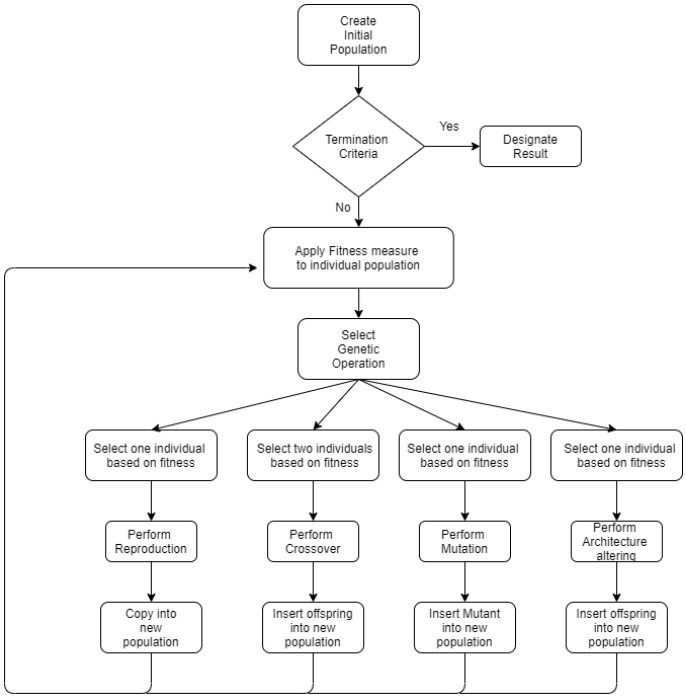


Fig. 1. Steps of Genetic Programming.

Select Roulette, Select Double Tournament, Select Stochastic Universal Sampling, etc. Once a suitable individual is selected four different operations can be performed: Reproduction, Crossover, Mutation, and Architecture Altering [30]. One individual is selected on which reproduction is performed. The new individual obtained is added to the initial population. Similarly, the crossover is performed by selecting two individuals and the new offspring is added in the initial population. In mutation, a single parent is selected and mutated. The mutated individual obtained is added to the initial population based on its fitness value. The process is carried out in a loop iteratively and is terminated by using certain criteria.

## IV. Proposed Method

The proposed method captivates the following: (A) Data Acquisition, (B) Preparing data for further processing, and (C) Implementation of genetic programming for optimal results.

### A. Data Acquisition

A novel dataset that contains modern kinds of DDoS attacks is used for this study. The Modern DDoS Dataset was generated using NS2 (Network Simulator) [4]. The dataset had 2,160,668 number of instances. The features of this dataset are listed in Table I. The distribution of Modern DDoS Dataset classes is comprised of Smurf, User Datagram Protocol-Flood (UDP-Flood), SQL Injection DDOS (SIDDOS), HTTP-Flood, and Normal consisting of 12590, 201344, 6665, 4110, and 1935959 records respectively [3].

1. **Smurf** forwards a ping to a broadcast address using a spoofed source IP address. The target server receives a huge number of ICMP echo request packets. The victim machine is brought down when a large number of ICMP responses are forwarded.

2. **User Datagram Protocol (UDP) flood** a massive volume of UDP traffic is sent to inundate the chosen server, which leads the server passive to other clients.

3. **SQL Injection DDOS (SIDDOS)** a malicious code element usually an SQL statement is forwarded from client-side and sent to sever-side database.

4. **HTTP flood** is an attack where attackers overwhelm a server or application with authorized HTTP GET or POST requests. They wear-out the server resources responding to every request by acting as a legitimate user requesting services.

5. **Normal** transaction data.

The study in this paper is focused on reducing the complexity of the GP algorithm by not processing symbolic features such as Flags, Node_Name_From and Node_Name_To which are shown in Table I. In Packet_Class feature, Smurf, UDP-Flood, SIDDOS, HTTP Flood are labeled as 1 and Normal is labeled as 0. Packet_Type feature consists of four packets namely tcp, cbr, ack and, ping which is labeled as 1, 2, 3, and 4 respectively.

TABLE I
Modern DDoS Dataset Features [3]

| Sr.no. | Attribute Name | Description |
|---|---|---|
| 1 | SRC_ADD | Source Address |
| 2 | DES_ADD | Destination Address |
| 3 | PKT_ID | Packet Identifier |
| 4 | FROM_NODE | Source Node |
| 5 | TO_NODE | Destination Node |
| 6 | PKT_TYPE | Packet Type |
| 7 | PKT_SIZE | Total Packet Size in Bytes |
| 8 | FLAGS | Flags |
| 9 | FID | Flag Identifier |
| 10 | SEQ NUMBER | Sequence Number |
| 11 | NUMBER_OF_PACKET | Total Number of Packets |
| 12 | NUMBER_OF_BYTE | Toatl Number of Bytes |
| 13 | NODE_NAME_FROM | Node Name From |
| 14 | NODE_NAME_TO | Node Name To |
| 15 | PKT_IN | Total time of packet inside queue |
| 16 | PKT_OUT | Total time of packet outside queue |
| 17 | PKT_R | Time of packet received |
| 18 | PKT_DELAY_NODE | Total packet delay within Node |
| 19 | PKT_RATE | Average packet rate |
| 20 | BYTE_RATE | Average byte rate |
| 21 | PKT_AVG_SIZE | Average packet size |
| 22 | UTILIZATION | Bandwidth utilization |
| 23 | PKT_DELAY | Total time packet delay |
| 24 | PKT_SEND_TIME | Time of sending packet |
| 25 | PKT_RESERVED_TIME | Time of receiving packet |
| 26 | FIRST_PKT_SENT | Time of first packet sent |
| 27 | LAST_PKT_RESERVED | Time of last packet received |

### B. Preprocessing

Principal Component Analysis (PCA) is an unsupervised dimensionality reduction technique that captures the maximum amount of variation in the data and finds principal components that are linear amalgams of initial attributes and that are orthogonal to each other [28].

PCA was imported from Scikit-learn [31], fit.transform function was used to train and test data. After applying PCA on the Modern DDoS Dataset the features are reduced to 8,16 and 20 principal components as shown in Table II. Though other numbers of principal components were also explored to study the loss of information and 8,16 and 20 were chosen based on the percentage of information loss. Since there is no significant difference in the 16 and 20 principal components in terms of information loss, 16 principal components were considered for simplicity for further processing.

TABLE II
PCA RESULTS

| No. of Principal Components | % Information Gain | %Information Loss |
|---|---|---|
| 8 | 94.92% | 5.08% |
| 16 | 98.48% | 1.52% |
| 20 | 99.6% | 0.4% |

### C. Implementation of Genetic Programming (GP)

For implementation, Distributed Evolutionary Algorithm (DEAP) framework is used which is built over Python programming language. It provides necessary elements for creating sophisticated evolutionary computing systems. The implementation of GP is performed in four steps. The first step is to build an appropriate type of problem in this case a GP type is built. This is done using the creator module. Runtime creation of classes is performed using the Creator module through inheritance and composition. Creator function consists of three parameters: name, base, and attribute. Attributes are dynamically added to the existing classes because of which creation of population is possible from any data-structure such as lists, sets, dictionaries, trees, etc. The second step is creating a fitness class using the creator module. The fitness of each individual is computed and the best individual is used for the next iteration. The third step is the initialization of operators in which the 'toolbox' module is used. The toolbox is a collection of operators. In the proposed model, the crossover operator used is single-point crossover hence the parameter passed into the toolbox is "cxOnePoint" Similarly, mutation operation is carried out using node replacement passing "mutNodeReplacement" as a parameter. Selection is performed using Double Tournament selection passing "selDoubleTournament" as a parameter. The final step consists of constructing the main function of the model in which the crossover rate, mutation rate, and the number of generations are set. This algorithm is terminated when the iterations of all the generations are completed. Fig. 2 shows the execution of steps carried out during implementation.

## V. EXPERIMENTS AND RESULTS

All the experiments and implementations were performed on Intel Core i7-8550U CPU Processor, 16GB RAM, and 64-bit Operating system. The software used was Spyder and Jupyter Notebook.

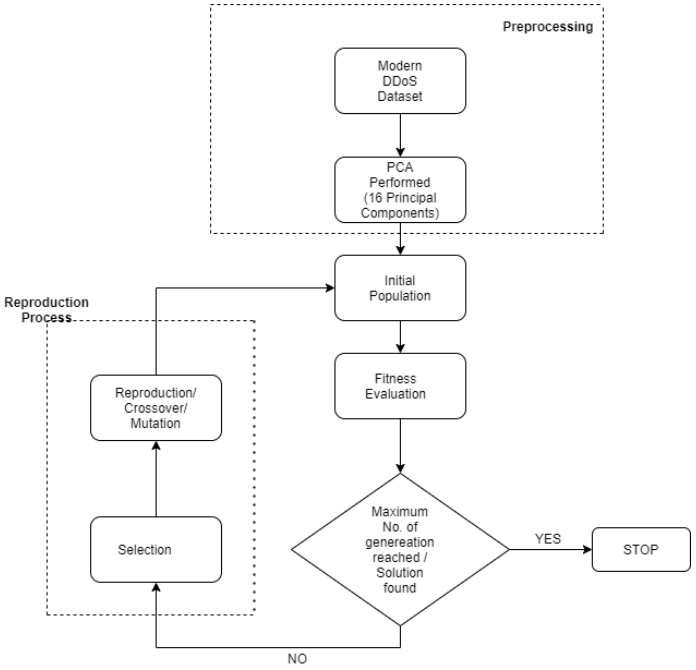


Fig. 2. Flow chart of Process.

DEAP [21], a novel evolutionary computation framework and TPOT [18], [19], [20], a tree based optimization tool is used for GP implementation. Table III summarizes the comparison of the accuracy of various existing intrusion detection systems and our proposed system.

The Modern DDoS dataset which is a supervised dataset is used for experimentation. The accuracy of the proposed algorithm can be evaluated in such a way that it should tell how malicious and normal behaviors are classified. The Modern DDoS dataset originally is having class labels as SMURF, UDP-Flood, SIDDOS, HTTP Flood, and Normal. Amongst these, as stated above, the first four are malicious DDoS attacks and Normal indicates no attack. So, these four attacks (class labels) are replaced by 1 and Normal by 0 to bring simplicity as the current study targets only at detecting an attack or no attack.

The confusion matrix is the most widely adopted statistical measure for binary classification problems. A confusion matrix consists of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). There are some derived measurements that are [3]:

$$DetectionRate(DR) = \frac{TP}{TP + FN} \tag{1}$$

$$Accuracy = \frac{TP + TN}{TN + TP + FN + FP} \tag{2}$$

$$FalsePositiveRate(FPR) = \frac{FP}{FP + TN} \tag{3}$$

$$FalseNegativeRate(FNR) = \frac{FN}{FN + TP} \tag{4}$$

TABLE III
COMPARISON OF VARIOUS MODELS AND PROPOSED APPROACH

| Author | Year | Model | Dataset | Accuracy |
|---|---|---|---|---|
| S. Umarani, D.Sharmila [6] | 2015 | Naive Bayes | 1998 World Cup Website | 95.95% |
| Naveen Bindra, Manu Sood [9] | 2019 | Random Forest | CIC IDS 2017 | 96.13% |
| Mo.Alkasassbeh et.al [4] | 2016 | Naive Bayes | Modern DDoS | 96.91% |
| Manjula Suresh, R. Anitha [13] | 2011 | Naive Bayes | CAIDA | 97.20% |
| Hasanen Alyasiri et.al [5] | 2018 | Genetic Programming: Cartesian | Modern DDoS | 97.19% |
| Mo.Alkasassbeh et.al [4] | 2016 | Random Forest | Modern DDoS | 98.02% |
| Proposed Model | 2020 | Genetic Programming | Modern DDoS | 98.67% |

$$FalseAlarmRate(FAR) = \frac{FPR + FNR}{2} \quad (5)$$

TP indicates the cases that are correctly classified as an attack or malicious behavior, TN indicates the cases that are correctly classified as normal behavior or no attack. FN indicates the cases that are incorrectly classified as malicious behavior and FP indicates the cases that are incorrectly classified as normal behavior, both of these being problematic. Eq.1 specifies the fraction of cases that are correctly classified as a malicious attack. Eq.2 describes the fraction of correctly predicted attacks to all attacks or non-attacks that are correctly classified. Eq.3 defines normal behaviors incorrectly classified as malicious. Eq.4 defines malicious behavior that is erroneously predicted as normal behavior. Eq.5 calculates the wrongly classified attacks [3].

The confusion matrix values of the respective models are shown in Table IV. Table V portrays the accuracy results of different classification models which are implemented using Modern DDoS supervised Dataset.

TABLE IV
CONFUSION MATRIX DETAILS OF VARIOUS CLASSIFIERS

| Model | TP | TN | FP | FN |
|---|---|---|---|---|
| KNN | 387179 | 38985 | 127 | 5843 |
| Naive Bayes | 378513 | 39200 | 8793 | 5628 |
| Logistic Regression | 387181 | 38987 | 125 | 5841 |
| Decision Tree | 381621 | 39125 | 5685 | 5703 |
| Random Forest | 384690 | 39099 | 2616 | 5729 |
| Stochastic Gradient Descent | 386897 | 38976 | 409 | 5852 |

TABLE V
ACCURACY RESULTS OF CLASSIFICATION MODELS

| Model | DR | FAR | Accuracy |
|---|---|---|---|
| KNN | 98.51 | 0.09 | 98.57 |
| Naive Bayes | 98.53 | 9.88 | 96.66 |
| Logistic Regression | 98.52 | 0.09 | 98.62 |
| Decision Tree | 98.52 | 7.09 | 97.38 |
| Random Forest | 98.53 | 3.86 | 98.07 |
| Stochastic Gradient Descent | 98.50 | 7.08 | 98.55 |

The GP implementation depends on various parameters such as the population size, number of generations, crossover rate, mutation rate, verbosity etc. After passing suitable values to the parameters it was observed that when the population size was 50, by passing a crossover rate of 0.01 an accuracy of 98.67% was obtained. Fig. 3 shows the relationship between the accuracy and population size of the proposed model. As the population size increases the accuracy is stabilizing towards 98.66%. Fig. 4 shows that as the number of generations increases by a significant amount, the accuracy did not change much.

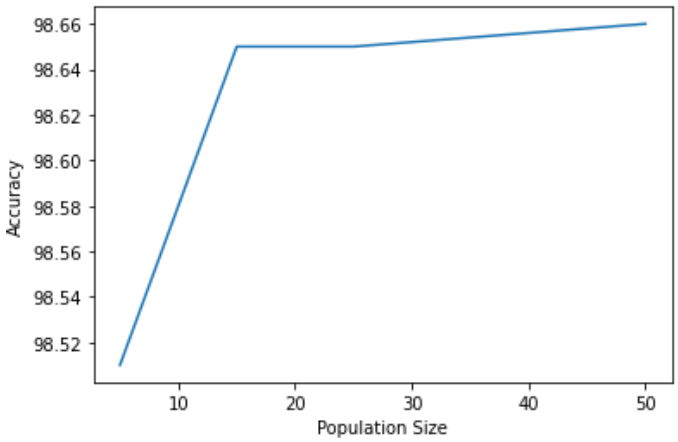


Fig. 3. Accuracy VS Population Size of Proposed Model.

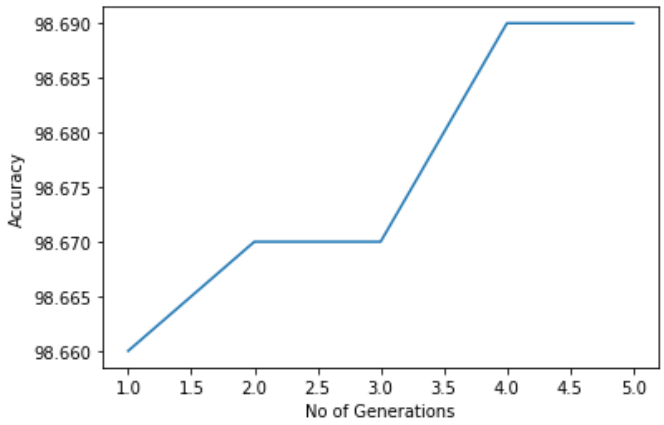


Fig. 4. Accuracy vs No. of Generations of Proposed Model.

## VI. Conclusion

This scientific analysis investigates an application of Genetic Programming (GP) for intrusion detection. For this study, the Modern DDoS dataset is used. This dataset contains contemporary threats gathered from various environments. The proposed GP model detects DDoS attacks with improved accuracy of 98.67% while comparing it with six established classification models. The obtained results highlight the advantages of adopting the GP model. However, it was observed that adopting other approaches for operations such as mutation or crossover can lead to better results. Due to limited resources, this was not tested. In the future, this model can be investigated for other types of attacks and can be used as a universal model to detect all kinds of well-known threats.

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