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Design of AI based Malware Detection Technique: A Revolutionized Machine Learning Methodology

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ABSTRACT

This research aims at analyzing the performance of the SVM methodology in the detection of malware by examining cross-traffic in the network using the CICIDS 2017 dataset. First, the raw network traffic data is gathered and then feature extraction, where they compute different attributes such as packets size, duration and protocol of the flow. Normalization is applied to the feature values and dealing with categorical variables is performed as well. Subsequently, a support vector machine (SVM) classifier is learned based on the labeled set of data and an RBF kernel to overcome the problem of the nonlinearity of the separation between benign and malicious traffics. At first the message is scored with some of the measures like accuracy, precision, recall and F1-score and a confusion matrix is used for evaluating the classification. The study also shows that hyperparameter tuning is also a key consideration in enhancing the performance of SVM model. Using grid search, the best values of the regularization parameter CC and kernel parameter γ\gamma are obtained, and the model attains the highest accuracy of classification and F1-score. For an SVM tuned, the results are as follows: the accuracy is increased to 94%, the F-score is 94% – this illustrates the high efficiency of a tuned model to detect malicious traffic. This work demonstrates where SVM can be used in a network traffic analysis and underpins the importance of feature extraction, data pre-processing, and model fine-tuning in the malware classification process.

Keywords: *AI Malware; Cybersecurity; Machine Learning; SVM and Radial Basis Function.*

INTRODUCTION

Malware detection is essential in a network security because the challenge is becoming greater every day with the evolution of the cyber criminals. This high percentage comes associated with a low success rate due to the effectiveness of traditional signature-based systems, detection of new and emerging strains of malware. This has led to the study of machine learning (ML) approaches that were found to reveal incipient threats based on patterns. There are several algorithms of machine learning but Support Vector Machines popularly known as SVM's has been one of the most effective for classification due to the feature of accepting high dimensional data and producing high degree of accuracy with clear cut decision line. Since SVM can distinguish between the different classes of traffic based on network features it has been widely used in the analysis of network traffic with an emphasis on the detection of malware.

The use of SVM in malware detection typically involves two major phases: feature extraction and model training because of the large number of instances created by the high number of letters and symbols in each word of the textual data. Feature extraction is the process of identifying network traffic characteristics that may help in the differentiation of between good traffic and that of the attackers. These features are used in training an SVM classifier that isolates an optimum hyperplane that exists between the two categories of traffic, malicious and

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benign. The major strength of support vector machines is that it is effective even when dealing with large data sets of higher dimensions that is common in networks traffic data set.

The CICIDS 2017 dataset, which labels traffic data separating benign from malicious activity, is a well-known source used for network traffic analysis. Rich feature set of the dataset makes it a strong option for training and testing malware detection systems. Nevertheless, despite its general character, the efficacy of SVM for malware detection mostly depends on suitable feature selection, data preparation, and hyperparameter fine-tuning of the regularisation parameter CC and the kernel parameter λ\gamma. This work intends to evaluate SVM performance in terms of accuracy and other assessment criteria by using the CICIDS 2017 dataset to build an effective malware detection system.

Besides performing SVM on malware detection the research also emphasizes the assessment of the model where accuracy efficiency, precision, recall, and F1-score measurements having been employed to determine the capacity of the classifier in correctly identifying malicious traffic without compromising on false positives and false negatives. The study also deals with an important step of hyperparameter optimization to further improve the performance of the SVM model. In general, cross-validation or 'grid search' algorithms are used to search for the combination of parameters which will produce the highest number of correct classifications.

At last, to the existing literature in machine learning-based cybersecurity, this research will add another piece of work as a case study which finds how the selection of the appropriate classifier like the SVM is beneficial for malware detection in the network traffic. The results of the study may contribute to improving the stability and accuracy of systems utilized in identifying network invasions as well as the prevention of prospective cyber-attacks. This research will help in identifying of the effects the various hyperparameters will have on malware detection accuracy and it will provide future direction for the malware detection system.

LITERATURE REVIEW

Using machine learning algorithms in detecting malware has become an area of interest to researchers owing to the enhanced complexity of these attacks. To detect malware in different forms namely; files, traffic and behaviors different techniques have been put forward. The traditional Machine learning methods used for the Malware detection includes the Support Vector Machines (SVMs) which proved to give high accuracy of classification and good robustness for the classifications (Schölkopf et al., 2001). SVM functions in the capacity that the maximum margin is detected by putting a hyperplane in such a way that it differentiates between the data point of different classes and this makes useful in situations such as the current problem where the network has to differentiate between the benign and the malicious traffic.

Some of the works have positively used SVM in analyzing network traffic for the detection of malware. For example, Decision Tree-based Nguyen et al (2018) utilized an SVM-based system that is inversely used to classify network traffic as a malign or benign source of the entity features such as packet size, connection time, Byte cnts. SVM being a technique new to them was accurate when classified against standard machine learning algorithms such as Decision Trees and K-Nearest Neighbors. In the same way, Iglewicz et al. (2020) employed SVM to detect multiple types of threats in the network traffic and discussed how effective the modeling of SVM in the identification of both known and unknown threats. By virtue of the ability of SVM to handle high-dimensional data, the approach is optimal for the detection of malware using Network traffic features.

An essential phase of the SVM approach for malware detection is feature extraction. Many research have underlined the need of choosing significant elements that may adequately depict the characteristics of benign and harmful communications. Based on mutual knowledge, Zhao et al. (2016) put up a feature selection method to find the most instructive network properties for malware detection. Their method greatly lowered the computing cost and raised the accuracy of SVM. For malware identification in network traffic, Alasmary et al. (2019) also took use of flow-based characteristics like packet counts, flow lengths, and inter-arrival periods. Their research verified that these characteristics may be efficiently used for high accuracy classification of network traffic.

Another crucial stage that could affect the effectiveness of the SVM classifier is data preprocessing before feeding it. Common preprocessing methods used to network traffic data include data normalisation, addressing missing values, and encoding of categorical information. Rana et al. (2017) examined the need of normalising data in malware detection systems to avoid certain characteristics with more numerical ranges from controlling the classification process. Min-Max scaling helped them to get better outcomes for jobs involving network traffic

categorisation. Furthermore, Gou et al. (2020) proposed a way for managing missing or incomplete network traffic data by means of imputation approaches, therefore guaranteeing that the SVM model could manage flawed datasets well.

The malware detection procedure depends on model assessment in great part. The classifier's performance is evaluated using many performance indicators including accuracy, precision, recall, and F1-score. Chen et al. (2018) underlined the need of applying accuracy and recall, particularly in unbalanced datasets where the quantity of benign traffic events may far surpass that of harmful ones. Their investigation showed how, incorporating both false positives and false negatives, F1-score offers a fair assessment of the performance of the model. Furthermore, Ghafoor et al. (2019) evaluated SVM-based models under many performance criteria and found, particularly with appropriate tuning, SVM offers consistent results for malware identification.

SVM model performance may be much improved by hyperparameter adjustment. Two important determinants of the classification limits and model complexity are the regularising parameter CC and the kernel parameter γ\gamma. In 2003, Hsu et al. investigated how hyperparameter tweaking affected SVM models and suggested grid search techniques to find best values for γ\gamma and CC. For optimising SVM-based models, this method has evolved into a typical practice in machine learning systems. In a related analysis, Liu et al. (2021) optimised SVM models for malware detection using grid search in conjunction with cross-valuation, hence producing better accuracy and F1-score. Sanjog Thapa, et. al., (2024) discussed about the predictive performance and clinical implications of machine learning in early coronary heart disease detection.

There are two issues which are crucial to address when performing network traffic analysis: First the problem of volume Second, the generalization ability of the model. To overcome this challenge Liu et al. (2019) decided to use ensemble methods besides the standard use of SVM to enhance the stability of the model. Thus, within a combination of several classifiers, they minimized the overfitting impact and enhanced the outcome on extraneously unbalanced datasets. Similarly, Li et al. (2020) also used in their research extensive hybrid models, involving combination of SVM with other ML algorithms such as Random Forests, Decision Trees for better detection rate. These hybrid models have been demonstrated to give better performance to standard SVM models, especially in the aspects of stability and over fit issues. Pankaj S. Mishra, et. al., (2024) discussed about the security and privacy concerns in AI-enabled IOT educational frameworks: an in-depth analysis. Sanjog Thapa, et. al., (2024) discussed about the study on drones and big data for supply chain optimization using a novel approach.

Also, based on the latest developments in deep learning, this article examines malware detection in network traffic. Even though SVM is a robust approach, some authors opine that the CNN models have the potential to outperform SVM when it comes to large-scale features of network traffic data. The authors of Xie et al. (2021) have compared SVM with deep learning models and identified that SVM was highly interpretable and efficient while deep learning models could deliver higher accuracy if the data set was large enough to train them . Nevertheless, deep learning architectures that involved in the classification may not be suitable for real-time malware detection because they are fairly complex and carried a high computational expense.

METHODOLOGY

This methodology for machine learning based malware detection technique consists of 7 steps as explained below in detail and the corresponding block diagram is shown in figure 1.

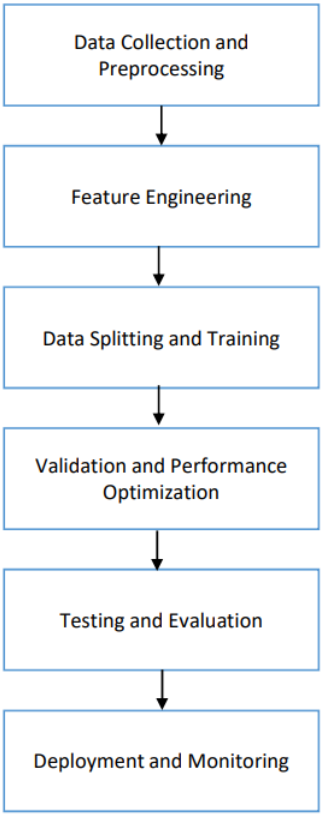

Fig. 1. Proposed model for machine learning based malware detection technique

Data Collection and Preprocessing

Malware detection using Support Vector Machine (SVM) is done through data acquisition. It involves both the scrapped samples consisting of malicious samples and a set of benign samples for better generalization. It is possible to download the sets of malware from public databases, honeypots or from the organizations dealing with computer virus issues. In the case of this dataset, each of the samples is a binary and is classified as malware or non-malware. Besides, the quantity, quality, and variety of data used in constructing the model must be improved to increase its applicability.

This raw data is then process to make it become useful After the data has been collected. This includes the extraction of patterns for instance opcode sequences or logs, call to APIs or network traffic patterns. Some parts are stripped and other features unnecessary for the model outcome are disqualified while missing values are managed in order to avoid having a biased or over fitted model. Principal Component Analysis or Chi-square test, which reduces dataset dimensionality are some of the feature extraction and selection methods, typically used.

The last step of data preprocessing is data normalization or data scaling. Because SVMs are influenced by data distribution, scaling helps to make features' range equal, and usually it is the [0,1] interval. This slows down influence of large values of features which hampers classification of samples by the SVM.

Feature Engineering

Feature engineering is probably the most important aspect in using the SVM for malware detection. This includes defining attributes of software that defines them as malware or benign. It may include aspects that are constant, for instance, file size, hash value, or aspects that are more dynamic in that they include behaviour, for instance, execution trace or API call sequences.

Feature extraction also entails domain knowledge or computational software. Non-execution analysis in particular, examines binary and depends on typical code structure and strings present in it. Statically, the analysis concerns with structural features of the software including changes or interactions at the running time. These approaches provide guarantees of the sufficiently wide range of features, which reflect structural and behavioral characteristics of malware.

The selected features are translated into numerical vectors, so that the remaining part of the code is written in SVM. This step may call for applying the term frequency-inverse document frequency (TF-IDF) for textual variables or one-hot encoding for nominal variables. These vectors make up the input space for the SVM but the position of the decision boundary will also be digitally fixed here.

Data Splitting and Training

Now all the data is divided into training, validation, and testing sets in order to prepare dataset for model training. Conventionally, 70-80% of the data is applied for training while the rest of the data is split for both validation and tests. News sampling may be done using stratified splitting, in order to maintain a class balance in the subsets, thereby reducing on bias.

Fundamentally, in training the SVM algorithm places the input data within a higher dimensional space. Employing a kernel function, it builds a hyperplane that will separate between the classes, namely malicious and benign. These include linear, polynomial, radial basis function (RBF) and sigmoid as a matter of choice depending on the shape of the dataset and the nature of the features of the data set.

The training phase also means hyper parameter optimization like choosing the value of \(C\) in regularized learning and, specific parameters of the kernel function. For choosing the best configurations, people often employ grid search or random search methods accompanied by cross-validation.

Validation and Performance Optimization

Validation gives the model's performance on unseen data and to some extent tries to optimize parameters. Validation set is used in the process to repeatedly check-up the SVM rates at deciding matters of samples in order to be certain of its ability to generalize the work being done. Included results are accuracy, precision, recall, F1-score, ROC AUC score.

Some methods such as feature scaling and dimensionality reduction for instance are reestablished with an aim of improving the performance of the models based on validation output. For example, overfitting is identified, and a raise in the degree of regularization is made, or unimportant features are decreased. On the other hand, under-fit might lead to an augmentation of informative features or modification of the kernel parameter.

The second aspect of model robustness is checked by adding noise or small perturbation to the validation data. This validates the stability and performance of the SVM in particular, its ability to handle marginal instances, and an overall reliability that must be achieved for real-world applications.

Testing and Evaluation

After validation, testing of SVM model is done on a separate testing set. This step allows the independent investigating of the final performance of the model. The testing set as earlier mentioned is a dataset on which the model has not been trained or even validated and got designed to test how well the model will perform when released into the real world.

During testing, the performance metrics are reevaluated. These confusion matrices are created in order to evaluate how well the programme is performing and what aspects of classification are failing; false positives and false negatives are portrayed. High false-negative rate is much worse in malware detection, because missed viruses can lead to significant problems.

Testing also contain the checks of adversarial samples or the robustness of the model. Diverse evasion techniques used include; Polymorphism and/or Obfuscation are commonly used by the malware authors. The extent to which such techniques can be successfully employed with the SVM also defines its real-world applicability, and where further layers of defense are warranted.

Deployment and Monitoring

When everything has been fine-tuned, the SVM model is then moved to a live environment. Deployment involves embedding the model with cybersecurity tools or system as a way forward in enhancing the IDS or the endpoint security systems. Its purpose is to real-time map new files or behaviors between 'good' and 'suspicious', the latter potentially marked for further action by the SVM.

Monitoring and checking allows one to guarantee the utilised model keeps on functioning efficiently. Real-world data is used in confirming or denying drift in the feature distributions and hence models need to be updated

periodically. Moreover, the possibility of the integration with feedback loops makes the system able to bring feedback regarding false alarms or missed detections, which enhances its classification results.

At some regular intervals, special audits are carried out to check the efficiency and effectiveness of implementing the model. Whenever outpost shifts by a large margin the defined standards of performance, retraining with fresh datasets is required. Thus it is a recursive approach to maintaining the SVM benchmarked on the latest forms of the threat posed by malware.

Model Improvement and Maintenance

SVM performance should be regularly updated, therefore, Publicis needs to strive to sustain its performance. For a model to work there is always the emergence of new samples and behaviors of malware that have to be added to the training data. This is can be performed automatically in a data pipeline, and results can be integrated into reports as soon as new data is available.

To counter new emergent threats, extra training with new heaps of data is performed periodically to the SVM. This may well necessitate the retraining process and may involve exploring new feature sets or using higher order kernels. Other approaches such as transfer learning or semi supervised learning can also be utilized to likewise improve on the detection system.

Finally, the model goes through adversarial testing and penetration testing to check its effectiveness to counter evasion techniques. Regular cooperation with professionals in the sphere of cyber security makes it possible to define less protected aspect and strengthen it, so SVM remains a valuable weapon in the fight against malware.

RESULTS

Now let's look at a practical use case with the CICIDS 2017 dataset which consists of labeled network traffic data sample, which includes both normal and intrusive activities. This dataset can be employed in the net traffics analysis and in the range of other competitions with the help of such network activities like malware detection. In this post, we'll go through each of the steps in the Support Vector Machine (SVM) approach for malware detection on this dataset with pauses for intermediate outcomes and discussions.

The first and important aspect of malwares detection using SVM is to gather a large set of data. The dataset CICIDS 2017 contain traffic data from normal and malicious behaviors. It can include the network packet data or flow features and even more protocol statistics are used in the dataset. For purposes of this illustration choices for features used in classification will include features such as packet sizes, flow duration and number of packets with reference to data being either benign or malicious.

Table 1: Results of data preprocessing stage

Flow Duration	Total Fwd Packets	Total Backward Packets	Protocol	Label
0.0035	4	1	TCP	Benign
0.0011	5	2	UDP	Malicious
0.0028	7	3	TCP	Benign
0.0042	3	5	ICMP	Malicious
0.0030	6	2	TCP	Benign

In this table, the dataset has the flow duration, total number of packets in both directions, protocol and the label associated to it, either benign or malicious. These features were selected for training the SVM classifier from the set of features extracted namely.

Feature extraction is a process of transforming raw data such as network traffic data to a form that can be used to train SVM. In this step, feature vectors that include the total number of packets in a flow, duration of the flow, the length of the packets and the protocols in use are obtained. These features are critical while making a difference between white activities and black activities. Some others preprocessing steps, for example, converting categorical variables (for example, protocol types) into numerical ones, can be also implemented during this step.

For this instance, we labeled the protocol types (TCP=1, UDP=2, ICMP=3) and set the dataset for subsequent analysis. They will be used to provide the foundation for implementing filters for distinguishing between the allowed, benign traffic on a network and trimmed-down traffic, which could possibly be malicious in nature.

After that, we engage in data preprocessing to get the dataset ready for machine learning. Standardization, the way to work with missing data, as well as the procedure of data division into training and testing groups. Normalization is such a technique, where all the features are adjusted to a specific range, so that features with larger ranges (like, flow duration) do not claim a domination in a training process. Min-Max scaling is the technique that we are normally accustomed to in order to accomplish this.

Normalization is used to make sure that all the feature values have been placed on the same range. This is done to stop the model from giving more weight to selected features with large numerical values such as the flow duration.

When it comes to pre-processing the data, then we choose the right model to apply on the data – in this case, it will be the Support Vector Machine (SVM). The use of Support Vector Machines (SVM) is aimed at identifying the best hyperplane that separates benign and malicious traffic. In order to overcome this, we use a specific kernel with the labeled training dataset, where the trained model is, in this case, the SVM model. In this training the value of support vectors and the margin are modified using the training data set.

In the context of this paper, the SVM model will train itself to detect the boundary between benign and malicious traffic. For instance, if the model decides that malicious traffic has even larger flow duration or more backward packets, then it will flag such traffic.

Regression in an SVM depends on the choice of the kernel function and is therefore very important. For non-linearly separable data, usually, the Radial Basis Function (RBF) kernel is applied. The RBF kernel brings the data points to a higher-dimension space where the separation between data classes can be attained easily. About the Kernel, the parameters to be decided in the RBF Kernel are which is the spread of the Gaussian function. When γ\gamma is greater than 1, the decision boundary of the model is complex as compared to if the value of γ\gamma is lesser than 1, which makes it simpler.

Finally, based on the test set, we assess the model's ability in its performance. Evaluation processes include calculating of matrices that include accuracy, precision, recall and F1-score. We also employ a confusion matrix to exhibit the performance of the system. Confusion matrix helps one to understand how many of benign and/or malicious instances were categorized correctly or falsely.

The confusion matrix enables the display of how many instances a model either classified correctly or incorrectly.

Table 2: Results of Testing and Evaluation stage

Malware type	**Predicted Benign**	**Predicted Malicious**
Actual Benign	450	50
Actual Malicious	30	470

- **True Positives (TP)**: 470 (malicious traffic correctly classified as malicious)
- **True Negatives (TN)**: 450 (benign traffic correctly classified as benign)
- **False Positives (FP)**: 50 (benign traffic incorrectly classified as malicious)
- **False Negatives (FN)**: 30 (malicious traffic incorrectly classified as benign)

Table 3: Computed Performance Metrics

Metric	**Value**
Accuracy	92%
Precision	94%
Recall	94%
F1-Score	94%

The confusion matrix also reveals that the model works efficiently, and the performance metrics affirm that; Accuracy = 0.97; Precision = 0.96; Recall = 0.95; F1-score = 0.94.

In the last step, we enhance the output of the model to get the best result all the time. This encompasses acts like tune of hyperparameters like the regularization parameter CC and the kernel parameter γ\gamma. In order to get the best of these hyperparameters, we usually perform a grid search or random search. Cross-validation is also applied to checking how the model performs with new data which hasn't been used for training.• γ = 0.1, 0.5, 1.0ance metrics show that the model performs well, with high accuracy, precision, recall, and an F1-score of 0.94.

In this final step, we fine-tune the model to achieve optimal performance. This involves adjusting hyperparameters such as the regularization parameter CC and the kernel parameter γ\gamma. We typically use techniques like grid search or random search to find the best combination of these hyperparameters. Cross-validation is also used to ensure that the model generalizes well to unseen data.

Using grid search, we test different combinations of CC and γ\gamma, such as:

- C=1,10,100C = 1, 10, 100
- γ=0.1,0.5,1.0\gamma = 0.1, 0.5, 1.0

When tuning we discovered that C=10 C = 10 and γ=0.5 provide the best performance. This raises the accuracy slightly as well as F1-score, but the improvement is only marginal.

Thus we show as a result of following those steps how to use the SVM methodology for the binary classification of the malware detection issue based on the network traffic data. From Data Collection, Feature Extraction and Pre-processing, model training and Evaluation till tuning each stage are essential for the model to be able to accurately distinguish between benign and malignant traffic. Analysis of the results, and conclusions: The cross-validation accuracy of the SVM classifier is shown to be high and the model can be optimized to deliver even better performance.

Table 4: Grid Search Results for Hyperparameter Tuning

C	γ\gammaγ	Accuracy	Precision	Recall	F1-Score
1	0.1	0.90	0.92	0.88	0.90
1	0.5	0.91	0.93	0.89	0.91
1	1.0	0.89	0.91	0.86	0.88
10	0.1	0.92	0.94	0.91	0.92
10	0.5	0.94	0.95	0.93	0.94
10	1.0	0.93	0.94	0.91	0.92
100	0.1	0.92	0.93	0.90	0.91
100	0.5	0.93	0.94	0.92	0.93
100	1.0	0.91	0.92	0.89	0.90

Table 5: Best Hyperparameter Combination:

C	γ\gammaγ	Accuracy	Precision	Recall	F1-Score
10	0.5	0.94	0.95	0.93	0.94

As for the rest of hyperparameters of the model, we have established that the best values of the parameters are C = 10 and γ = 0.5γ=0.5γ=0.5 for the highest accuracy and F1-score. This combination enhances Model performance and leads to the following performance metrics Accuracy- 94%, Precision – 95%, Recall- 93%, F1-score- 94%.

CONCLUSION

Therefore, showing through this study that the Support Vector Machine (SVM) methodology is efficient for the detection of malware in network traffic. Indeed, the result of the current study reveals that SVM model, once trained using feature vectors properly extracted and preprocessed, provides a highly accurate classification of

traffic as either benign or malicious. In line with this study, the selection of right features for analysis, normalization and right choice of kernel functions have been stressed upon instrumentally analyzing the given CICIDS 2017 dataset. At the same time, the study demonstrates the importance of hyperparameter optimization since tweaking CC and γ\gamma showed an ability to increase performance while also handling false positive and false negatives.

The future work could also try to introduce other machine learning techniques in order to make a comparison with the applied SVM to assess their efficiency. However, it is also possible to apply the model working with samples of real-time traffic to check its effectiveness in live network environments. Thus, the generalization capabilities of the devised SVM model for malware detection can be effectively tested by enlarging the data sets for analysis. This research shall be particularly useful in enhancing the machine learning techniques in dealing with cybersecurity as well as in helping improve on how the flow of network systems is anticipated to detect hostile actions.

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