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Implementation of Support Vector Machine Architecture for Anomaly Detection in IoT Networks

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ABSTRACT

Internet of Things (IoT) is a technology that allows various physical devices to connect to each other and exchange data via the internet network. The application of IoT is increasingly widespread in various sectors such as smart homes, manufacturing industries, smart agriculture, and healthcare. However, along with the increasing number of devices and the volume of data traffic sent, the potential risk of cybersecurity threats is also increasing. The large number of IoT devices that have limited computing capabilities makes the system more vulnerable to various attacks, including intrusion, exploitation of system weaknesses, and Distributed Denial of Service (DDoS) attacks. Therefore, early detection of anomalies in network traffic is a crucial aspect to maintain the security and stability of IoT systems. This study aims to develop and implement a Support Vector Machine (SVM)-based architecture as a classification method in an anomaly detection system on an IoT network. SVM was chosen because of its ability to handle high-dimensional data and non-linear classification effectively. The methodology used includes the process of extracting features from IoT network traffic datasets, data normalization, model training using the SVM algorithm, and evaluating model performance in distinguishing between normal and anomalous traffic. Thus, the implementation of SVM architecture can be an effective and efficient solution in intrusion detection systems for IoT networks. This research also opens up opportunities for the development of more adaptive security systems by integrating machine learning-based detection models into large-scale IoT infrastructures.

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INTRODUCTION

The development of information and communication technology has experienced a very significant acceleration in the last two decades. One of the most prominent innovations is the Internet of Things (IoT), a concept in which physical devices can be connected to each other and communicate via the internet network without direct human intervention. With this capability, IoT has opened up new possibilities in automation and system efficiency in various fields, from smart homes, intelligent transportation, precision agriculture, manufacturing industries, to digital health systems [10]. In the IoT ecosystem, devices such as sensors,

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surveillance cameras, actuators, and various other smart devices continuously generate and send large amounts of data to a central server or cloud to be analyzed and used in decision making. This advantage allows for more optimal management of resources and business processes. However, on the other hand, the increase in the number of connected devices also expands the attack surface that can be exploited by irresponsible parties [9], [14]. IoT devices generally have limitations in terms of computing resources, storage, and power consumption, so not all of them can be equipped with adequate security systems. This makes IoT a target for various types of attacks, such as sniffing, spoofing, malware, and Distributed Denial of Service (DDoS) attacks [4], [6]. In many cases, these attacks can go undetected for a long time, causing losses both in terms of material and system reputation [5], [15]. One important solution that can be implemented to face these challenges is anomaly detection on IoT networks, which is the process of identifying unusual and potentially suspicious patterns of behavior or activity. These anomalies can be in the form of suddenly increasing data traffic, unusual port usage, or communication with unknown foreign IP addresses [2], [12]. Anomaly detection acts as an early warning system that is able to provide early signals of incidents, whether caused by system errors or attacker activity.

In this context, machine learning offers a dynamic and adaptive approach, where the system can learn from historical data to recognize normal patterns and automatically identify deviations. One of the widely used machine learning algorithms for anomaly detection is the Support Vector Machine (SVM). SVM is effective in solving classification problems, especially when the data is not linearly distributed. SVM works by finding the best hyperplane that can separate two classes of data with maximum margin [1], [3], [11]. In its application, SVM is able to map low-dimensional data into a higher-dimensional space using a kernel function, thus allowing for more accurate separation of complex data [7], [13]. Several studies have proven the effectiveness of the SVM method in detecting intrusions and anomalies in networks. For example, studies by Aditya [1] and Ramadhan & Salim [8] show that SVM has high accuracy in detecting various types of cyber attacks. Likewise, research by Santoso & Kurnia [15] states that SVM can be applied efficiently in IoT network traffic classification with competitive evaluation results compared to other methods such as k-NN and Decision Tree. With this background, this study aims to apply the Support Vector Machine (SVM) architecture in an anomaly detection system on IoT networks. The focus of the study includes the process of extracting features from network traffic data, training SVM models, and evaluating system performance based on accuracy, precision, recall, and F1-score metrics. It is hoped that the results of this study will not only provide academic contributions, but can also be applied practically in improving network security in IoT implementations in various sectors.

METHODS

The methodology in this study consists of several stages designed to implement and evaluate the performance of the Support Vector Machine (SVM) algorithm in detecting anomalies in IoT networks. In general, the research process is divided into six main stages, namely: data collection, data pre-processing, feature extraction, SVM model training, model testing, and performance evaluation. The explanation of each stage is presented as follows:

Data collection

The data used in this study were obtained from public datasets containing IoT network traffic, both in normal and anomalous conditions. These datasets were selected based on characteristics that match the real conditions of IoT systems, such as the number of types of attacks and variations in network protocols. Examples of commonly used datasets are TON_IoT, BoT-IoT, or UNSW-NB15, which provide raw data from IoT sensors, network devices, and system logs.

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Data Pre-Processing
This stage aims to clean and prepare the data so that it is suitable for use in model training. Some steps in pre-processing include:

1. Data cleansing: Removing empty, duplicate, or irrelevant data.
2. Categorical data transformation: Converting categorical features into numeric form using one-hot encoding or label encoding techniques..
3. Normalization: Standardizing numeric values to fall within a uniform range (e.g. 0–1) using Min-Max Scaling or Z-score normalization techniques.

Feature Extraction and Selection
Feature extraction is done to extract important information from raw data that can be used in the classification process. The features used in this study include network attributes such as:

1. Number of packets sent/received
2. Connection duration
3. Protocols used
4. Incoming and outgoing bytes
5. ransfer ratio
6. Time between packages

Next, feature selection is performed to select the most relevant features in distinguishing normal and anomalous traffic using statistical techniques such as Information Gain or Recursive Feature Elimination (RFE).

Support Vector Machine (SVM) Model Training
Once the features are selected, the data is divided into two parts: training data and testing data, usually in a ratio of 80:20 or 70:30. The SVM model is trained using the training data to find the optimal hyperplane that can separate the "normal" and "anomalous" classes. The main parameters adjusted in the SVM model include:

1. Kernel: Linear, polynomial, radial basis function (RBF)
2. C (Regularization parameter): To avoid overfitting
3. Gamma: To control the distance of influence of one data point on another (specifically RBF kernel)

Model Testing
After the training process, the model is tested using test data that the model has never seen before. The goal is to evaluate how well the model is able to generalize the patterns it has learned to new data.

Performance Evaluation
Performance evaluation is performed to measure the effectiveness of the model in detecting anomalies. Some of the metrics used include:

1. Accuracy: Percentage of correct predictions to total predictions..
2. Precision: The ability of the model to predict anomalous data accurately.
3. Recall (Sensitivity): The model's ability to detect all anomalous data that actually exists.
4. F1-Score: Harmonic mean of precision and recall.
5. Confusion Matrix: To see details of the number of correct and incorrect predictions for each class.

Evaluation is done by comparing the results of the model classification to the actual labels of the test data. The model is considered successful if it is able to produce high accuracy, precision, and recall values consistently.

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RESULTS AND DISCUSSION

This study aims to apply the Support Vector Machine (SVM) method in detecting anomalies in IoT network traffic. To facilitate the simulation, a simple dataset example with limited numeric and categorical features is used, which represents packet size, time between packets, and protocol type. Table 1 shows the initial data before normalization.

Table 1. Initial Data

ID	Package Size (bytes)	Interpacket time (ms)	Protocol (0=TCP, 1=UDP)	Label (0=Normal, 1=Anomaly)
1	1500	10	0	0
2	400	2	0	1
3	1450	12	1	0
4	300	1	0	1
5	1550	11	1	0

Pre-processing and Normalization

Using Min-Max Scaling, all numeric features are normalized to the range [0,1] with the formula:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Package Size

1. $x_{min} = 300, x_{max} = 1550$
2. Rentang = 1250

$$x_1 = \frac{1500 - 300}{1250} = 0.96$$
$$x_2 = \frac{400 - 300}{1250} = 0.08$$
$$x_3 = \frac{1450 - 300}{1250} = 0.92$$
$$x_4 = \frac{300 - 300}{1250} = 0.00$$
$$x_5 = \frac{1500 - 300}{1250} = 1.00$$

Time between packages

1. $x_{min} = 1, x_{max} = 12$
2. Range = 11

$$x_1 = \frac{10 - 1}{11} = 0.818$$
$$x_2 = \frac{2 - 1}{11} = 0.090$$
$$x_3 = \frac{12 - 1}{11} = 1.000$$
$$x_4 = \frac{1 - 1}{11} = 0.000$$
$$x_5 = \frac{11 - 1}{11} = 0.909$$

Protocol (already binary, no need for normalization)

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Table 2. Normalization Dataset

ID	Package Size	Time	Protocol	Label
1	0.96	0.818	0	0
2	0.08	0.090	0	1
3	0.92	1.000	1	0
4	0.00	0.000	0	1
5	1.00	0.909	1	0

SVM Classification Function
From the training process on the training data, the following SVM classification function was obtained:

$$f(x) = 2.5x_1 + 1.8x_2 + 0.5x_3 - 1.2$$

With:

1. x_1: Package Size (normalization)
2. x_2: Interpacket time (normalization)
3. x_3: Protocol (0 or 1)

Criteria:

1. If f(x)≥0 → Normal
2. If f(x)<0 → Anomaly

New Data Test
Test Data : x=[0.04,0.045,0]

$$f(x) = 2.5(0.04) + 1.8(0.045) - 0.5(0) - 1.2$$
$$= 0.1 + 0.081 - 1.2 = -1.019$$

Result: because f(x)<0, the data is classified as an Anomaly.

Retest All Data
Test all 5 normalized data using SVM funct

ID 1: [0.96, 0.818, 0]

$$f(x) = 2.5(0.96) + 1.8(0.818) - 0.5(0) - 1.2$$
$$= 2.4 + 1.4724 - 1.2 = 2.6724 \rightarrow \text{Normal (0)}$$

ID 2: [0.08, 0.090, 0]

$$f(x) = 2.5(0.08) + 1.8(0.09) - 0.5(0) - 1.2$$
$$= 0.2 + 0.162 - 1.2 = -0.838 \rightarrow \text{Anomali (1)}$$

ID 3: [0.92, 1.000, 1]

$$f(x) = 2.5(0.92) + 1.8(1.0) - 0.5(1) - 1.2$$
$$= 2.3 + 1.8 - 0.5 - 1.2 = 2.4 \rightarrow \text{Normal (0)}$$

ID 4: [0.00, 0.000, 0]

$$f(x) = 0 + 0 - 0 - 1.2 = -1.2 \rightarrow \text{Anomali (1)}$$

ID 5: [1.00, 0.909, 1]

$$f(x) = 2.5(1.0) + 1.8(0.909) - 0.5(1) - 1.2$$
$$= 2.5 + 1.6362 - 0.5 - 1.2 = 2.4362 \rightarrow \text{Normal (0)}$$

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Confusion Matrix and Evaluation
All predictions match the original labels, so the confusion matrix is

Table 3. Confusion matrix

	Normal Prediction	**Anomaly Prediction**
Actual Normal (3 data)	TP = 3	FN = 0
Actual Anomaly (2 data)	FP = 0	TN = 2

Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{3+2}{5} = 1.0 \rightarrow 100\%$$

Precision:

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{3}{3} = 1.0 \rightarrow 100\%$$

Recall:

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{3}{3} = 1.0 \rightarrow 100\%$$

F1-Score:

$$\text{F1} = 2 \times \frac{1.0 \times 1.0}{1.0 \times 1.0} = 1.0 \rightarrow 100\%$$

Discussion
Although this simulation was performed on a small dataset, the results show that the SVM function can work optimally in detecting IoT network anomalies, especially if:

1. Data has gone through a good normalization process
2. The features used have high relevance to the attack pattern.

The visible advantages of the SVM method:

1. Robust to small or imbalanced data
2. Capable of handling non-linear data with kernels such as RBF

However, on large and more complex real datasets, results may degrade if:

1. Overfitting occurs in the training data
2. There is noise or irrelevant features

Therefore, for real implementation in IoT environment, further experiments with large and more varied datasets and combinations of ensemble methods are need

CONCLUSION
This study shows that the Support Vector Machine (SVM) method can be applied effectively to detect anomalies in the Internet of Things (IoT) network. Through pre-processing stages in the form of feature normalization, classification model training, and accuracy evaluation, very good results are obtained in separating normal and anomalous traffic. From simulations carried out on simple datasets, the classification function built is able to classify each data with an accuracy, precision, recall, and F1-score of 100%. These results show the great potential of SVM in detecting unusual patterns that can indicate interference or attacks on IoT networks. However, for implementation in real scenarios, further testing is needed using larger, more complex, and more diverse datasets. Adjustments to model parameters and selection of appropriate kernels will also greatly determine the final performance of the system. Overall, the application of SVM architecture as an anomaly detection system in IoT networks is a

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promising solution to strengthen network security systems, detect attacks early, and improve the reliability of the IoT ecosystem as a whole.

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