



AN EFFICIENT SPAM DETECTION TECHNIQUE FOR IOT DEVICES USING MACHINE LEARNING

SANKET^[1] VEDANT^[2] RUTUJA^[3] GANESH^[4]

*¹Dept. Of IT, Undergraduate Students Sanket Kawle, Rutuja Bhangade, Ganesh Pawar, Vedant Sangole

ABSTRACT

The Internet of Things (IoT) is a group of millions of devices having sensors and actuators linked over wired or wireless channel for data transmission. IoT has grown rapidly over the past decade with more than 25 billion devices are expected to be connected by 2020. The volume of data released from these devices will increase many-fold in the years to come. In addition to an increased volume, the IoT devices produce a large amount of data with a number of different modalities having varying data quality defined by its speed in terms of time and position dependency. In such an environment, machine learning algorithms can play a significant role in ensuring security and authorization based on biotechnology, anomalous detection to improve the usability and security of IoT systems. On the other hand, attackers often view learning algorithms to exploit the vulnerabilities in smart IoT-based systems. Motivated from these, in this paper, we propose the security of the IoT devices by detecting spam using machine learning. To achieve this objective, Spam Detection in IoT using Machine Learning framework is proposed. In this framework, five machine learning models are evaluated using various metrics with an enormous collection of input features sets. Each model computes a spam score by considering the refined input features. This score depicts the trustworthiness of IoT devices under various parameters. REFIT Smart Home dataset is used for the validation of proposed technique. The results obtained proves the effectiveness of the proposed scheme in comparison to the other existing schemes.

I. INTRODUCTION

Machine Learning is a system of computer algorithms that can learn from example through self-improvement without being explicitly coded by a programmer. Machine learning is a part of artificial Intelligence which combines data with statistical tools to predict an output which can be used to make actionable insights. The breakthrough comes with the idea that a machine can singularly learn from the data (i.e., example) to produce accurate results. Machine learning is closely related to data mining and Bayesian predictive modeling. The machine receives data as input and uses an algorithm to formulate answers. A typical machine learning task is to provide a recommendation. For those who have a Netflix account, all recommendations of movies or series are based on the user's historical data. Tech companies are using unsupervised learning to improve the user experience with personalizing recommendations. Machine learning is also used for a variety of tasks like fraud detection, predictive maintenance, portfolio optimization, automatize task and so on. Traditional programming differs significantly from machine learning. In traditional programming, a programmer codes all the rules in consultation with an expert in the industry for which software is being developed. Each rule is based on a logical foundation; the machine will execute an output following the logical statement. When the system grows complex, more rules need to be written. It can quickly become unsustainable to maintain. Traditional programming differs significantly from machine learning. In traditional programming, a programmer code all the rules in consultation with an expert in the industry for which software is being developed. Each rule is based on a logical foundation; the machine will execute an output following the logical statement. When the system grows complex, more rules need to be written. It can quickly become unsustainable to maintain.

II. LITERATURE SURVEY

The Internet of Things (IoT) opens opportunities for wearable devices, home appliances, and software to share and communicate information on the Internet. Given that the shared data contains a large amount of private information, preserving information security on the shared data is an important issue that cannot be neglected. In this paper, we begin with general information security background of IoT and continue on with information security related challenges that IoT will encounter. Finally, we will also point out research directions that could be the future work for the solutions to the security challenges that IoT encounters.

The idea of Internet of Things (IoT) is implanting networked heterogeneous detectors into our daily life. It opens extra channels for information submission and remote control to our physical world. A significant feature of an IoT network is that it collects data from network edges. Moreover, human involvement for network and devices maintenance is greatly reduced, which suggests an IoT network needs to be highly self-managed and self-secured. Since the use of IoT is growing in many important fields, the security issues of IoT need to be properly addressed. Among all, Distributed Denial of Service (DDoS) is one of the most notorious attacking behaviors over network which interrupt and block genuine user requests by flooding the host server with huge number of requests using a group of zombie computers via geographically distributed internet connections. DDoS disrupts service by creating network congestion and disabling normal functions of network components, which is even more disruptive for IoT. In this paper, a lightweight defensive algorithm for DDoS attack over IoT network environment is proposed and evaluated against several scenarios to dissect the interactive communication among different types of network nodes.

III. METHODOLOGY

SUPERVISED LEARNING

An algorithm uses training data and feedback from humans to learn the relationship of given inputs to a given output. For instance, a practitioner can use marketing expense and weather forecast as input data to predict the sales of cans.

You can use supervised learning when the output data is known. The algorithm will predict new data. There are two categories of supervised learning:

- Classification task
- Regression task

Classification

Imagine you want to predict the gender of a customer for a commercial. You will start gathering data on the height, weight, job, salary, purchasing basket, etc. from your customer database. You know the gender of each of your customer, it can only be male or female. The objective of the classifier will be to assign a probability of being a male or a female (i.e., the label) based on the information (i.e., features you have collected). When the model learned how to recognize male or female, you can use new data to make a prediction. For instance, you just got new information from an unknown customer, and you want to know if it is a male or female. If the classifier predicts male = 70%, it means the algorithm is sure at 70% that this customer is a male, and 30% it is a female.

The label can be of two or more classes. The above Machine learning example has only two classes, but if a classifier needs to predict object, it has dozens of classes (e.g., glass, table, shoes, etc. each object represents a class)

Regression

When the output is a continuous value, the task is a regression. For instance, a financial analyst may need to forecast the value of a stock based on a range of features like equity, previous stock performances, macroeconomics index. The system will be trained to estimate the price of the stocks with the lowest possible error.

Unsupervised learning

Unsupervised learning algorithms take a set of data that contains only inputs, and find structure in the data, like grouping or clustering of data points. The algorithms, therefore, learn from test data that has not been labeled, classified, or categorized. Instead of responding to feedback, unsupervised learning algorithms identify commonalities in the data and react based on the presence or absence of such commonalities in each new piece of data. A central application of unsupervised learning is in the field of density estimation in statistics, such as finding the probability density function. Though unsupervised learning encompasses other domains involving summarizing and explaining data features.

1. Home page
IV. RESULT

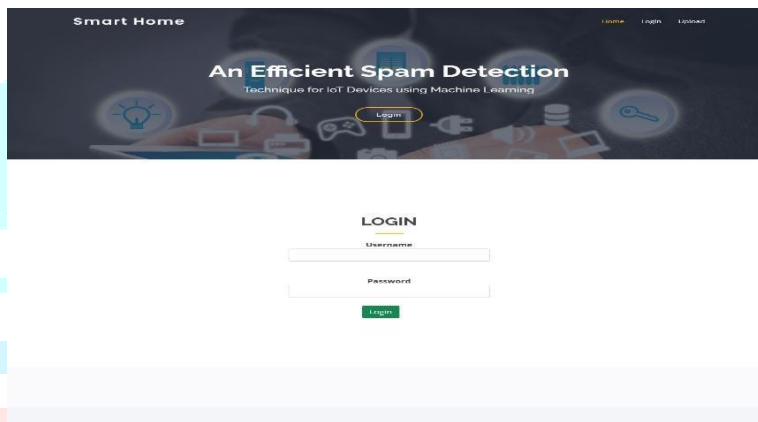


ABSTRACT

The Internet of Things (IoT) is a group of networks of devices, having various uses and functions, which can connect or communicate for data transmission. IoT has grown rapidly over the past decade with more than 20 billion devices are expected for the year 2020. The volume of data received from these devices will continue to grow over the years to come. In addition to an increased volume, the IoT devices produce a large amount of data with a number of different modalities having varying data quality defined by its speed in terms of time and position dependency. In such an environment, machine learning algorithms can play an important role in analyzing data for identification based on biotechnology, sequential detection to improve the stability and security of IoT systems. On the other hand, attackers often use learning algorithms to cause the system against smart IoT devices systems. Motivated from this, in this paper, we propose the security of the IoT devices by detecting spam data machine learning, to achieve this objective, Spam Detection is using Machine Learning Framework is proposed. In this Framework, the machine learning models are trained using a large number of spam, non-spam, and spam data. The machine learning model is used for identifying the spam data. This article reports the classification of IoT device under various parameters. The IoT device is better dataset is used for the validation of proposed technique. The results obtained proves the effectiveness of the proposed scheme in comparison to the other existing schemes.

This is the home page of our project here Admin can login by clicking admin login option and user can login clicking the option.

2. Admin login:



LOGIN

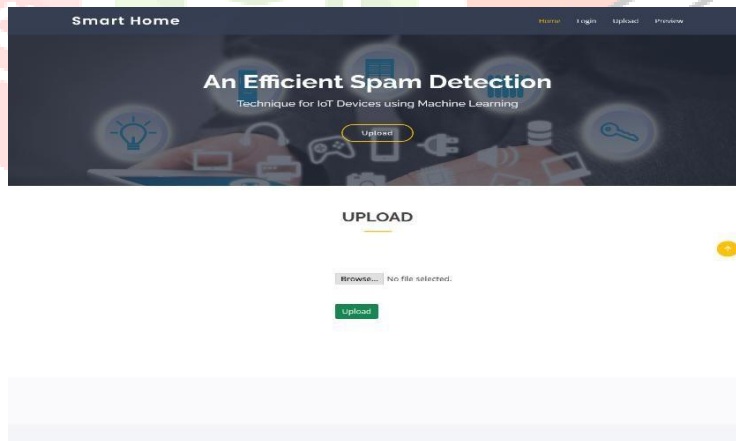
Username

Password

Fig 2:admin login

In this page admin can use user name and password .a user name is uniquely identify the user.

Uploads



UPLOAD

No file selected.

Fig 3: upload

In this page we can upload all of our project details.Preview

PREVIEW

Id	House		Dishwasher		Furnace		Home office		Wine cellar		Garage door		Kitchen		Kitchen		Barn		Well		Microwa	
	gen [kW]	overall [kW]	[kW]	1 [kW]	2 [kW]	[kW]	[kW]	[kW]	[kW]	[kW]	[kW]	12 [kW]	14 [kW]	38 [kW]	[kW]	[kW]	[kW]	[kW]	[kW]	[kW]	[kW]	[kW]
1	0.003483	0.932833	0.000033	0.020700	0.061917	0.442633	0.124150	0.006983	0.013083	0.000417	0.000150	0.000000	0.031350	0.001017	0.00406							
2	0.003467	0.934333	0.000000	0.020717	0.063817	0.444067	0.124000	0.006983	0.013117	0.000417	0.000150	0.000000	0.031500	0.001017	0.00406							
3	0.003467	0.931817	0.000017	0.020700	0.062217	0.446067	0.123533	0.006983	0.013083	0.000433	0.000167	0.000017	0.031517	0.001000	0.00406							
4	0.003483	1.022050	0.000017	0.106900	0.068517	0.446583	0.123133	0.006983	0.013000	0.000433	0.000217	0.000000	0.031500	0.001017	0.00406							
5	0.003467	1.139400	0.000133	0.236933	0.063983	0.446533	0.122850	0.006850	0.012783	0.000450	0.000333	0.000000	0.031500	0.001017	0.00406							

Fig 4: preview
 In this page all of the preview details are there. all of the preview we can see here.Prediction

Fig 5: prediction
 In this page all the prediction details are there. What can we predict the spam detection.

V. CONCLUSION

The proposed framework detects the spam parameters of IoT devices using machine learning models. The IoT dataset used for experiments is pre-processed by using feature engineering procedure. By experimenting with the framework with machine learning models, each IoT appliance is awarded with a spam score. This refines the conditions to be taken for successful working of IoT devices in a smart home. In future, we are planning to consider the climatic and surrounding features of IoT devices to make them more secure and trustworthy.

VI. REFERENCES

- [1] Z.-K. Zhang, M. C. Y. Cho, C.-W. Wang, C.-W. Hsu, C.-K. Chen, and S. Shieh, "Iot security: ongoing challenges and research opportunities," in 2014 IEEE 7th international conference on service-oriented computing and applications. IEEE, 2014, pp. 230–234.
- [2] A. Dorri, S. S. Kanhere, R. Jurdak, and P. Gauravaram, "Blockchain for iot security and privacy: The case study of a smart home," in 2017 IEEE international conference on pervasive computing and communications workshops (PerCom workshops). IEEE, 2017, pp. 618–623.
- [3] E. Bertino and N. Islam, "Botnets and internet of things security," Computer, no. 2, pp. 76–79, 2017.
- [4] C. Zhang and R. Green, "Communication security in internet of thing: preventive measure and avoid ddos attack over iot network," in Proceedings of the 18th Symposium on Communications & Networking. Society for Computer Simulation International, 2015, pp. 8–15.
- [5] W. Kim, O.-R. Jeong, C. Kim, and J. So, "The dark side of the internet: Attacks, costs and responses," Information systems, vol. 36, no. 3, pp. 675–705, 2011.
- [6] H. Eun, H. Lee, and H. Oh, "Conditional privacy preserving security protocol for nfc applications," IEEE Transactions on Consumer Electronics, vol. 59, no. 1, pp. 153–160, 2013.
- [7] R. V. Kulkarni and G. K. Venayagamoorthy, "Neural network based secure media access control protocol for wireless sensor networks," in 2009 International Joint Conference on Neural Networks. IEEE, 2009, pp. 1680–1687.
- [8] M. A. Alsheikh, S. Lin, D. Niyato, and H.-P. Tan, "Machine learning in wireless sensor networks: Algorithms, strategies, and applications," IEEE Communications Surveys & Tutorials, vol. 16, no. 4, pp. 1996–2018, 2014.
- [9] A. L. Buczak and E. Guven, "A survey of data mining and machine learning methods for cyber security intrusion

detection," IEEE Communications Surveys & Tutorials, vol. 18, no. 2, pp. 1153–1176, 2015.

- [10] F. A. Narudin, A. Feizollah, N. B. Anuar, and A. Gani, "Evaluation of machine learning classifiers for mobile malware detection," Soft Computing, vol. 20, no. 1, pp. 343–357, 2016.
- [11] Z. Tan, A. Jamdagni, X. He, P. Nanda, and R. P. Liu, "A system for denial-of-service attack detection based on multivariate correlation analysis," IEEE transactions on parallel and distributed systems, vol. 25, no. 2, pp. 447–456, 2013.
- [12] Y. Li, D. E. Quevedo, S. Dey, and L. Shi, "Sinr-based dos attack on remote state estimation: A game-theoretic approach," IEEE Transactions on Control of Network Systems, vol. 4, no. 3, pp. 632–642, 2016.
- [13] L. Xiao, Y. Li, X. Huang, and X. Du, "Cloud-based malware detection game for mobile devices with offloading," IEEE Transactions on Mobile Computing, vol. 16, no. 10, pp. 2742–2750, 2017.

