

# Prediction of Cyber-Attacks Using Data Science Techniques

Mr. Sudarsanam<sup>1</sup>, Sudharsan M<sup>2</sup>, Sakthivell V<sup>3</sup>, Sakthi Vignesh P<sup>4</sup>, Raghavendra Rao D<sup>5</sup>

Assistant Professor, Department of Cyber Security<sup>1</sup>

UG Scholor, Department of Computer Science and Engineering<sup>2,3,4,5</sup>

SRM Valliammai Engineering College, Chengalpattu, India

**Abstract:** *Cyber-attacks aim to destroy or maliciously manipulate a computing environment or infrastructure, as well as disrupt data integrity or crack all information. This poses a risk to the organisation, perhaps resulting in data loss. The data from device sensors is collected as big data, which has a wealth of information that can be utilised for targeted assaults. Although existing methodologies, models, and algorithms have given the foundation for cyber-attack predictions, new models and algorithms based on data representations other than task-specific techniques are required. Its non-linear information processing architecture, on the other hand, can be customised to learn alternative data representations of network traffic in order to classify different types of network attacks. In this study, we treat cyber-attack prediction as a classification issue, in which networking sectors must use machine learning approaches to forecast the type of network assault from a given dataset. The supervised machine learning technique (SMLT) is used to analyse a dataset in order to capture multiple pieces of information, such as variable identification, uni-variate analysis, bi-variate and multi-variate analysis, missing value treatments, and so on. A comparison of machine learning algorithms was conducted to evaluate which algorithm is the best accurate at predicting the types of cyber-attacks. DOS Attack, R2L Attack, U2R Attack, and Probe Attack are the four types of attacks we classify. The findings reveal that the suggested machine learning algorithm technique has the best accuracy with entropy calculation, precision, recall, F1 Score, sensitivity, specificity, and entropy calculation.*

**Keywords:** Cyber-attack, DOS Attack, R2L Attack, U2R Attack, Probe Attack

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