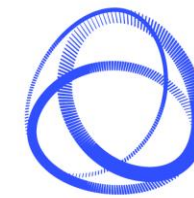


Investigating Security Issues (Multilayer Attacks) on IoT Devices Using Machine Learning

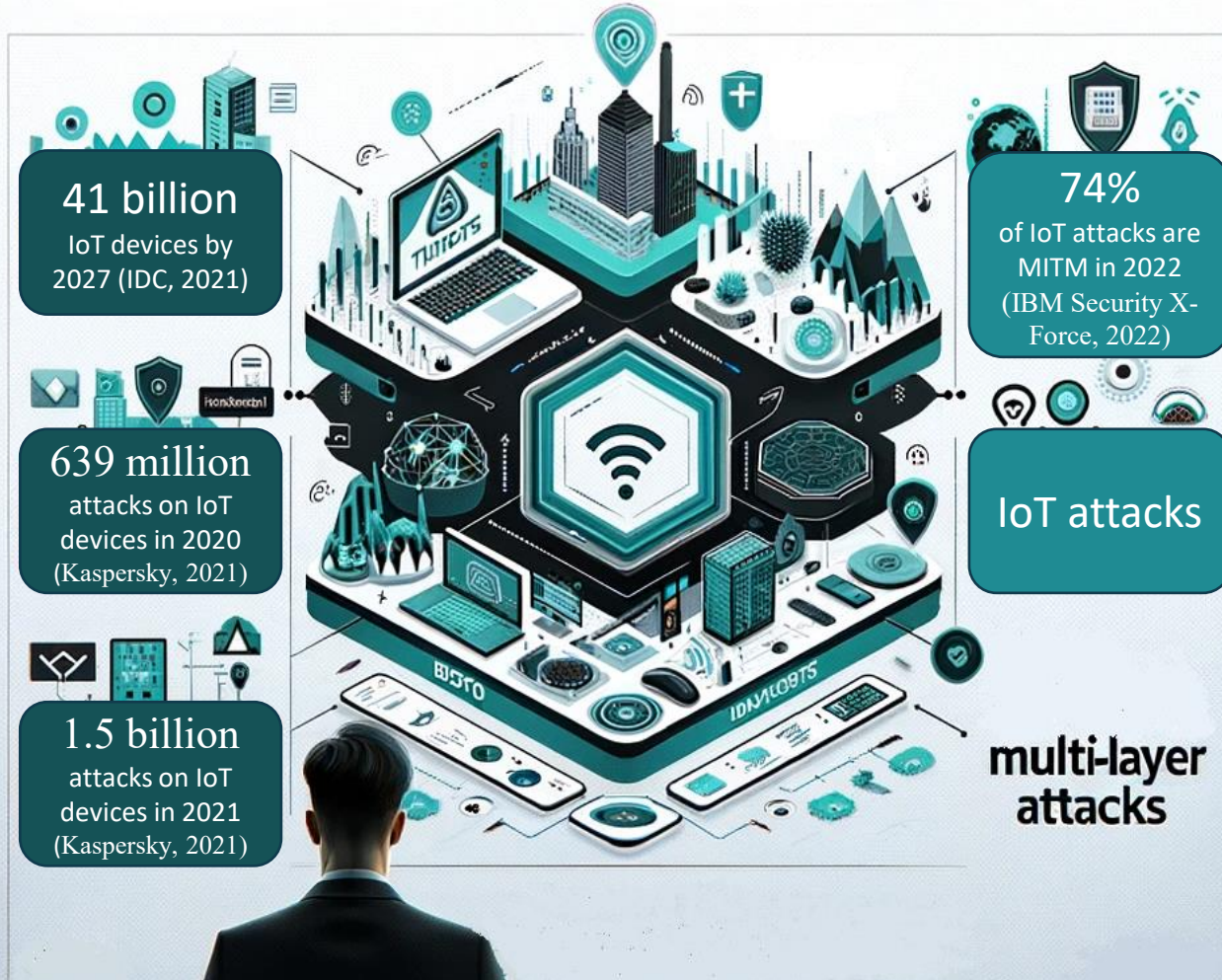
Presented by: Badeea Al Sukhni

Supervisors: Soumya Manna and Leishi Zhang





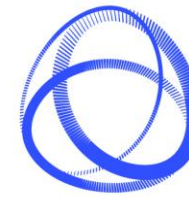
Key points about Internet of things (IoT)



Background

IDC: International Data Corporation

Background



IoT Security Impacts:

- Significant financial losses
- Reputational damage
- Personal information theft

Application Layer:

- Web and mobile applications based on IoT devices.
- Protocols: HTTP, SSH, DNS, etc.



Network Layer:

- Wireless communication systems: Wi-Fi, Bluetooth, Zigbee, etc.
- Protocols: TCP, UDP, IPv4, IPV6, etc.

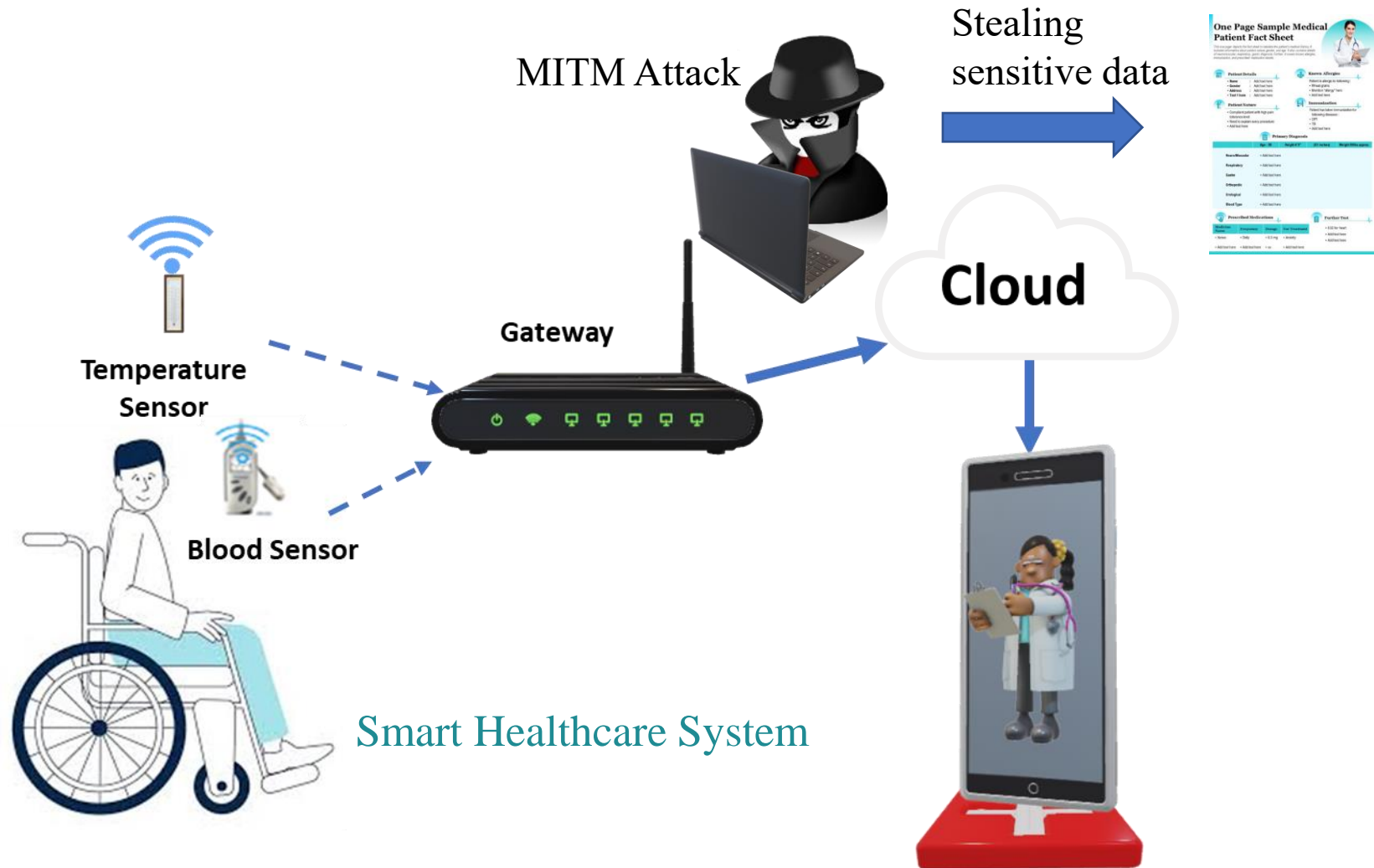
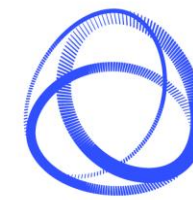


Physical Layer:

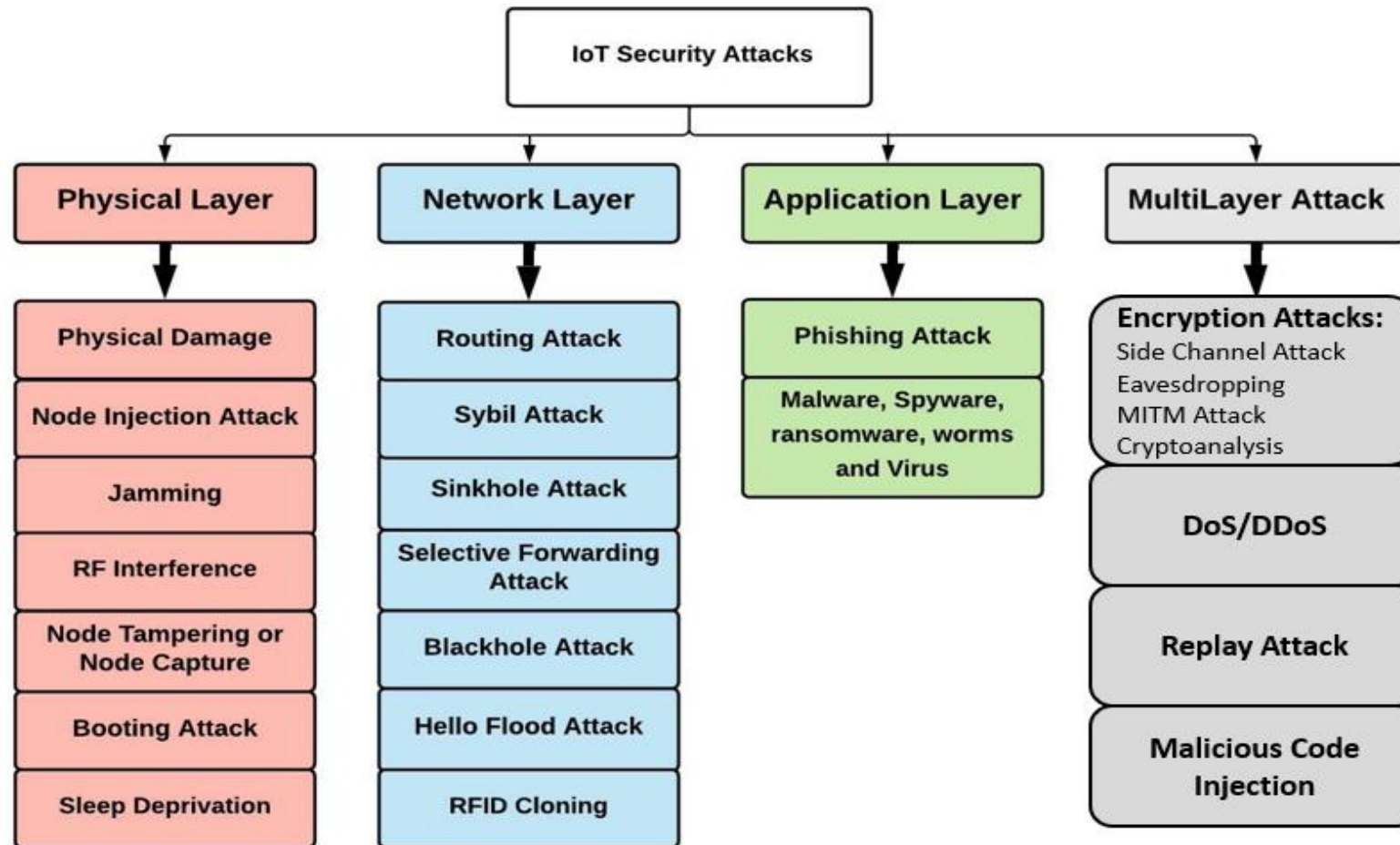
- Data gathering using sensors.
- Protocols: IEEE 802.15.4e, IEEE 802.11ah, Z-Wave, etc.



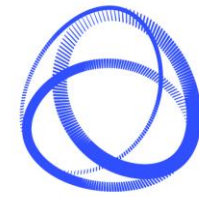
Background



The IoT Security Attacks



Aims and Objectives

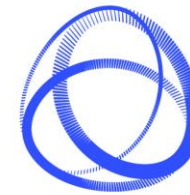


In this research, we aim to create a robust multilayer attack detection through machine learning.



- 1 Identify MultiLayer security attacks and their behavioral patterns.
- 2 Investigate ML and datasets that enhance IoT security against multilayer attacks.
- 3 Explore a variety of feature selection algorithms..
- 4 Apply feature weighting.
- 5 Increase detection efficiency by utilizing significant features.
- 6 Fine-tune hyperparameters for ML classification models.

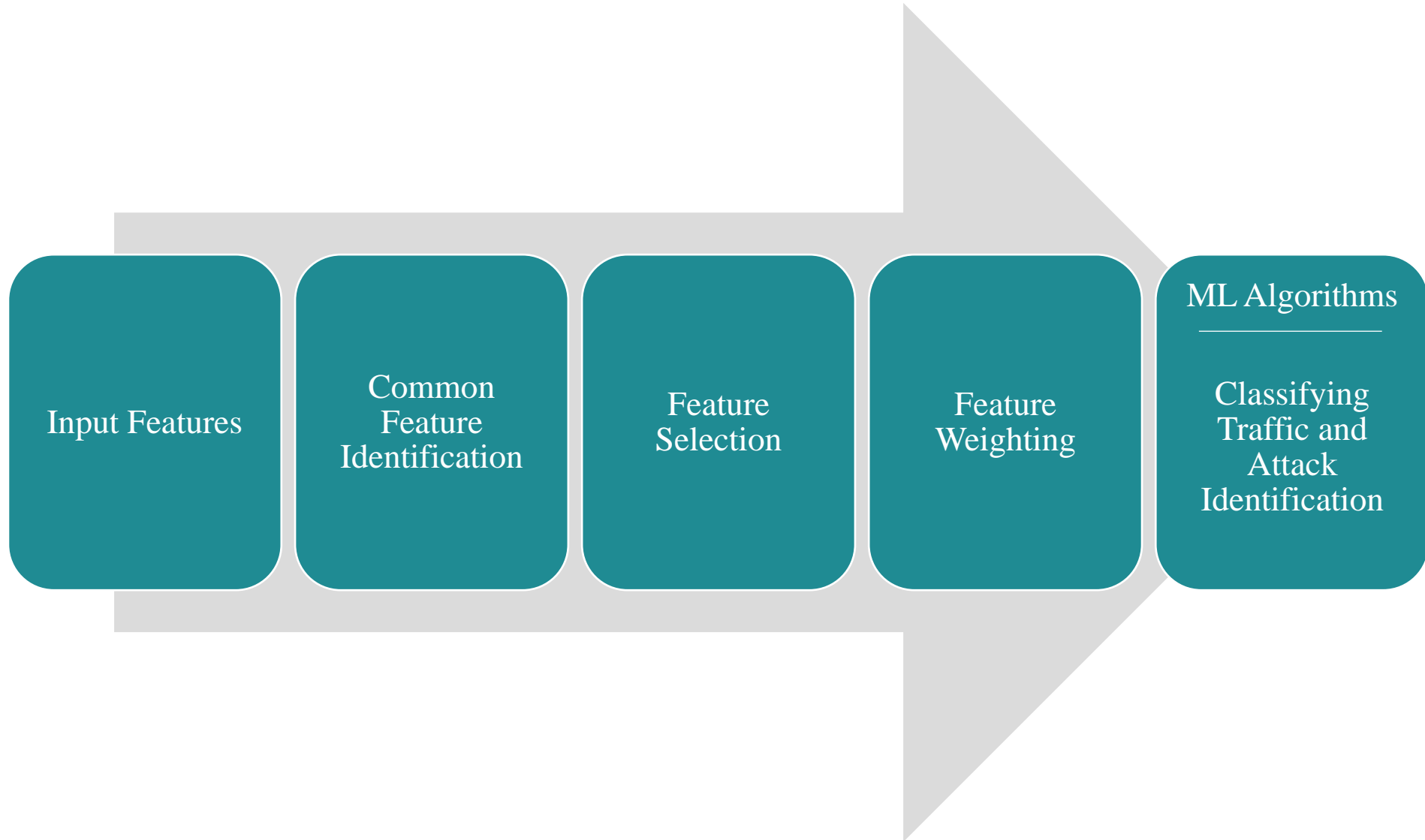
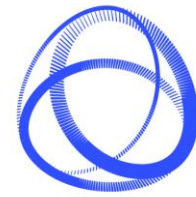
Datasets Analysis



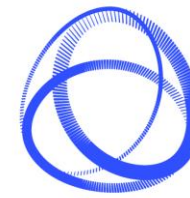
Dataset	Year	IoT Specific	Total Features	Total Attacks	Multilayer Attacks
KDDCUP 99	1999	No	41	4	DoS
NSL-KDD	2009	No	43	4	DoS
UNSW-NB15	2015	No	49	9	DoS
CICIDS2017	2017	No	80	14	DoS, XSS, SQL Injection
BoT-IoT	2018	Yes	45	10	DoS/DDoS
N-BaIoT	2018	Yes	115	2	Botnet attacks (Mirai and Gafgyt)
ToN-IoT	2020	Yes	44	9	DoS/DDoS, SQL Injection, XSS, MITM
Edge-IIoTset	2022	Yes	62	14	DoS/DDoS, SQL Injection, XSS, MITM



Methodology



Case Study



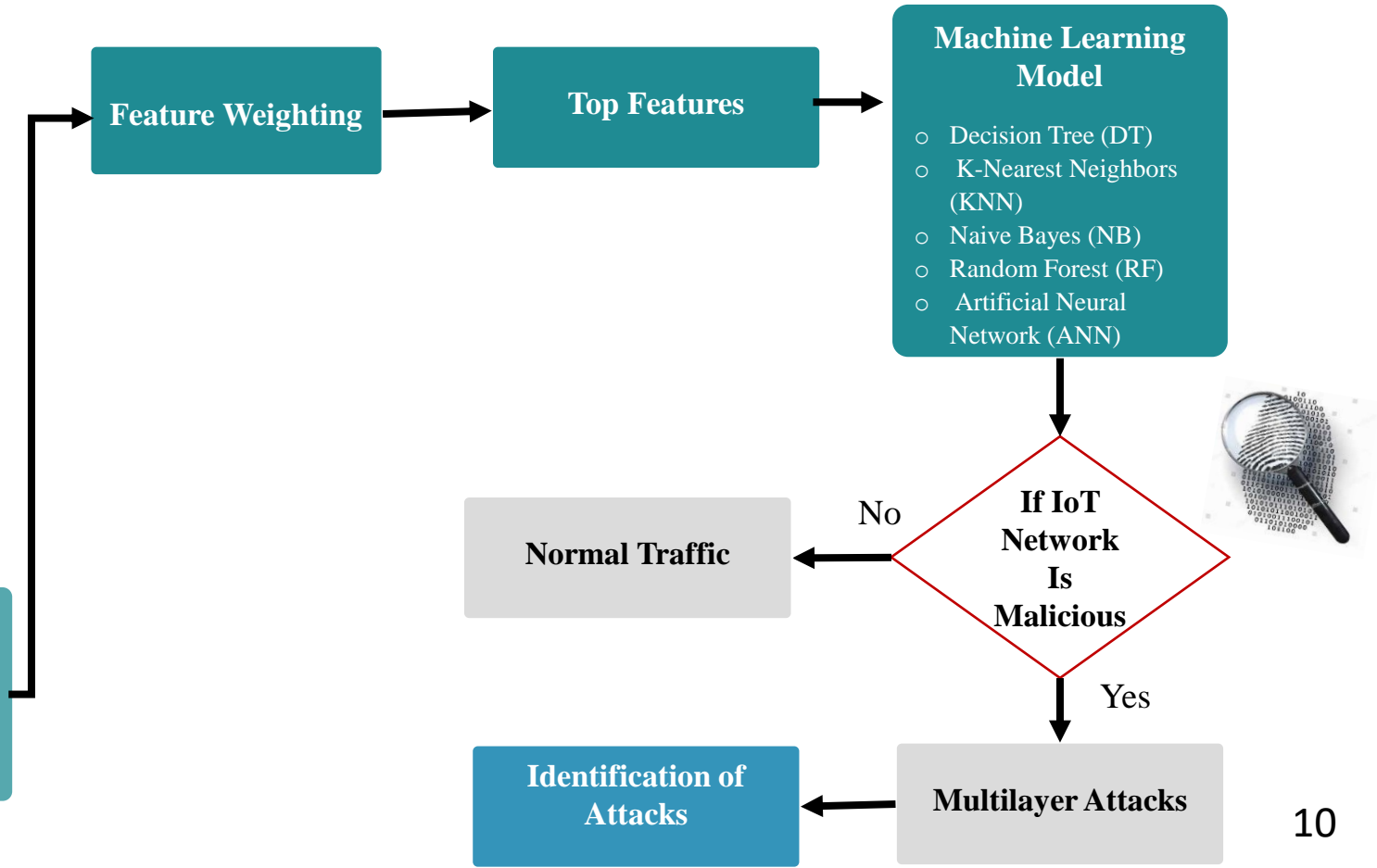
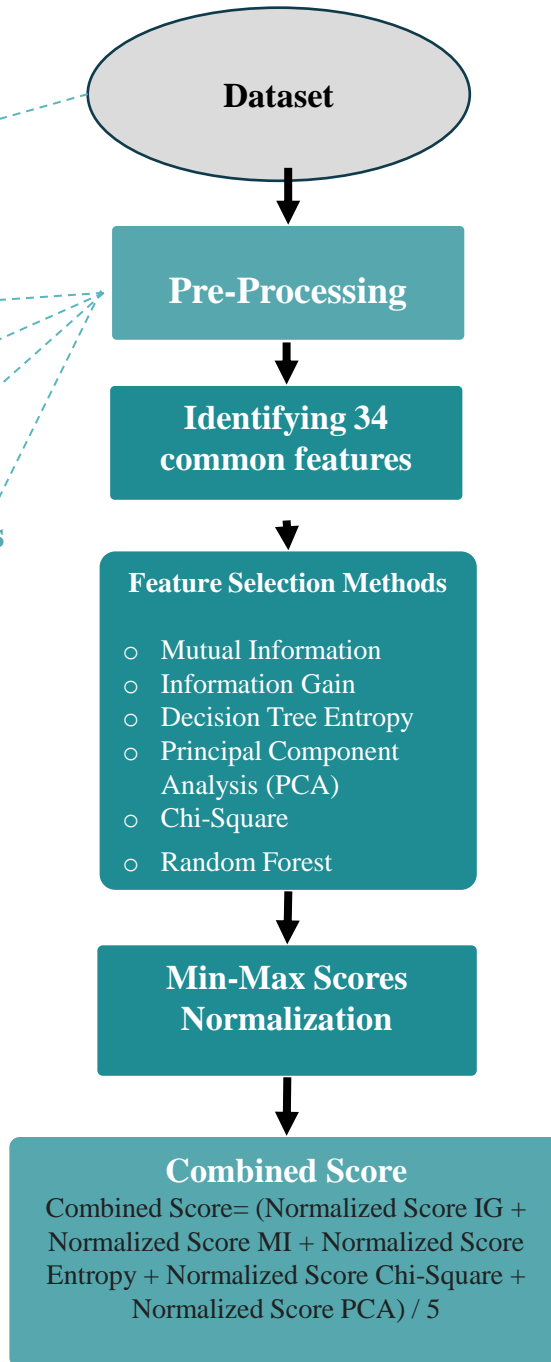
Edge-IIoTset Dataset

Handling missing data

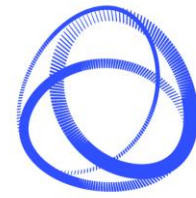
Label Encoding

Data Standardization

Mitigating data imbalances



Common Feature Selection



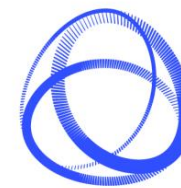
Canterbury
Christ Church
University

Iterate over
attack_type
feature

Feature listing
for selected
attack

Count feature
occurrences

Identify
common
features



Feature Selection Methods



Chi-Square: All 34 features are critical.

Mutual Information: 26 out of 34 features as significant.

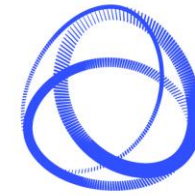
Information Gain: 31 significant features.

PCA: 33 significant features.

Decision Tree Entropy: Seven significant features.

Random Forest: 27 out of 34 features as significant.

Hyperparameter Tuning



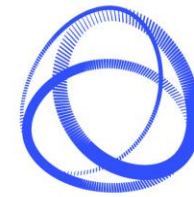
- Hyperparameter Tuning via Randomized Search
- Goal: Classify IoT Network Traffic into Normal and Multilayer Attacks

- Tuned Classifiers:

- Random Forest (RF)
- Decision Tree (DT)
- k-Nearest Neighbors (KNN)
- Artificial Neural Network (ANN)
- Naïve Bayes (NB)

Decision Tree	Random Forest	KNN	ANN	Naïve Bayes
<ul style="list-style-type: none">• Criterion: entropy• max_depth: 5• min_samples_split: 10• max_features: sqrt• min_samples_leaf: 4	<ul style="list-style-type: none">• criterion: gini• max_depth: 10• n_estimators: 10	<ul style="list-style-type: none">• n_neighbors: 5• P: 1• Metric: manhattan	<ul style="list-style-type: none">• Activation: ReLU• Optimizer: adam• loss function:• Metrics: accuracy, binary_crossentropy• Epochs: 10• batch_size: 32	<ul style="list-style-type: none">• var_smoothing: 1.232846739442066e-08

Results of Feature Selection



Evaluation of Five ML Classification Models

- Considered a full set of 62 features of Edge-IIoTset dataset.
- 34 common features.
- Significant features by applying Feature selection methods.

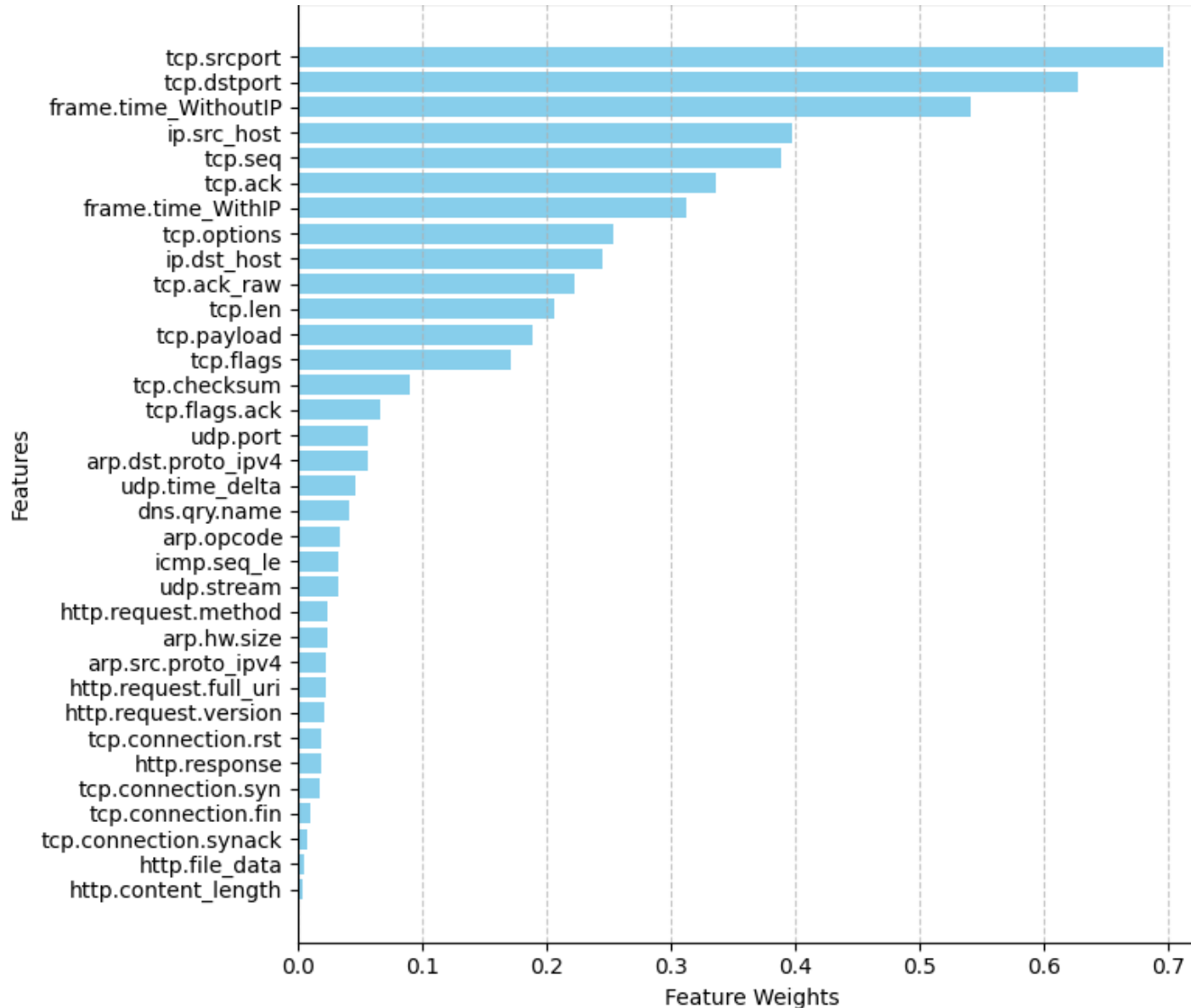
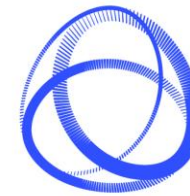
Accuracy Rates

- Mutual Information feature selection: impressive accuracy with only 26 features.
- RF classifier achieved the highest accuracy, while Naïve Bayes model achieved the lowest accuracy.

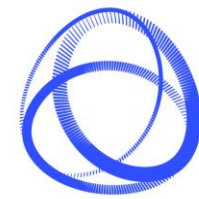
MI	FS Methods							
	All 62	All 34	IG	DTE	MI	Chi ²	PCA	RF
DT	94.3	99.87	85.74	71.03	97.13	99.87	99.87	94.32
RF	94.58	95.78	98.41	99.84	99.86	95.78	98.46	84.9
KNN	98.4	97.89	97.89	99.93	97.95	97.89	84.84	97.88
ANN	76.1	86.41	98.88	92.92	92.7	86.41	80.56	92.25
NB	66.77	61.22	61.19	38.48	61.17	61.22	43.96	61.31



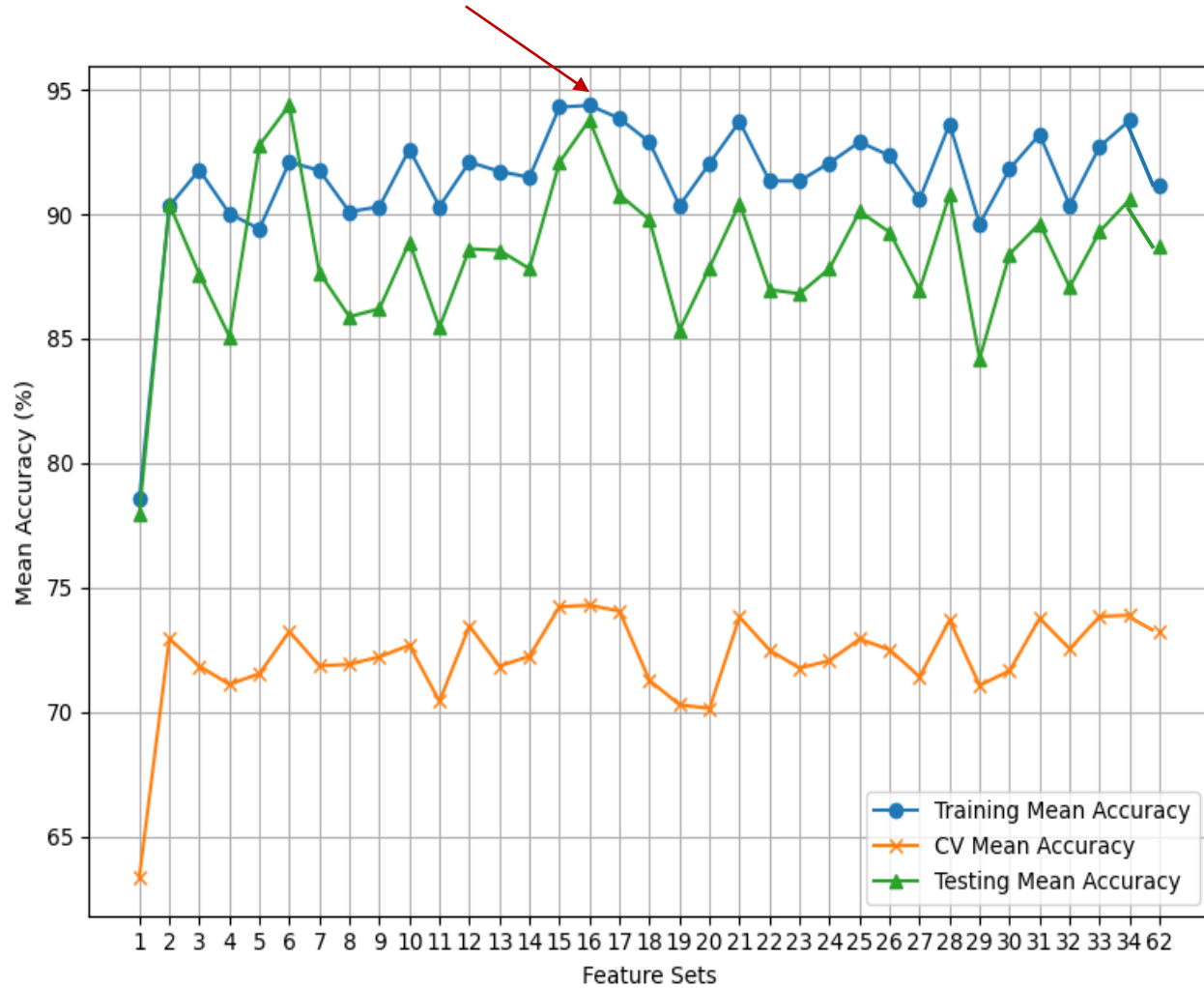
Feature Weighting



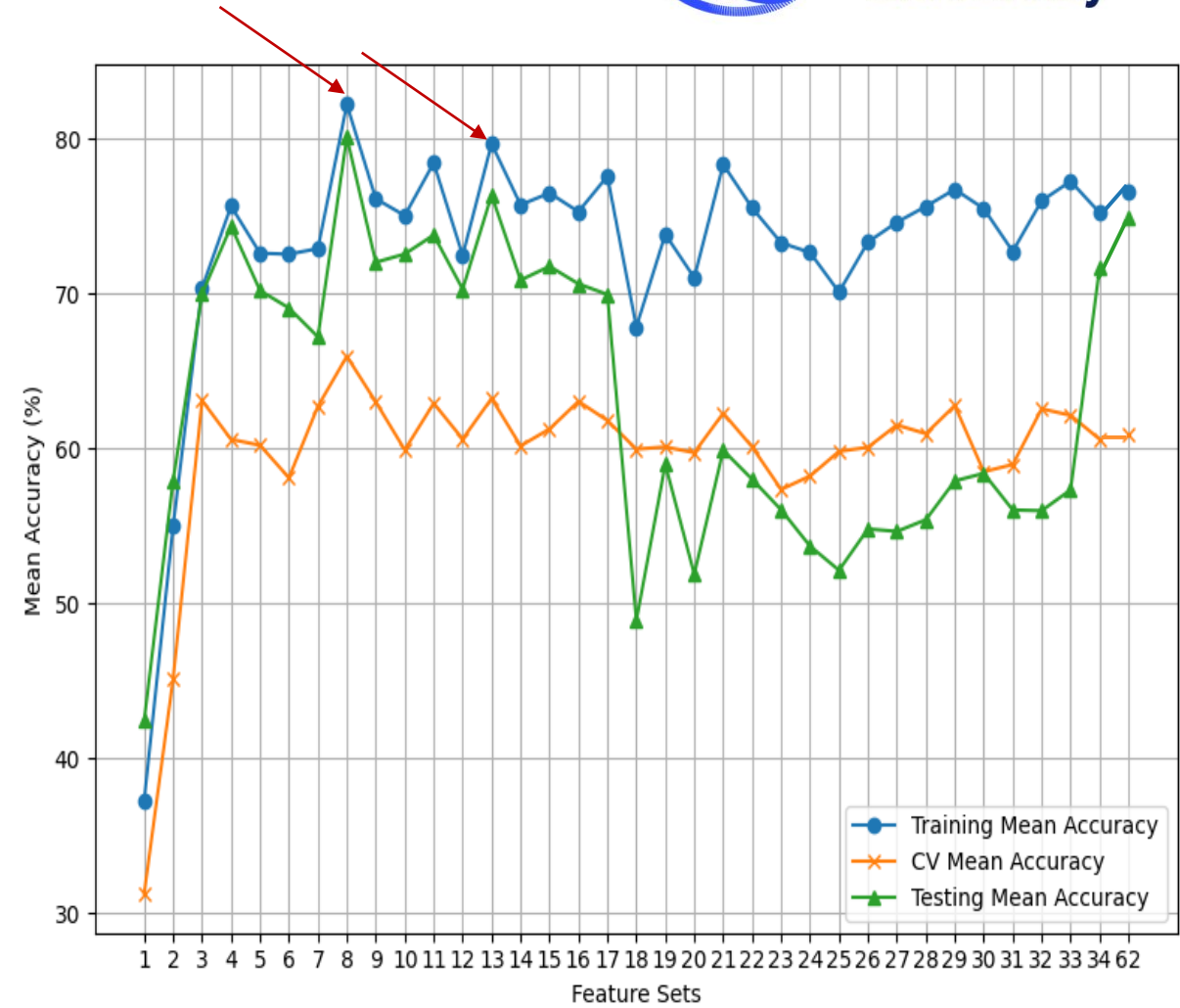
Semi-Automated Tool



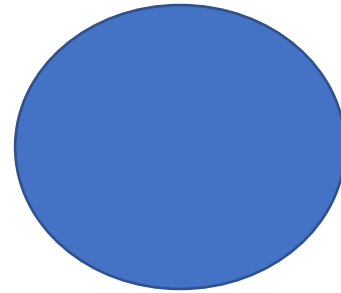
Canterbury
Christ Church
University



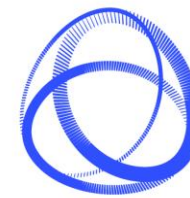
Binary Classification



Multiclass Classification

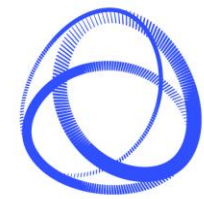


Evaluation of 13 Features



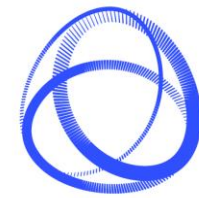
Alg	Metric	Normal	DDoS_TCP	DDoS_UDP	DDoS_HTTP	DoS_ICMP	SQL injection	XSS attacks	MITM	Password
NB	Pr	0.99	1.00	1.00	0.36	0.96	0.84	0.02	1.00	1.00
	Rc	0.22	0.63	1.00	0.99	1.00	0.42	0.04	1.00	1.00
	f1	0.36	0.77	1.00	0.53	0.98	0.56	0.03	1.00	1.00
RF	Pr	0.79	0.84	1.00	1.00	0.99	0.60	0.59	0.72	1.00
	Rc	0.73	0.60	1.00	1.00	1.00	0.98	0.46	1.00	1.00
	f1	0.76	0.70	1.00	1.00	0.99	0.74	0.52	0.83	1.00
DT	Pr	0.96	0.99	1.00	0.85	1.00	0.30	0.66	0.71	1.00
	Rc	0.60	0.65	1.00	0.38	0.99	1.00	0.34	1.00	0.97
	f1	0.74	0.78	1.00	0.52	0.99	0.47	0.45	0.83	0.98
ANN	Pr	0.93	0.85	1.00	0.45	0.99	0.58	0.36	0.97	0.38
	Rc	0.44	0.88	1.00	0.30	0.99	0.89	0.82	1.00	0.30
	f1	0.60	0.86	1.00	0.36	0.99	0.70	0.50	0.98	0.33
KNN	Pr	1.00	1.00	1.00	0.70	1.00	0.70	0.83	1.00	0.79
	Rc	1.00	1.00	1.00	0.72	1.00	0.80	0.95	1.00	0.54
	f1	1.00	1.00	1.00	0.71	1.00	0.75	0.89	1.00	0.64

Evaluation of 8 Features



Alg	Metric	Normal	DDoS_TCP	DDoS_UDP	DDoS_HTTP	DoS_ICMP	SQL injection	XSS attacks	MITM	Password
NB	Pr	0.99	1.00	1.00	0.45	0.96	0.71	0.02	1.00	1.00
	Rc	0.17	0.60	1.00	0.99	1.00	0.63	0.04	1.00	1.00
	f1	0.29	0.75	1.00	0.62	0.98	0.67	0.03	1.00	1.00
RF	Pr	0.79	0.66	1.00	1.00	0.96	0.46	0.00	1.00	1.00
	Rc	0.96	1.00	1.00	0.99	1.00	0.98	0.00	1.00	1.00
	f1	0.79	0.79	1.00	0.99	0.98	0.98	0.00	1.00	1.00
DT	Pr	0.98	0.97	1.00	0.85	1.00	0.93	0.79	0.63	1.00
	Rc	0.89	1.00	1.00	1.00	0.98	0.98	0.93	0.78	0.99
	f1	0.93	0.99	1.00	0.92	1.00	0.95	0.85	0.69	1.00
ANN	Pr	0.57	1.00	1.00	0.19	0.91	0.56	0.12	0.95	0.42
	Rc	0.64	0.67	1.00	0.18	1.00	0.87	0.11	1.00	0.17
	f1	0.60	0.80	1.00	0.19	0.95	0.68	0.11	0.97	0.25
KNN	Pr	1.00	0.99	1.00	0.83	1.00	0.87	0.90	1.00	1.00
	Rc	1.00	0.98	1.00	0.80	1.00	0.87	0.96	1.00	0.98
	f1	1.00	0.98	1.00	0.81	1.00	0.87	0.93	1.00	0.99

Conclusion and Future Work



Conclusion:

- Broader focus on multilayer attacks (physical, network, and application layers).
- Extracted common features from the dataset.
- Utilized multiple feature selection methods.
- Enhanced accuracy through hyperparameter tuning.
- By using the results of Mutual Information features, the RF model achieved the highest accuracy, while Naïve Bayes model achieved the lowest accuracy.
- Implemented feature weighting to identify optimal features for multilayer IoT attack detection.
- Only 13 features are critical for efficient detection and classification of multilayer attacks.



Future Work:

- Expand the research to diverse IoT datasets.
- Real-time implementation and deployment assessment.

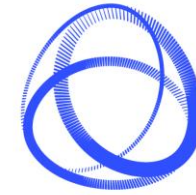
Research Outputs



1. Sukhni, B. A., Dave, J. M., Manna, S. K., and Zhang, L. 2022. Investigating the Security Issues of Multi-layer IoT Attacks Using Machine Learning Techniques in International Conference on Human-centred Cognitive Systems (IEEE_HCCCS), 17th -18th December, Shanghai, China pp. 1-9, doi: 10.1109/HCCS55241.2022.10090400.
2. Sukhni, B. A., Manna, S. K., Dave, J. M., and Zhang, L. 2022. Investigating the security issues of multi-layer IoMT attacks using machine learning techniques (Poster presentation). In Exploring Research and Development in the MedTech, Life Science and Healthcare sectors, Maidstone Innovation Centre, 9 Nov 2022.
3. Al Sukhni, B., Manna, S.K., Dave, J.M., Zhang, L. (2023). Machine Learning-Based Solutions for Securing IoT Systems Against Multilayer Attacks. In: Tomar, R.S., et al. Communication, Networks and Computing. CNC 2022. Communications in Computer and Information Science, vol 1893. Springer, Cham. https://doi.org/10.1007/978-3-031-43140-1_13
4. AL Sukhni, B. A., Manna, S. K., Dave, J. M., and Zhang, L. 2023. Exploring Optimal Set of Features in Machine Learning for Improving IoT Multilayer Security in IEEE 9th World Forum on Internet of Things. Aveiro, Portugal, Oct 2023, in Press.

References

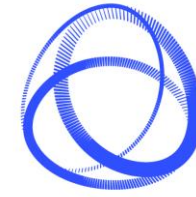
- [1] Malhotra, P. et al. (2021) “Internet of Things: Evolution, concerns and security challenges,” *Sensors* (Basel, Switzerland), 21(5), p. 1809. doi: 10.3390/s21051809.
- [2] Hassija, V. et al. (2019) “A survey on IoT security: Application areas, security threats, and solution architectures,” *IEEE access: practical innovations, open solutions*, 7, pp. 82721–82743. doi: 10.1109/access.2019.2924045.
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- [4] Atlam, H. F. and Wills, G. B. (2020) “IoT security, privacy, safety and ethics,” in *Internet of Things*. Cham: Springer International Publishing, pp. 123–149.
- [5] Khanam, S. et al. (2020) “A survey of security challenges, attacks taxonomy and advanced countermeasures in the internet of things,” *IEEE access: practical innovations, open solutions*, 8, pp. 219709–219743. doi: 10.1109/access.2020.3037359.
- [6] Ahmad, R. and Alsmadi, I. (2021) “Machine learning approaches to IoT security: A systematic literature review,” *Internet of Things*, 14(100365), p. 100365. doi: 10.1016/j.iot.2021.100365.
- [7] Kumar, R. and Sharma, R. (2022) “Leveraging blockchain for ensuring trust in IoT: A survey,” *Journal of King Saud University - Computer and Information Sciences*, 34(10), pp. 8599–8622. doi: 10.1016/j.jksuci.2021.09.004.
- [8] Mohanta, B. K. et al. (2021) “Addressing security and privacy issues of IoT using blockchain technology,” *IEEE internet of things journal*, 8(2), pp. 881–888. doi: 10.1109/jiot.2020.3008906.



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