IoT Device and Attack Prediction

Busher Bridi, Jamie Cohen,
& Marcelo Rodrigues

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Overview

- **IoT devices have become increasingly prevalent in today's interconnected world**
  - IoT devices play a vital role in many industries, enhancing efficiency, and ease of use.
- **Clustering IoT devices can provide insight into device management and security**
  - **Problem Statement 1:** Determine whether IoT devices can be clustered based on their features
- **It is crucial to keep IoT devices safe from cyber attacks, especially mission critical ones. Analyzing IoT traffic can detect and possibly mitigate possible threats.**
  - **Problem Statement 2:** Determine whether malicious network activity can be identified and predicted

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Objective

- **Objective 1:** Create a model that will show which features can be used to identify different types of IoT devices
  - **Success:** An equal amount of distinct cluster to the amount of unique IoT Devices in the datasets

- **Objective 2:** Create a model that can accurately predict type of IoT attack
  - **Success:** 50% accuracy

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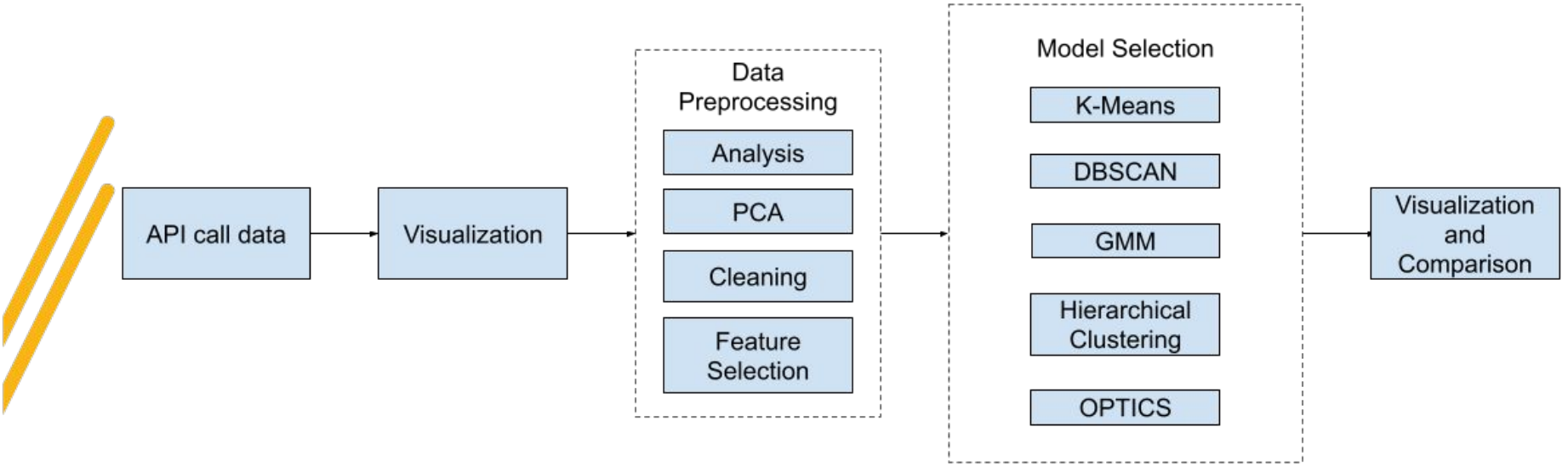
Methodology - Device Identification



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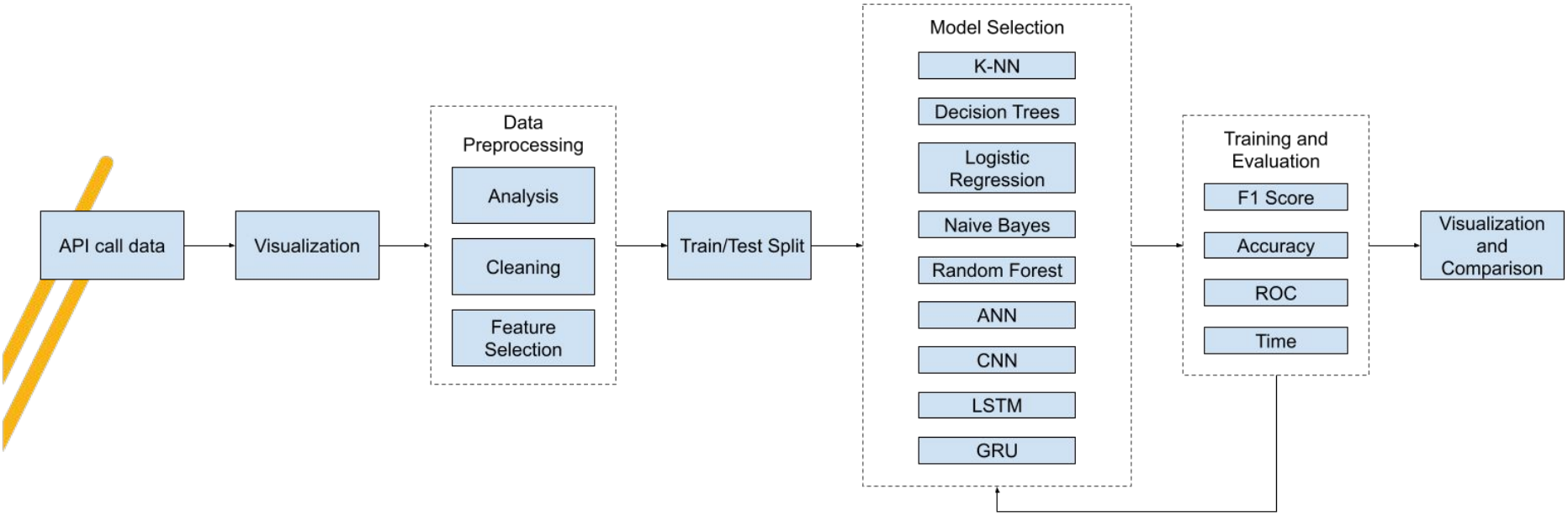
Methodology - Attack Prediction



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Datasets

- **Dataset 1: IoT Device Identification**
  - 297 Features
  - 10 Types of IoT Devices within dataset
  - 13,701 data points

- **Dataset 2: IoT Attack Prediction**
  - 16 Features
  - Labeled with attack type
    - Possible types of attack include: SHA, DFA, SFA, SYA, and VNA
  - 10,845 data points

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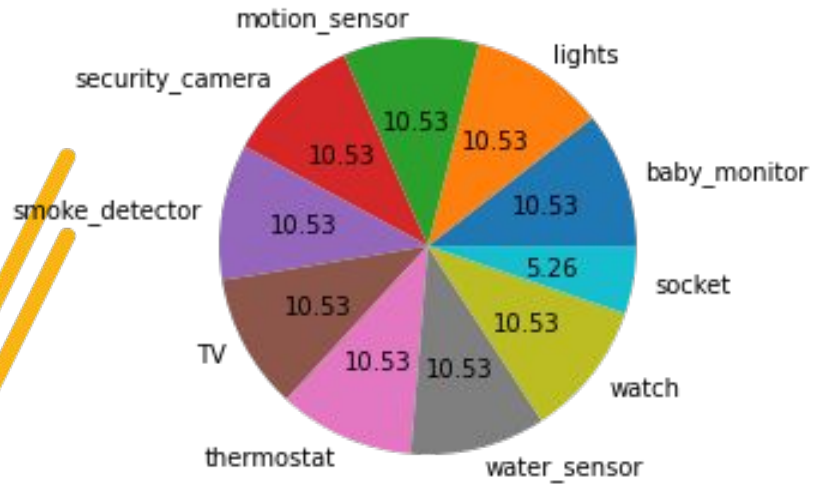
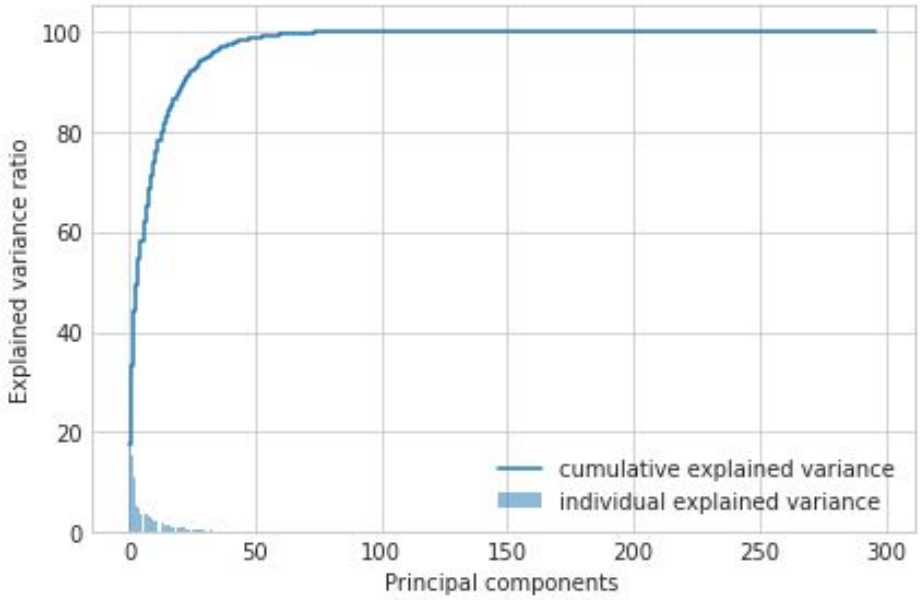
Visualization - Device





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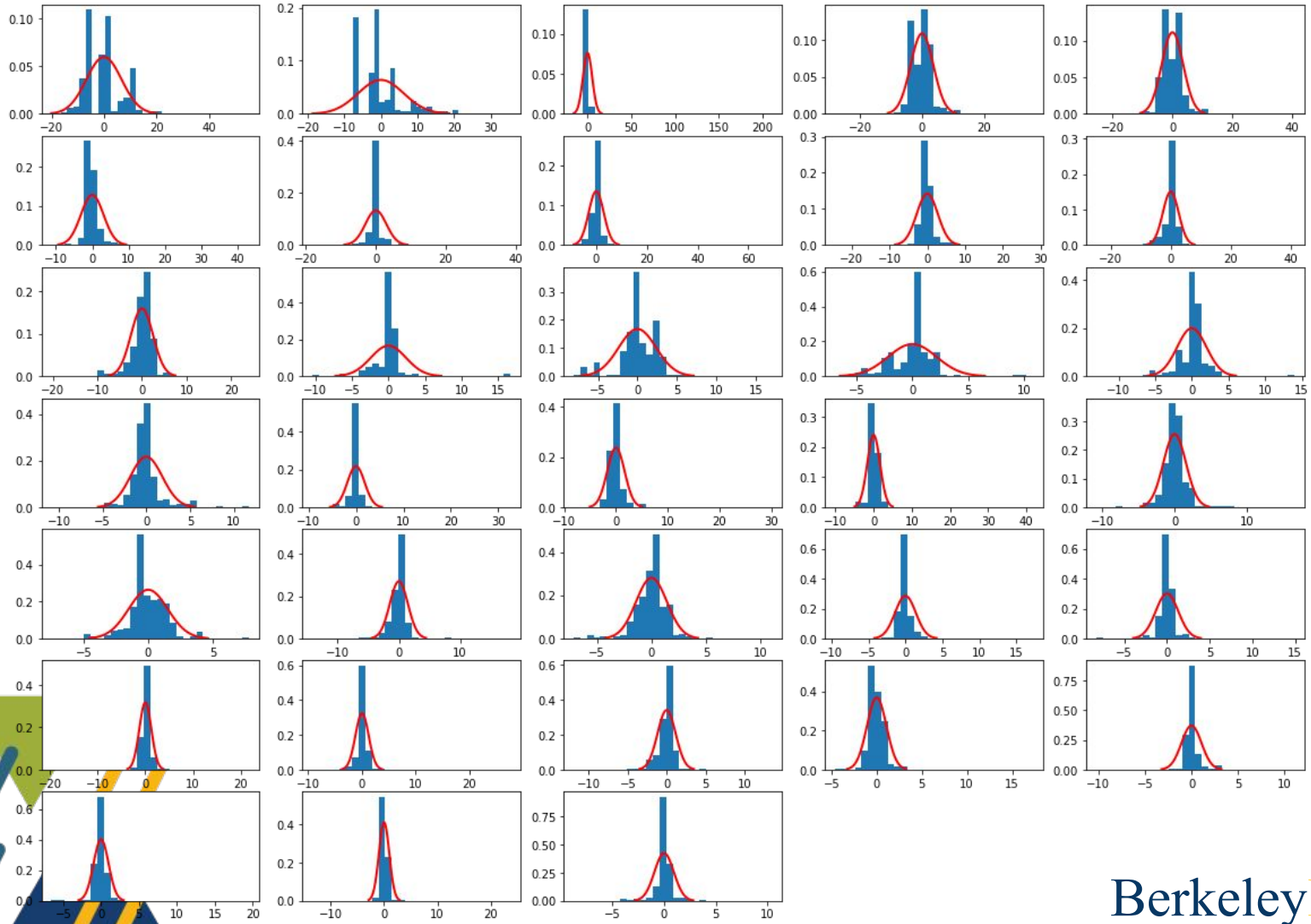
Visualization - Device



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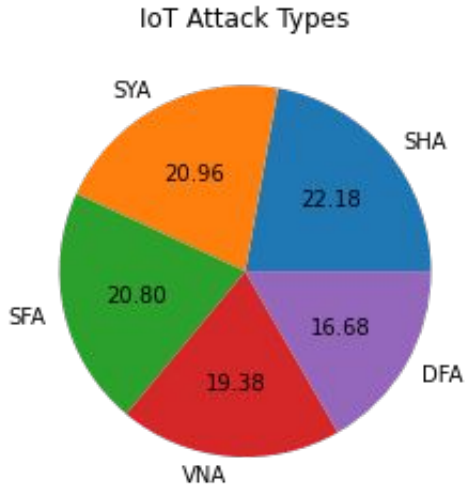
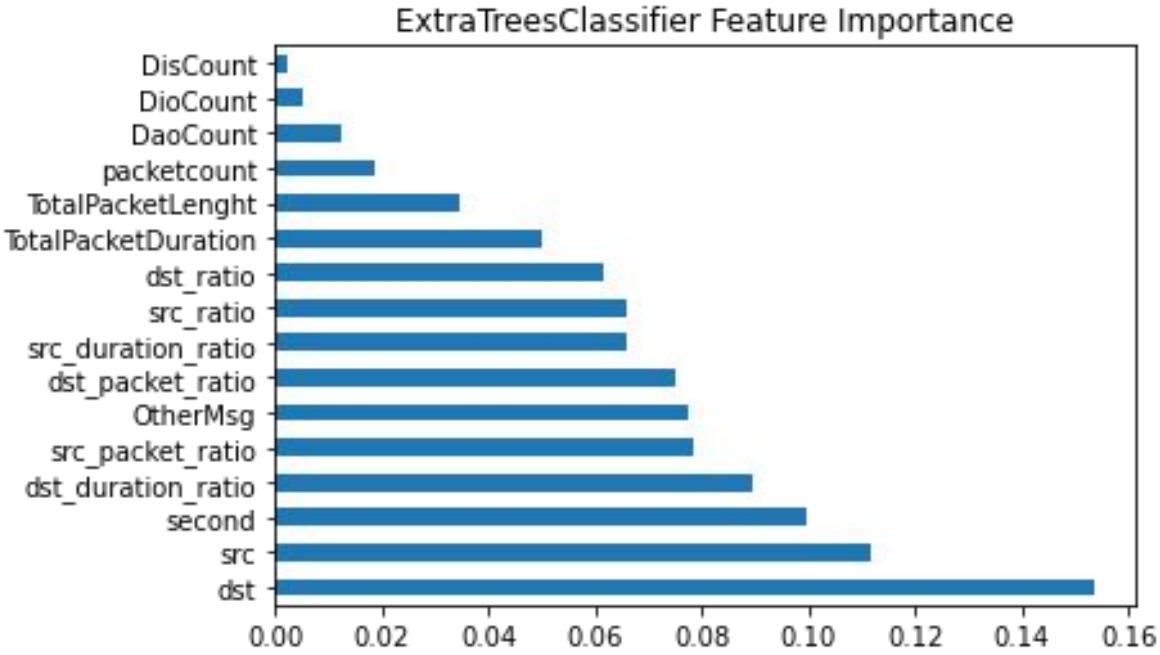
Visualization - Prediction





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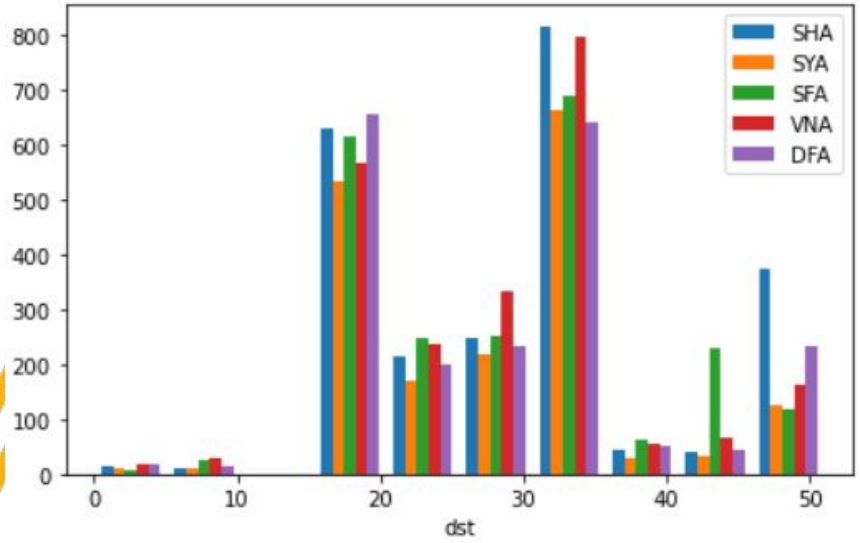
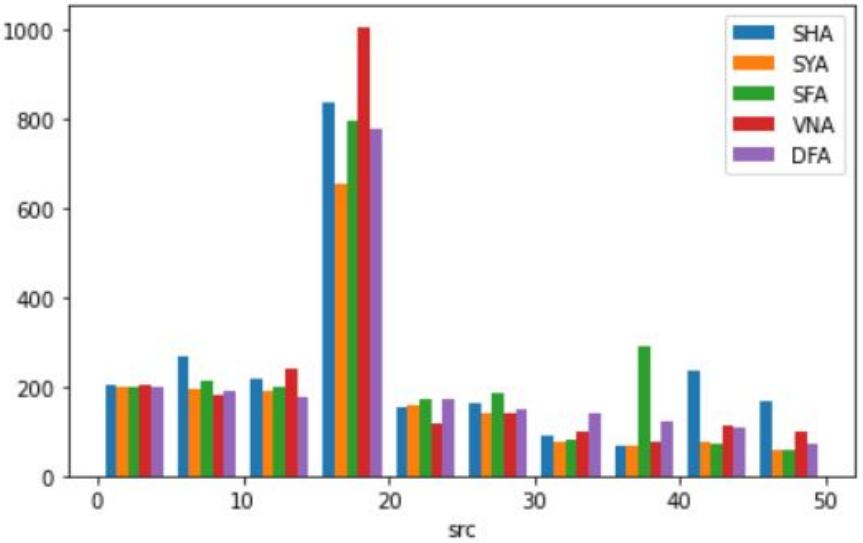
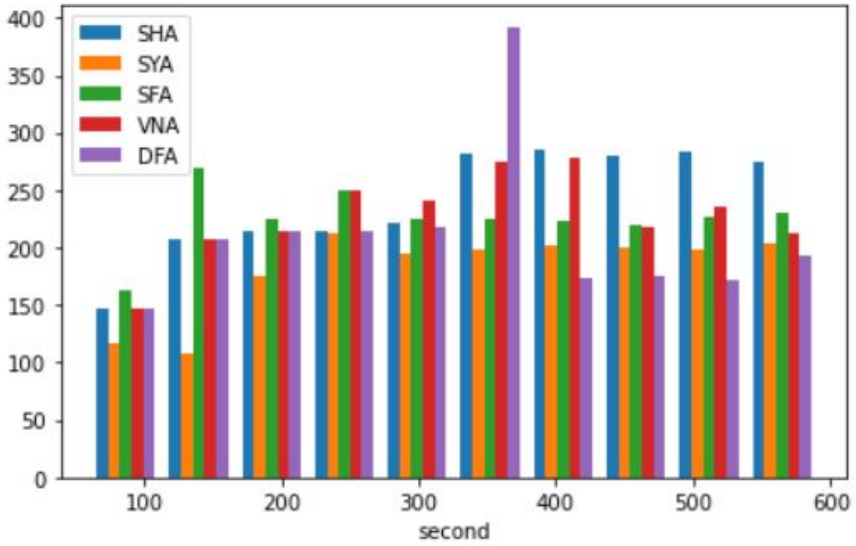
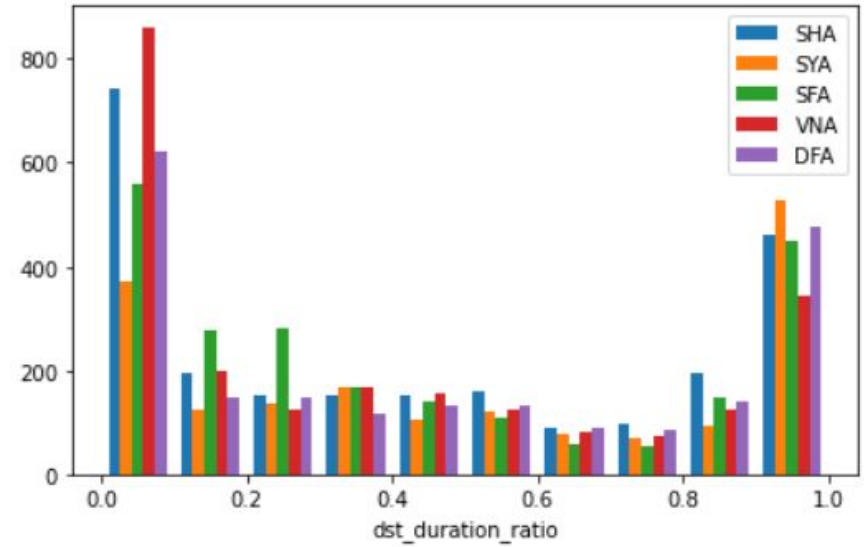
Visualization - Prediction









Device Identification

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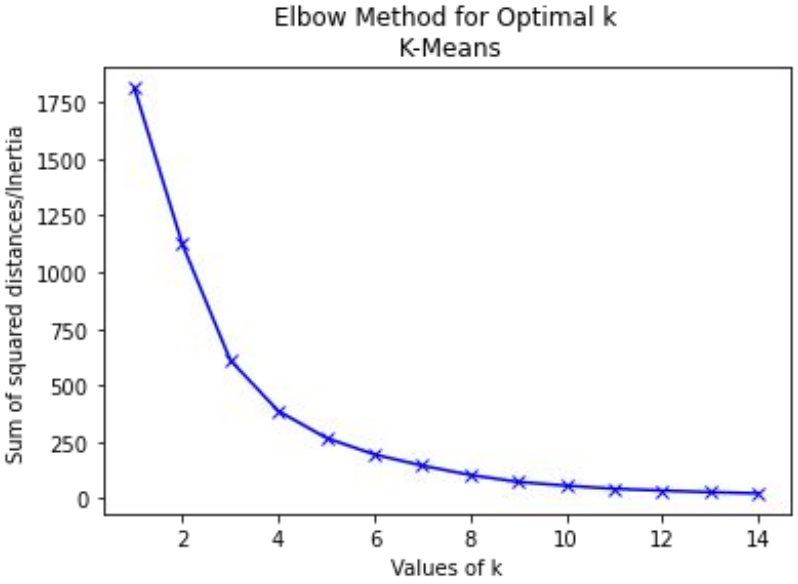
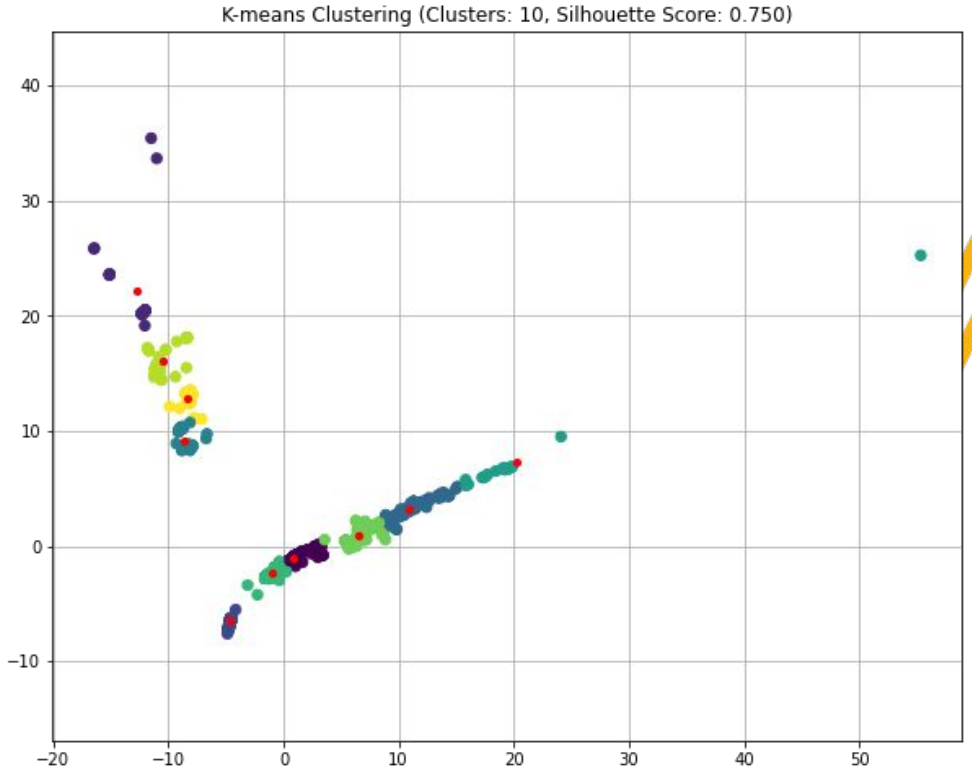
K-Means





Average mean clusters BIC: 6.84

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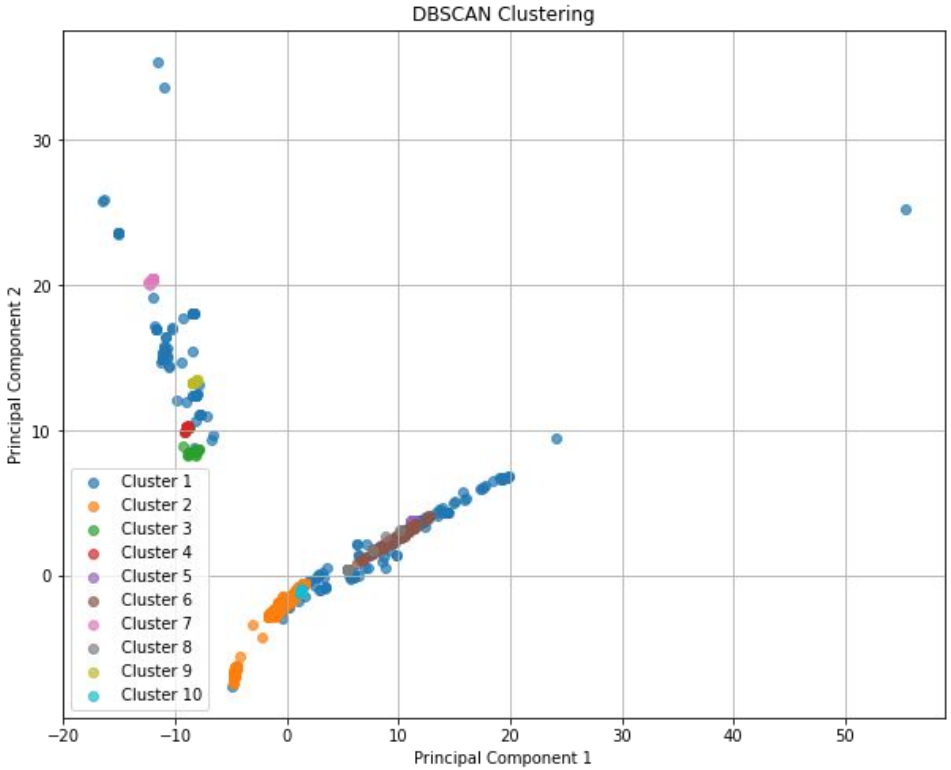
DBSCAN

- Epsilon = 6, Minimum_Samples = 20
- Silhouette Coefficient: 0.418



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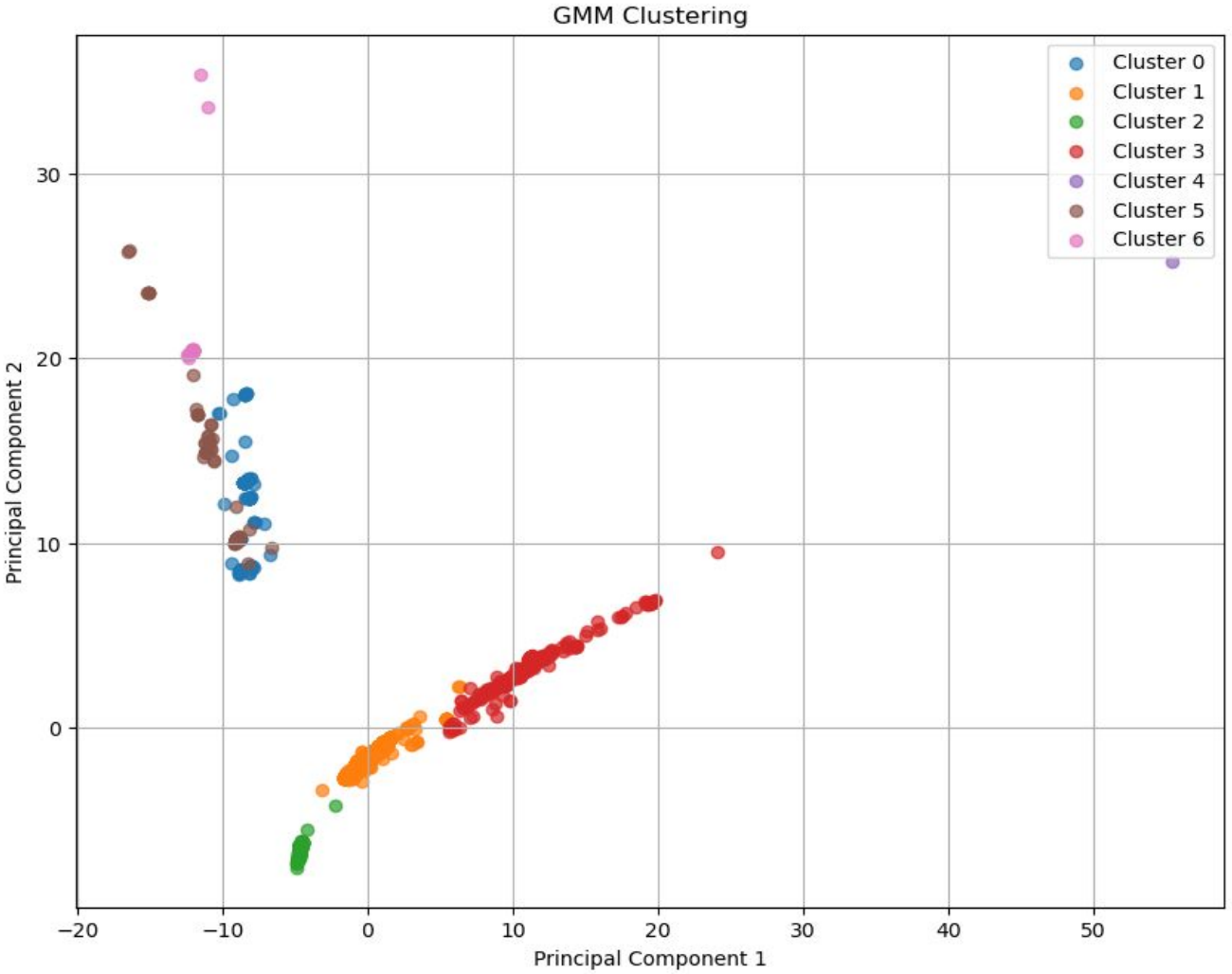
Gaussian Mixture Model



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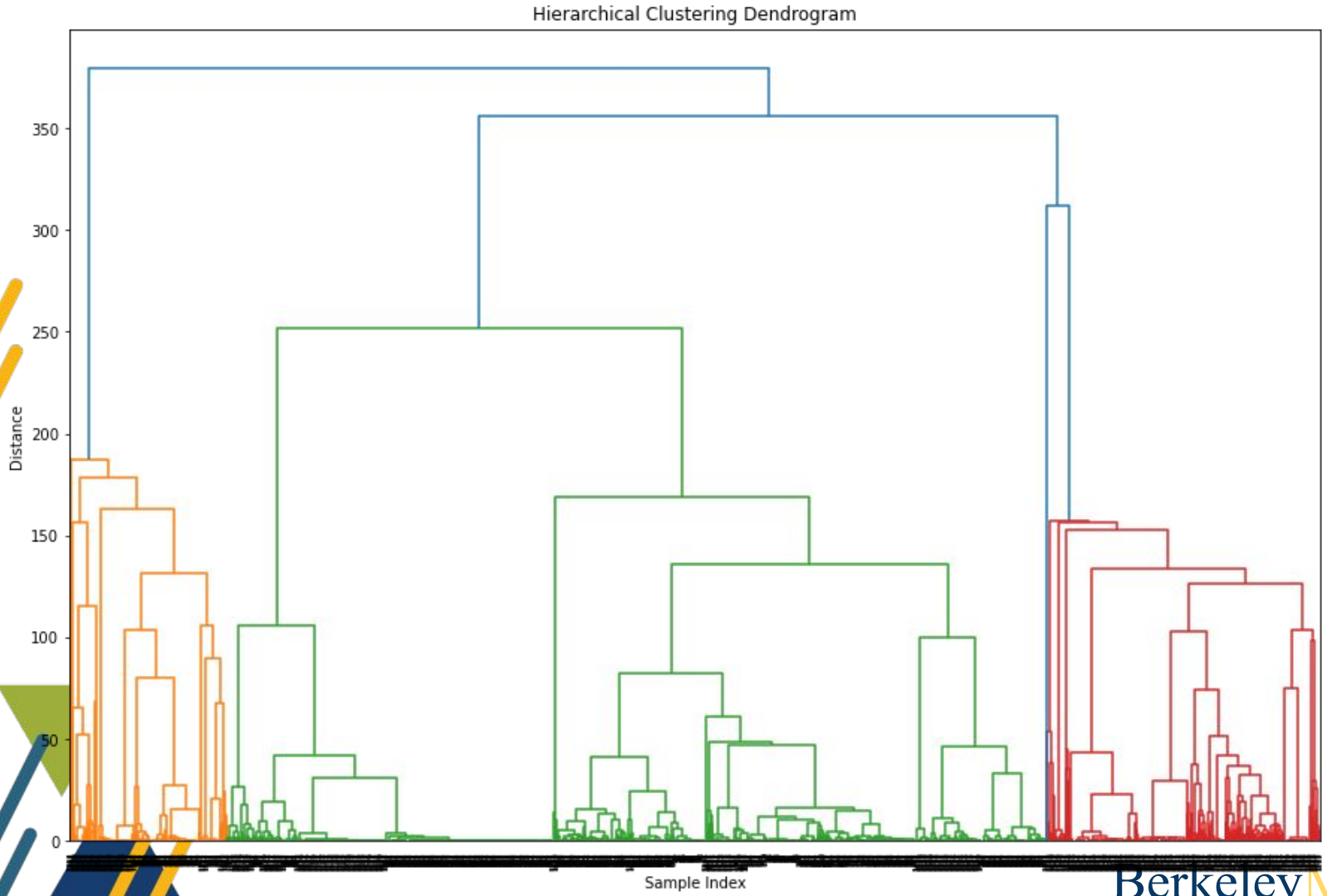
Hierarchical Clustering



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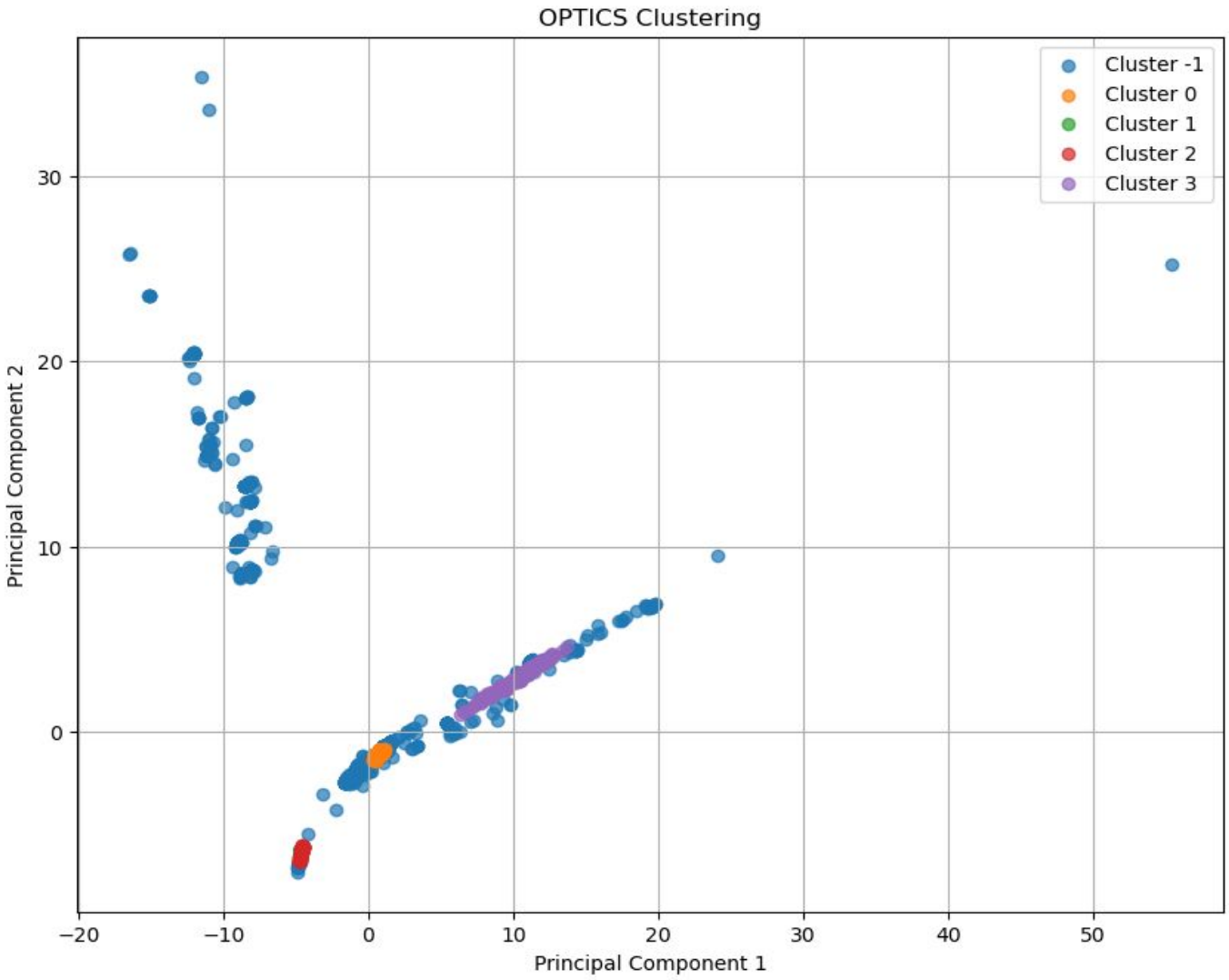
Optics



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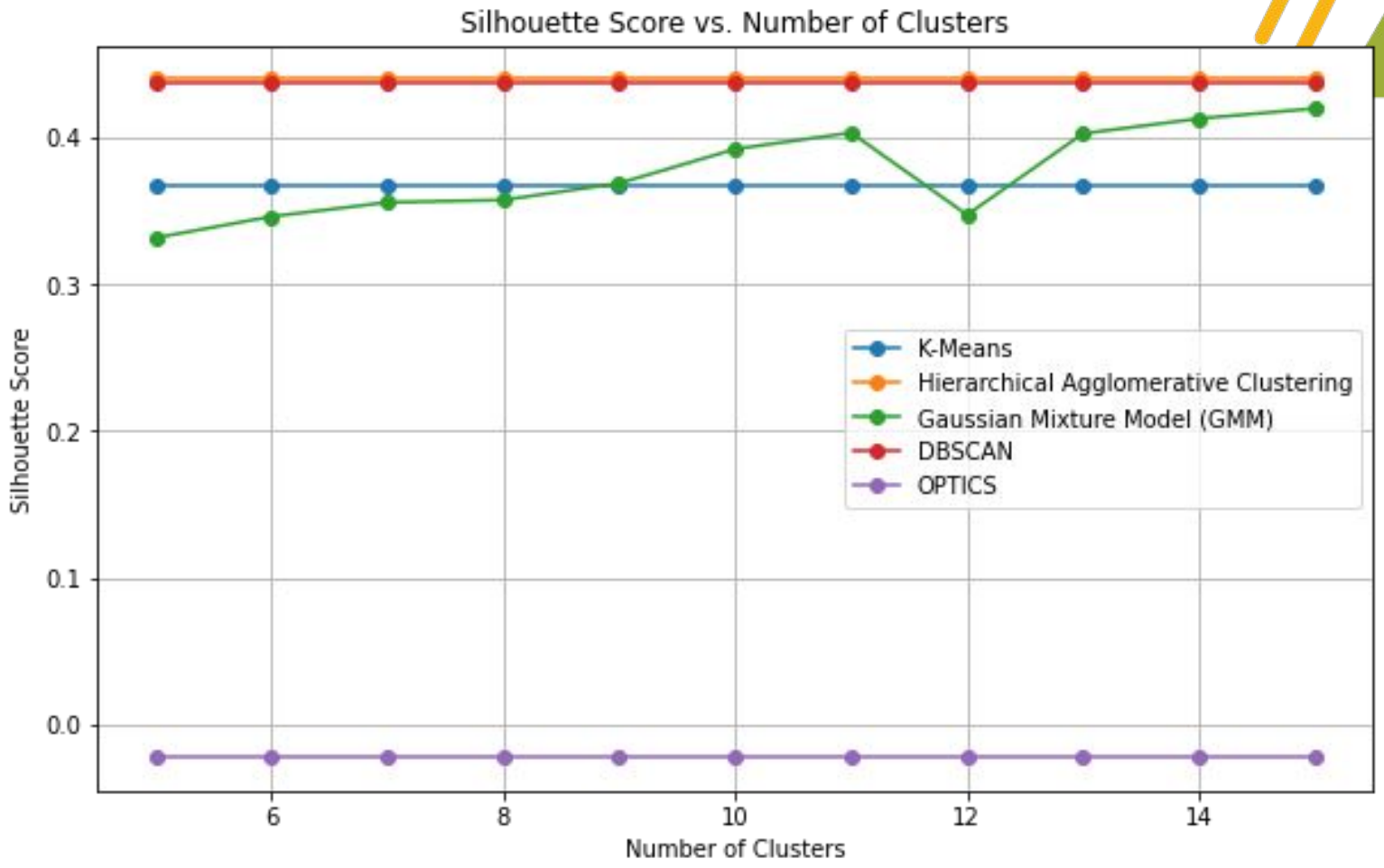
Comparison



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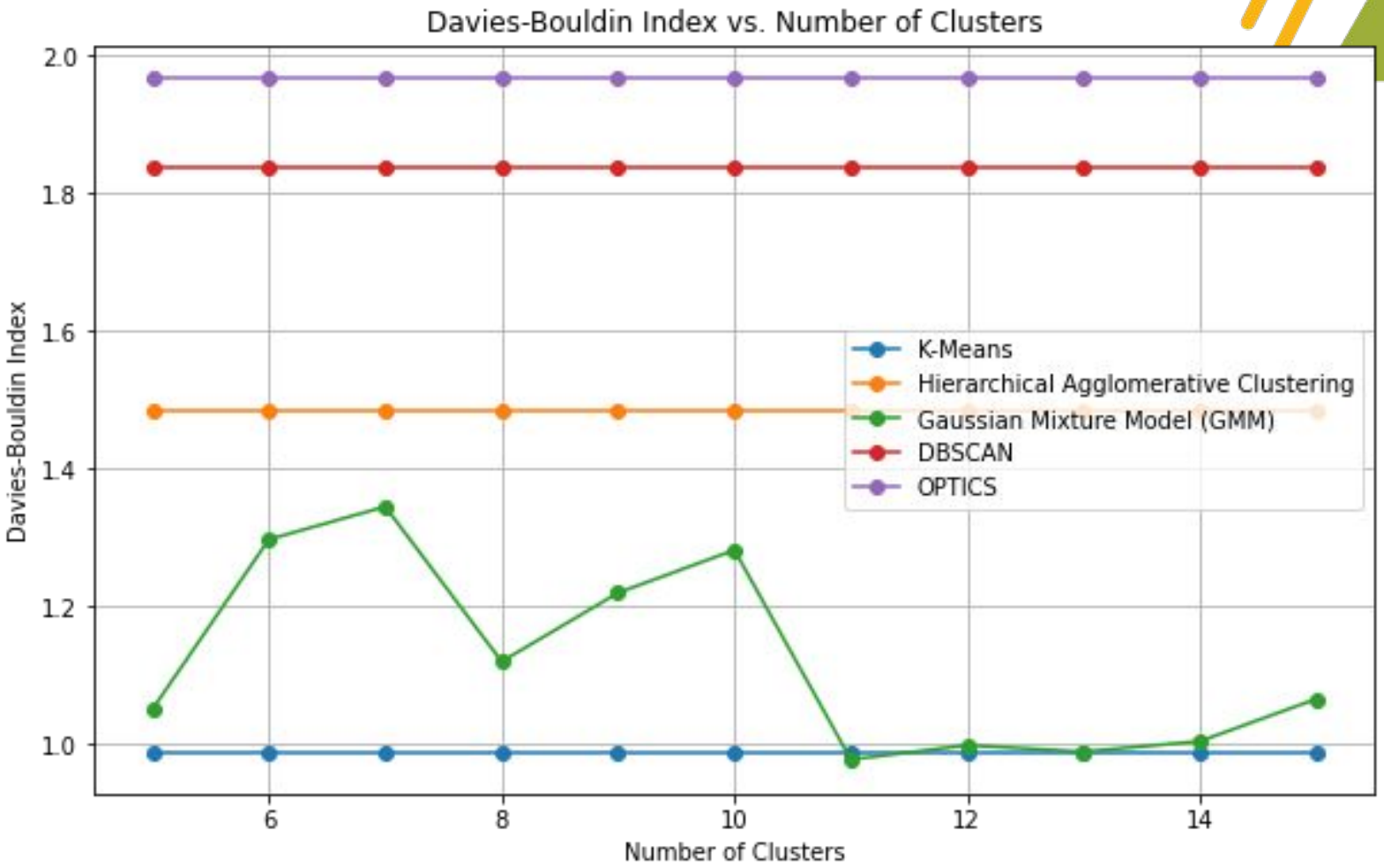

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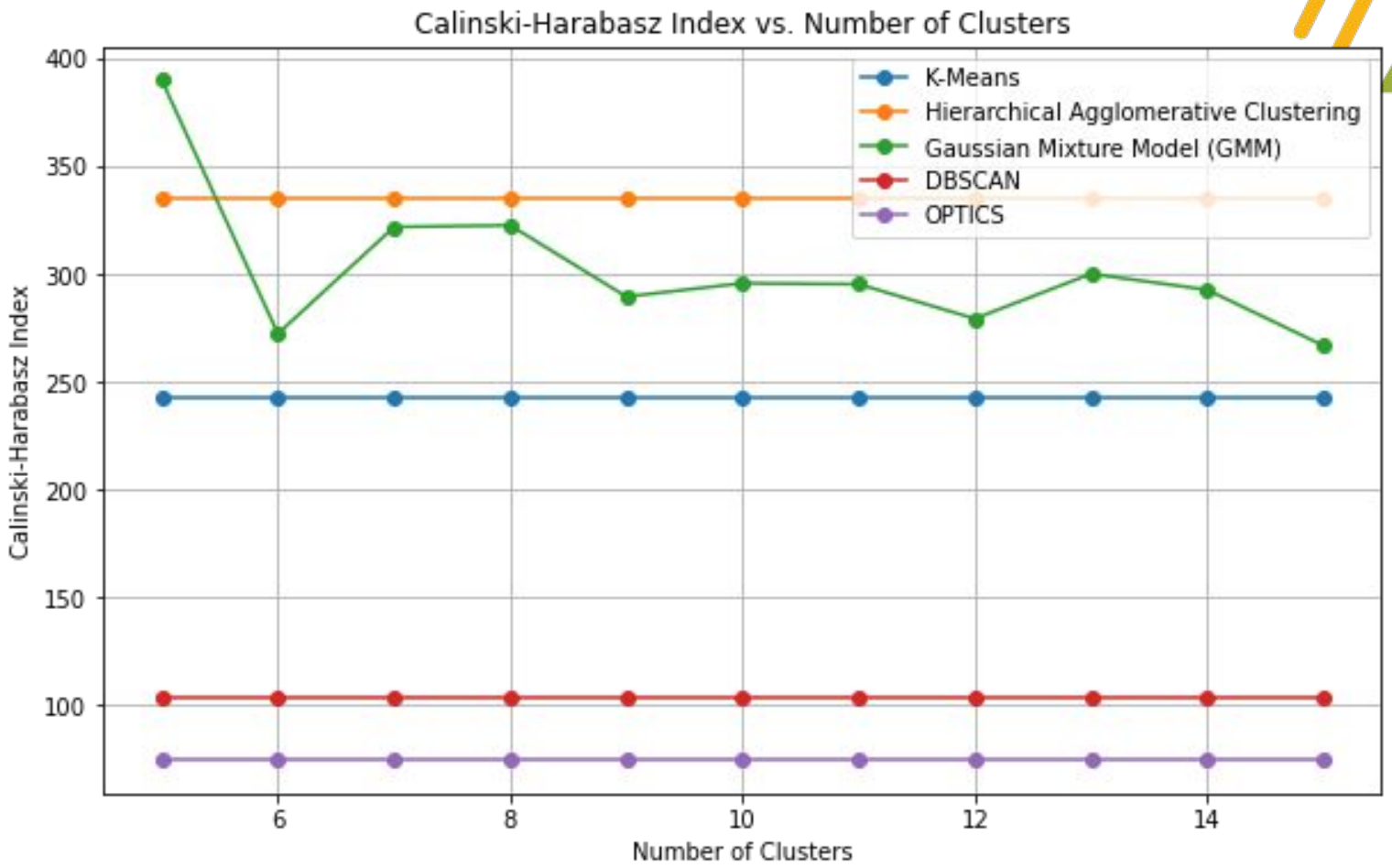
Comparison



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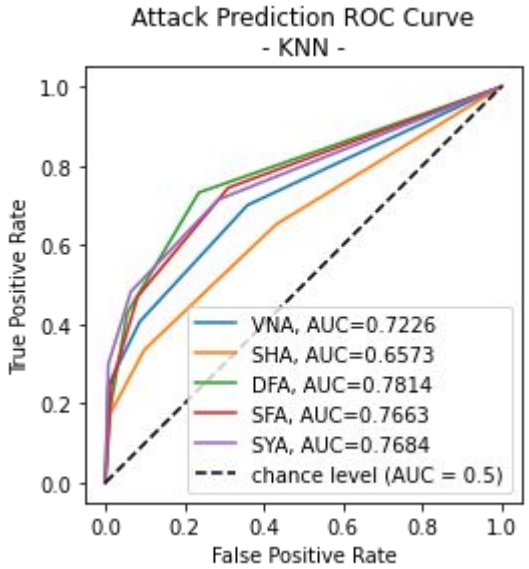
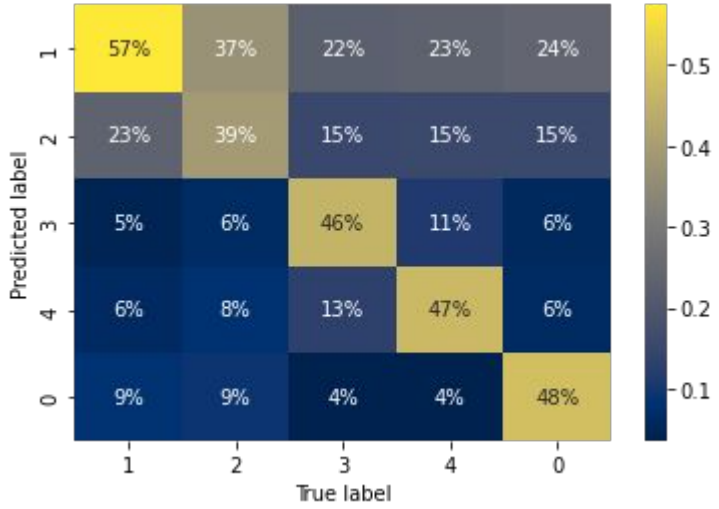
Attack Prediction

K-Nearest Neighbors

	precision	recall	f1-score	support
0	0.33	0.57	0.42	622
1	0.39	0.39	0.39	727
2	0.57	0.46	0.51	542
3	0.60	0.47	0.53	662
4	0.67	0.48	0.56	701
accuracy			0.47	3254
macro avg	0.51	0.48	0.48	3254
weighted avg	0.51	0.47	0.48	3254





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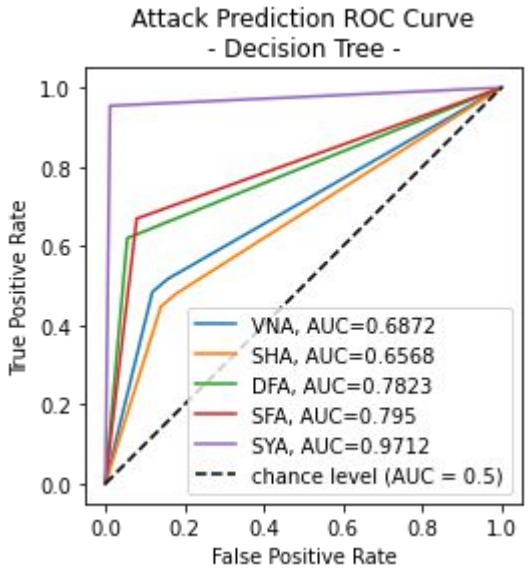
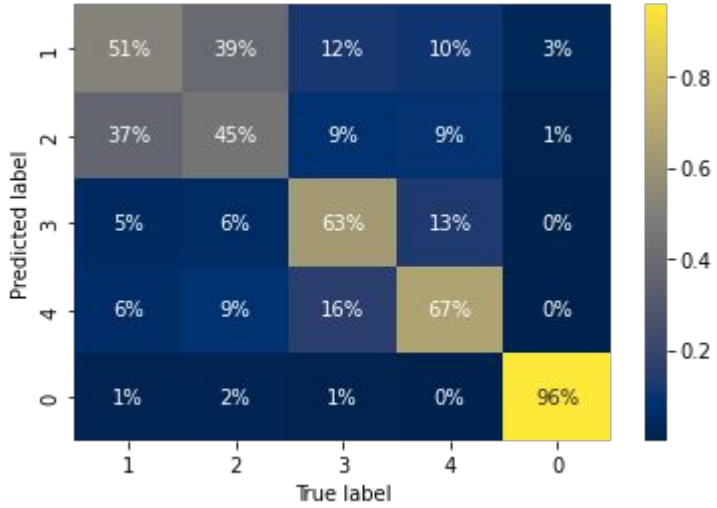
Decision Trees

	precision	recall	f1-score	support
0	0.42	0.51	0.46	622
1	0.49	0.45	0.47	727
2	0.68	0.63	0.66	542
3	0.70	0.67	0.69	662
4	0.96	0.96	0.96	701
accuracy			0.65	3254
macro avg	0.65	0.64	0.65	3254
weighted avg	0.65	0.65	0.65	3254





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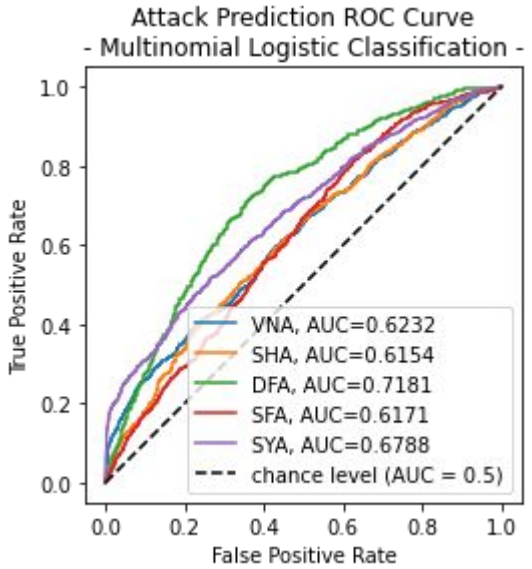
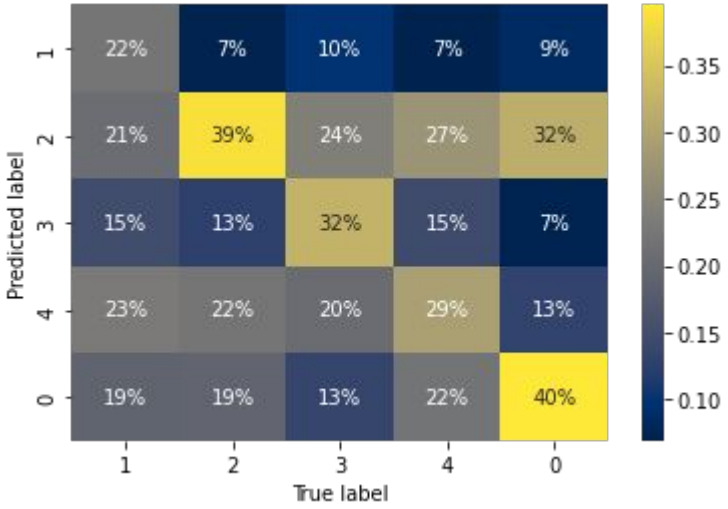
Logistic Regression

	precision	recall	f1-score	support
0	0.39	0.22	0.28	622
1	0.30	0.39	0.34	727
2	0.34	0.32	0.33	542
3	0.28	0.29	0.28	662
4	0.37	0.40	0.38	701
accuracy			0.33	3254
macro avg	0.34	0.32	0.32	3254
weighted avg	0.33	0.33	0.32	3254





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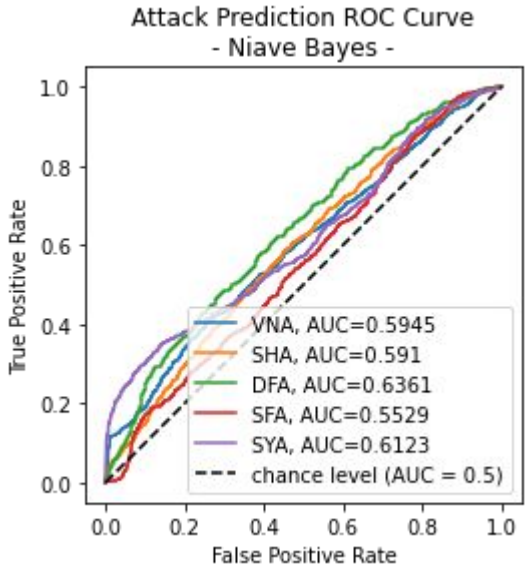
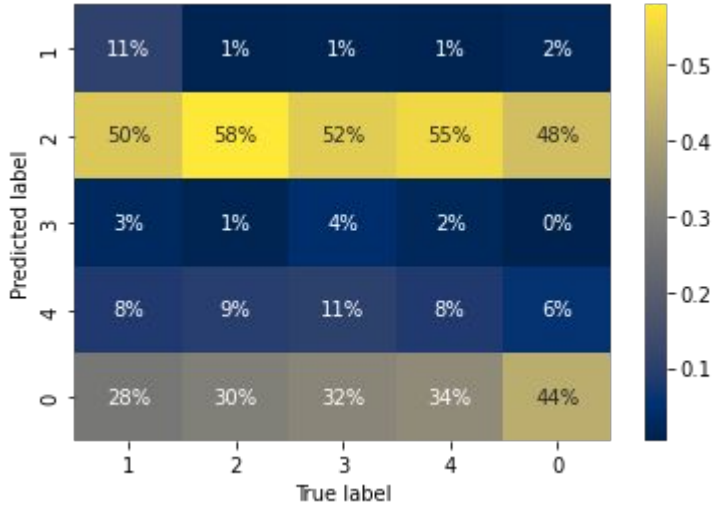
Naive Bayes

	precision	recall	f1-score	support
0	0.67	0.11	0.19	622
1	0.25	0.58	0.34	727
2	0.35	0.04	0.08	542
3	0.20	0.08	0.12	662
4	0.28	0.44	0.34	701
accuracy			0.27	3254
macro avg	0.35	0.25	0.21	3254
weighted avg	0.34	0.27	0.22	3254





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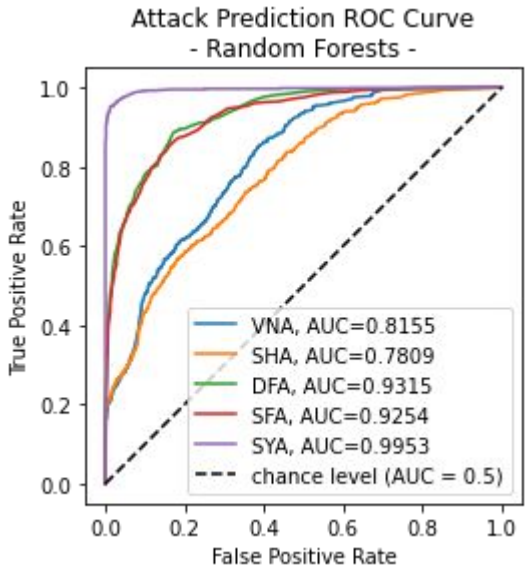
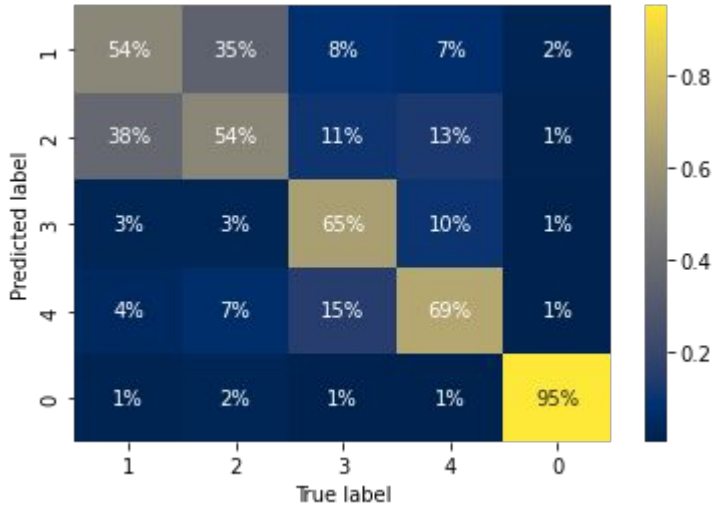
Random Forests

	precision	recall	f1-score	support
0	0.48	0.54	0.51	622
1	0.50	0.54	0.52	727
2	0.76	0.65	0.70	542
3	0.74	0.69	0.71	662
4	0.95	0.95	0.95	701
accuracy			0.68	3254
macro avg	0.69	0.67	0.68	3254
weighted avg	0.69	0.68	0.68	3254





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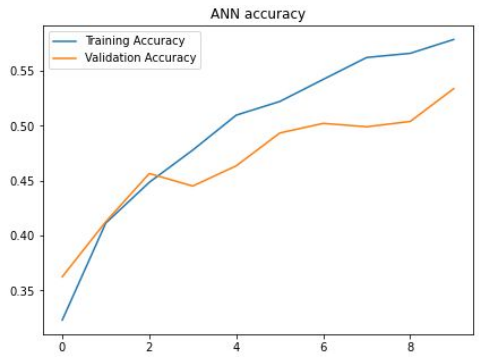
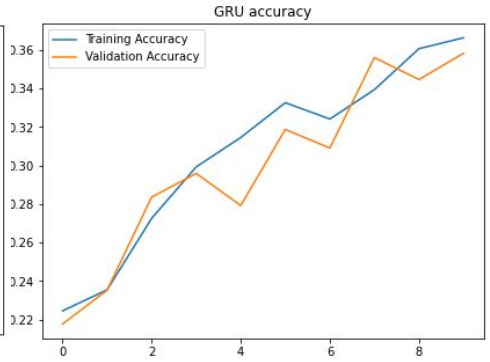
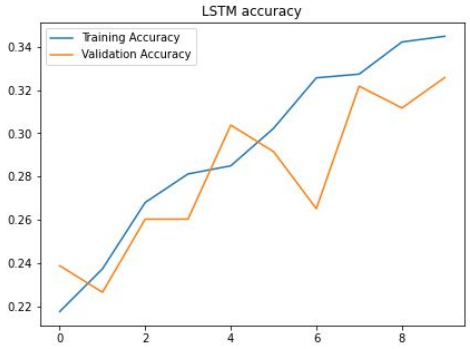
Same Conditions Neural Networks

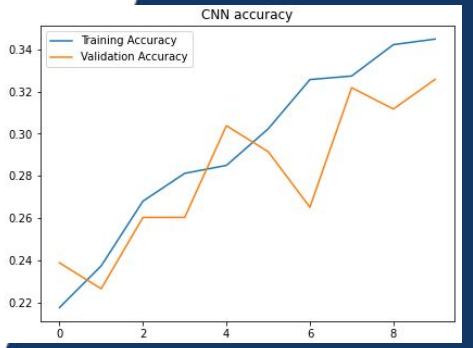
Hidden Layers = [256,256,256,64,64]
Learning rate = 0.001
Optimizer = Adam
Batch size = 25
Epochs = 10

	Accuracy	F1-Score	AUC	Time-To-Compute
ANN	53%	54%	74%	14.163 seconds
GRU	36%	41%	63%	405.860 seconds
LSTM	32%	37%	59%	462.704 seconds
CNN	42%	46%	69%	8.793 seconds









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Comparison

	Accuracy	F1-Score	AUC	Time-To-Compute
K-NN	47%	48%	74%	0.400 seconds
Decision Trees	65%	65%	78%	0.338 seconds
Logistic Regression	33%	32%	65%	0.508 seconds
Naive Bayes	27%	21%	60%	0.261 seconds
Random Forest	68%	68%	89%	2.923 seconds
ANN	53%	54%	74%	14.163 seconds
GRU	36%	41%	63%	405.860 seconds
LSTM	32%	37%	59%	462.704 seconds
CNN	42%	46%	69%	8.793 seconds

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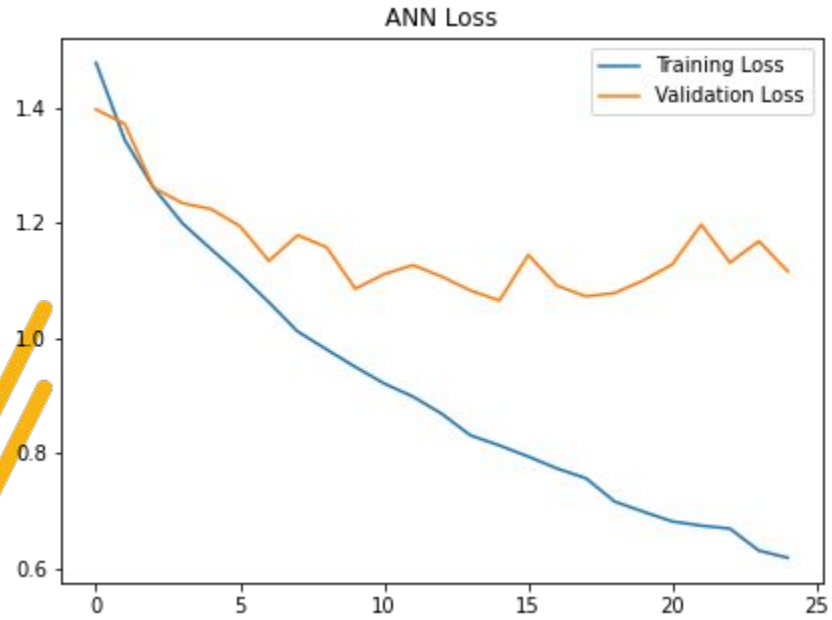
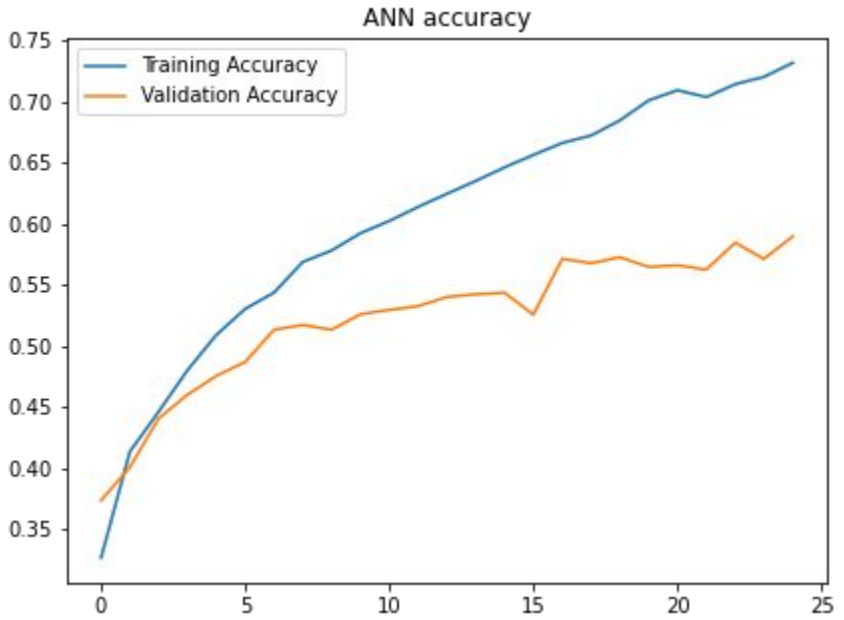
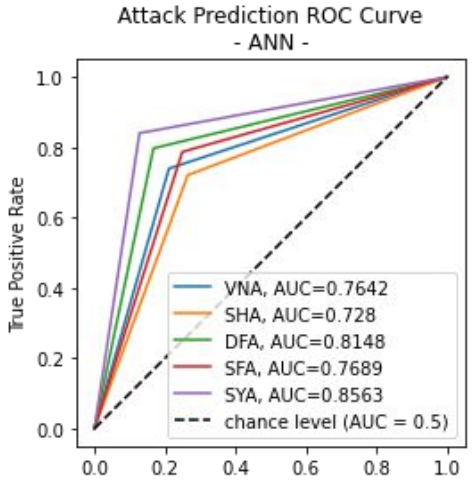
Artificial Neural Network (ANN)

Hidden Layers = [256,256,256,64,64]
Learning rate = 0.001
Optimizer = Adam
Batch size = 25
Epochs = 10



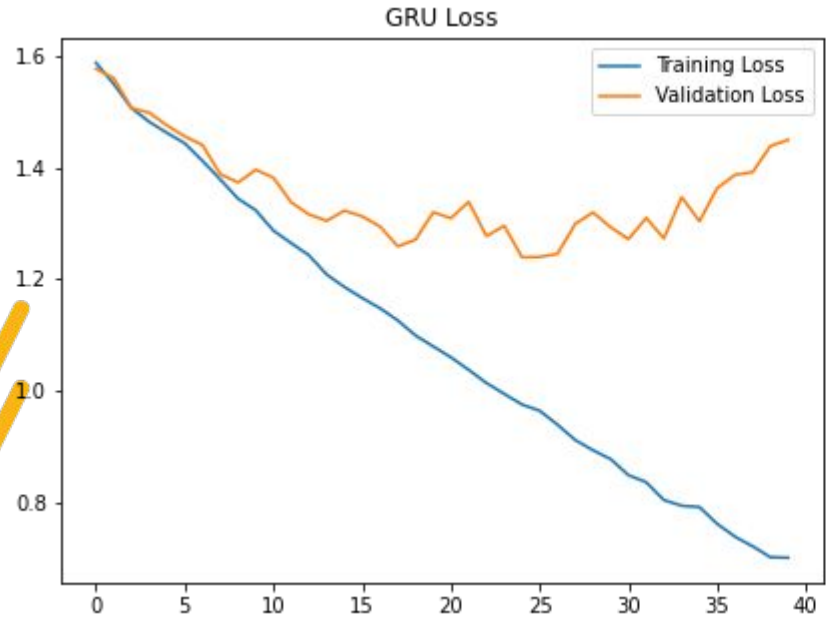


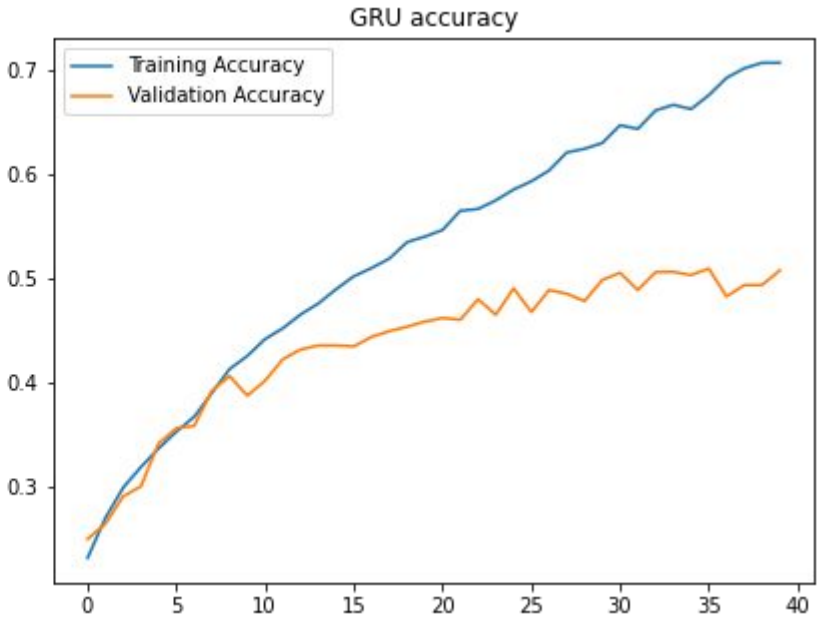
	precision	recall	f1-score	support
VNA	0.45	0.74	0.56	622
SHA	0.44	0.72	0.55	727
DFA	0.49	0.80	0.61	542
SFA	0.45	0.79	0.57	662
SYA	0.64	0.84	0.73	701
micro avg	0.49	0.78	0.60	3254
macro avg	0.49	0.78	0.60	3254
weighted avg	0.50	0.78	0.60	3254
samples avg	0.59	0.78	0.65	3254



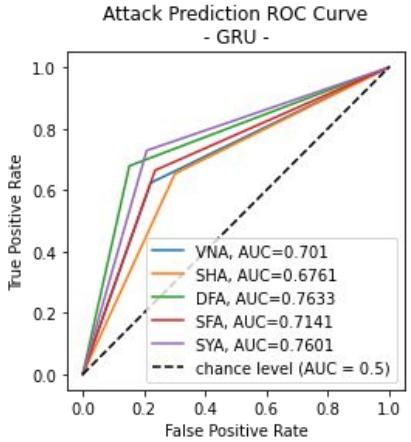
Gated Recurrent Unit (GRU)

Hidden Layers = [64,64]
Learning rate = 0.001
Optimizer = Adam
Batch size = 5
Epochs = 40



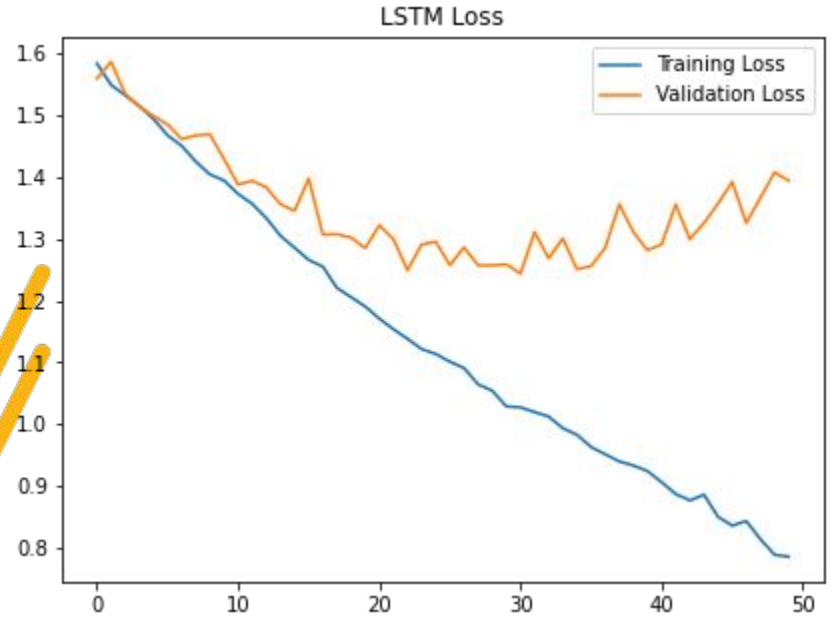


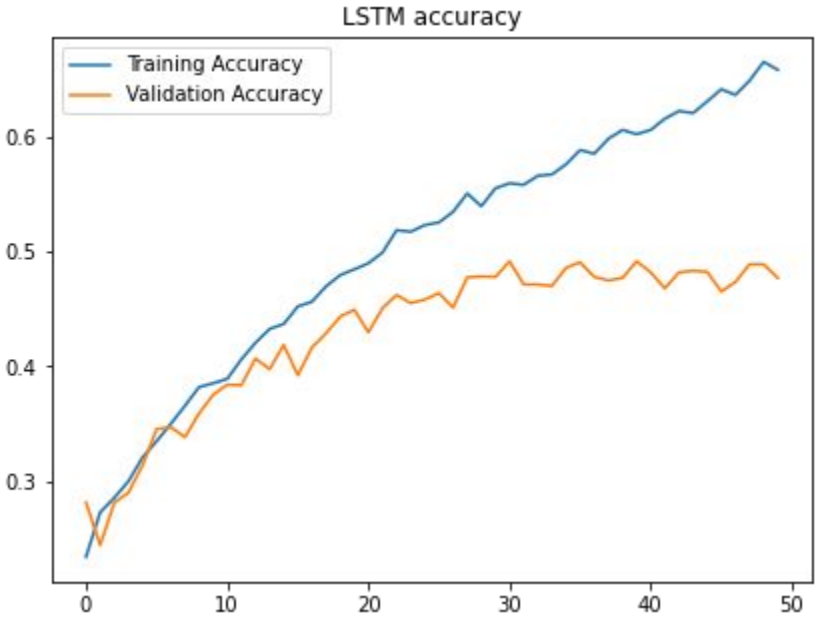
	precision	recall	f1-score	support
VNA	0.40	0.62	0.49	622
SHA	0.38	0.65	0.48	727
DFA	0.47	0.68	0.56	542
SFA	0.42	0.66	0.51	662
SYA	0.49	0.73	0.59	701
micro avg	0.43	0.67	0.52	3254
macro avg	0.43	0.67	0.53	3254
weighted avg	0.43	0.67	0.52	3254
samples avg	0.50	0.67	0.55	3254



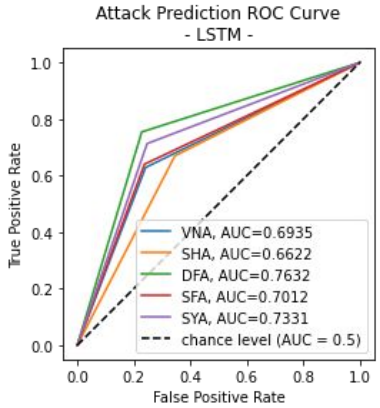
Long Short-Term Memory (LSTM)

Hidden Layers = [64,64]
Learning rate = 0.001
Optimizer = Adam
Batch size = 20
Epochs = 50
Dropout Rate = 0.2



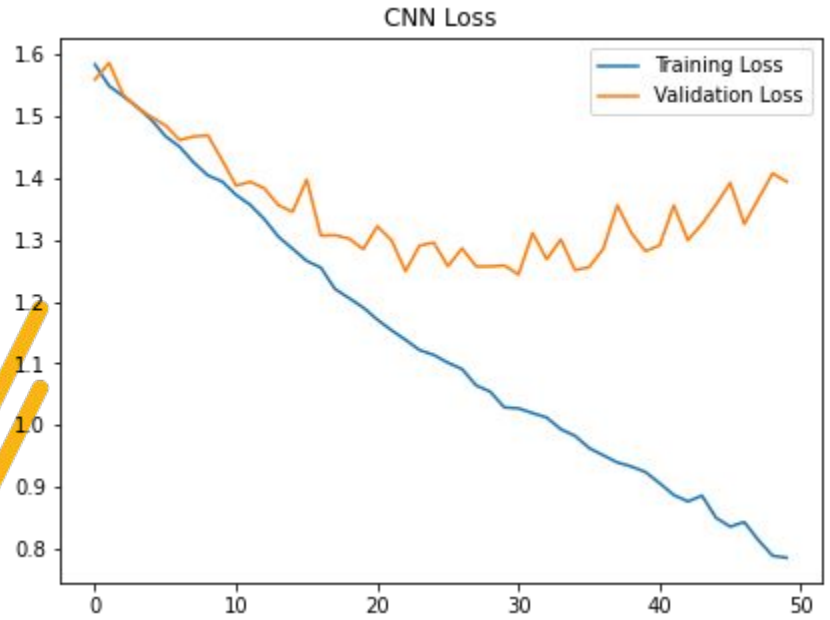


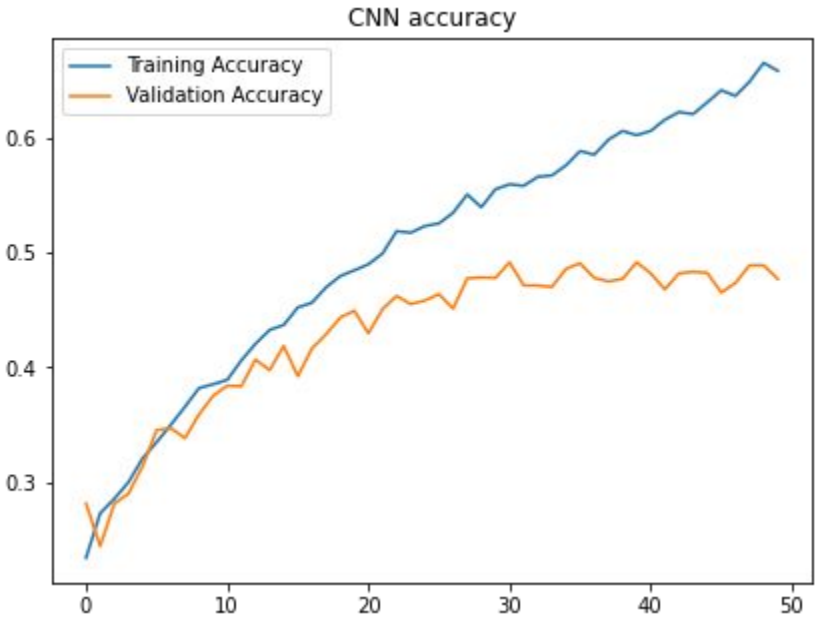
	precision	recall	f1-score	support
VNA	0.38	0.63	0.47	622
SHA	0.36	0.67	0.47	727
DFA	0.40	0.75	0.52	542
SFA	0.41	0.64	0.50	662
SYA	0.44	0.71	0.55	701
micro avg	0.40	0.68	0.50	3254
macro avg	0.40	0.68	0.50	3254
weighted avg	0.40	0.68	0.50	3254
samples avg	0.47	0.68	0.53	3254



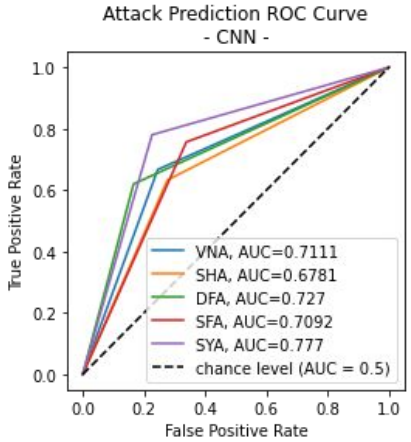
Convolutional Neural Network (CNN)

Hidden Layers = [64,64]
Learning rate = 0.001
Optimizer = Adam
Batch size = 5
Epochs = 50





	precision	recall	f1-score	support
VNA	0.39	0.67	0.49	622
SHA	0.40	0.63	0.49	727
DFA	0.43	0.62	0.51	542
SFA	0.36	0.76	0.49	662
SYA	0.49	0.78	0.60	701
micro avg	0.41	0.69	0.52	3254
macro avg	0.41	0.69	0.52	3254
weighted avg	0.41	0.69	0.52	3254
samples avg	0.49	0.69	0.55	3254



Comparison

	Accuracy	F1-Score	AUC	Time-To-Compute
ANN	61%	60%	79%	25.077 seconds
GRU	51%	52%	72%	831.946 seconds
LSTM	49%	50%	71%	318.898 seconds
CNN	50%	52%	72%	47.961 seconds

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Fairness and Bias

- IoT Device
  - Sample size bias
  - Device similarities
- IoT Prevention

Limitations

- Lack of data
  - Similarities in labels/devices
- Computational Power
  - Ineffectiveness of certain models tested
- Time and Experience

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Future Work

- Fine tuning clustering models
- Optimization of neural networks
- Hybrid models
- Expand datasets

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Questions?

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