Handcrafted and Neural Network based Features for Outlier Modulation Detection

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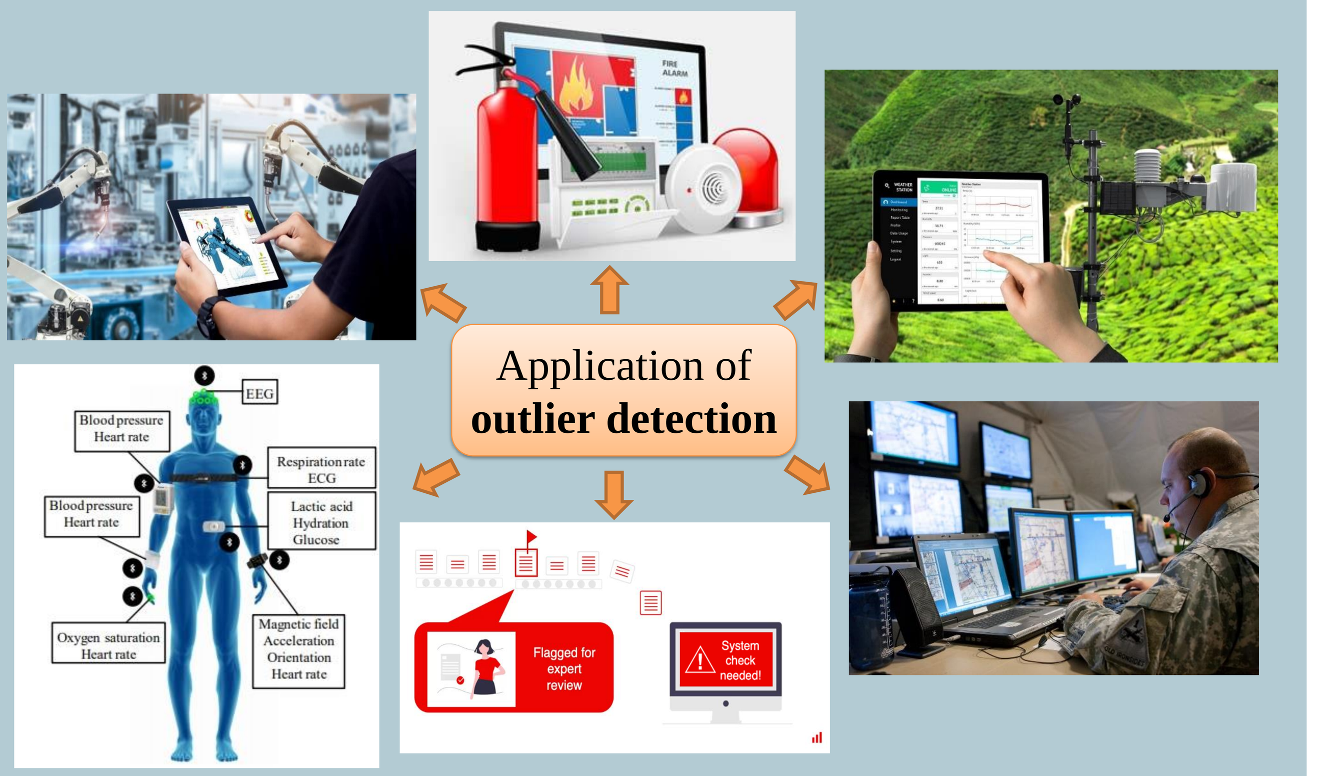
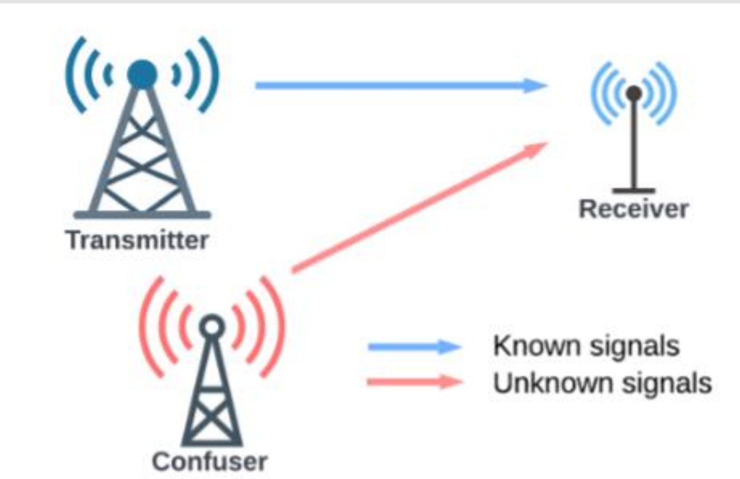
Outlier detection



Outlier signals: undesired signals that might bring in **interference** and **confusion** to receivers.

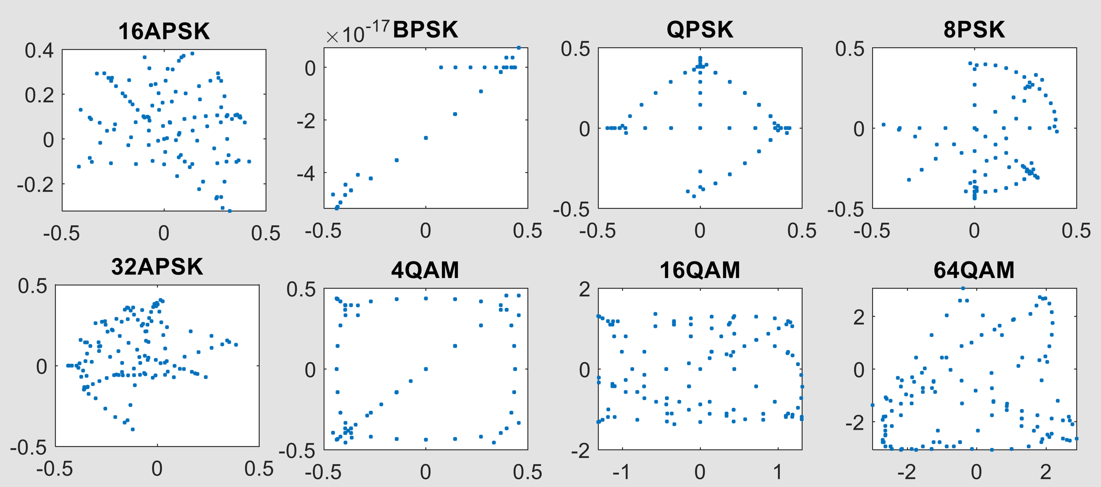
Motivations



- Characterize inliers and outliers.
- Support dynamic spectrum access [1].
- Detect before AMC.

Difficulties

- No knowledge of the outlier signals is available in the training stage.
- Existing classifiers, such as k-means clustering, is effective on simple modulation datasets.
- Strong confuser (16QAM to QPSK) is hard to identify.



Main Contribution

- Proposed selected handcrafted features from feature engineering with distance-based classifier.
- Handcrafted and NN-based features with different classifiers, including k-means, OCSVM, iForest, and OCNN.

Feature extraction

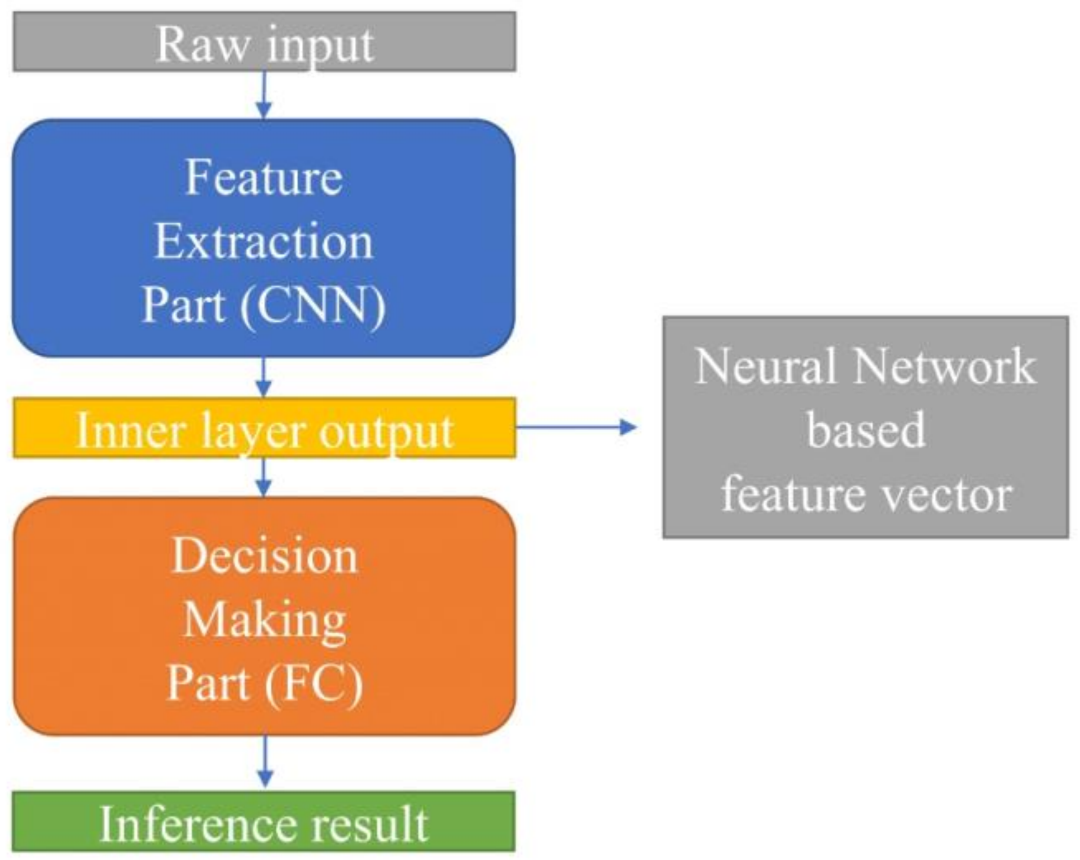
Handcrafted features

- Instantaneous time domain features: Mean, Variance, Kurtosis, skewness.
- Transform domain features: power spectral density.
- Statistical features: Higher order moment (HOM), higher order cumulants (HOC), and higher order cyclic cumulants (HOCCs), etc.

$$M_{pq} = \mathbb{E}[r^{p-q}(t)(r^*(t))^q]$$

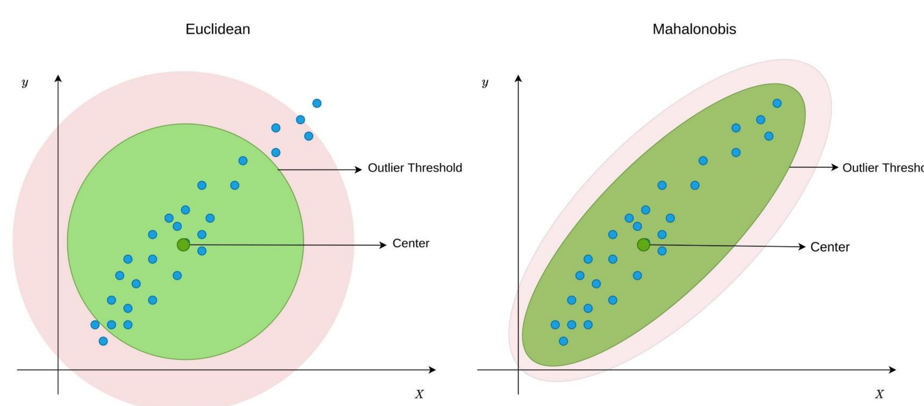
HOM	M_{20} M_{21} M_{40} M_{41} M_{42} M_{43} M_{60} M_{61} M_{62} M_{63}
HOC	C_{20} C_{21} C_{40} C_{41} C_{42} C_{43} C_{60} C_{61} C_{62} C_{63}

DNN-based features

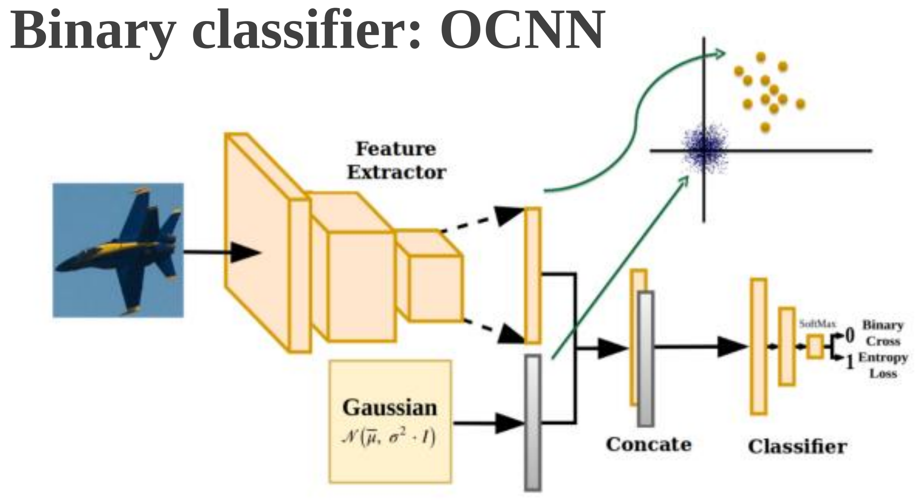


Classification

Distance-based



Binary classifier: OCNN

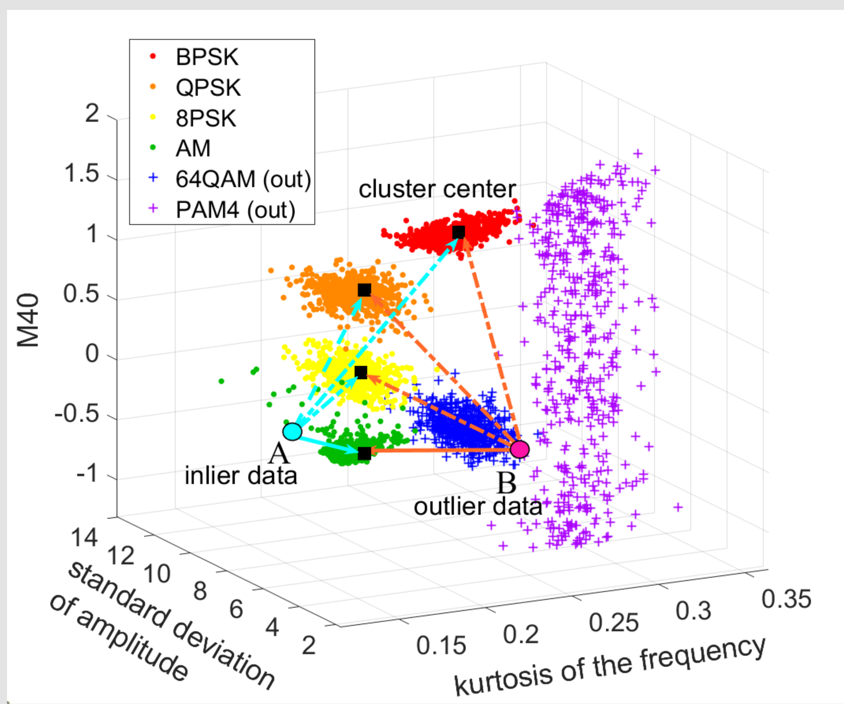


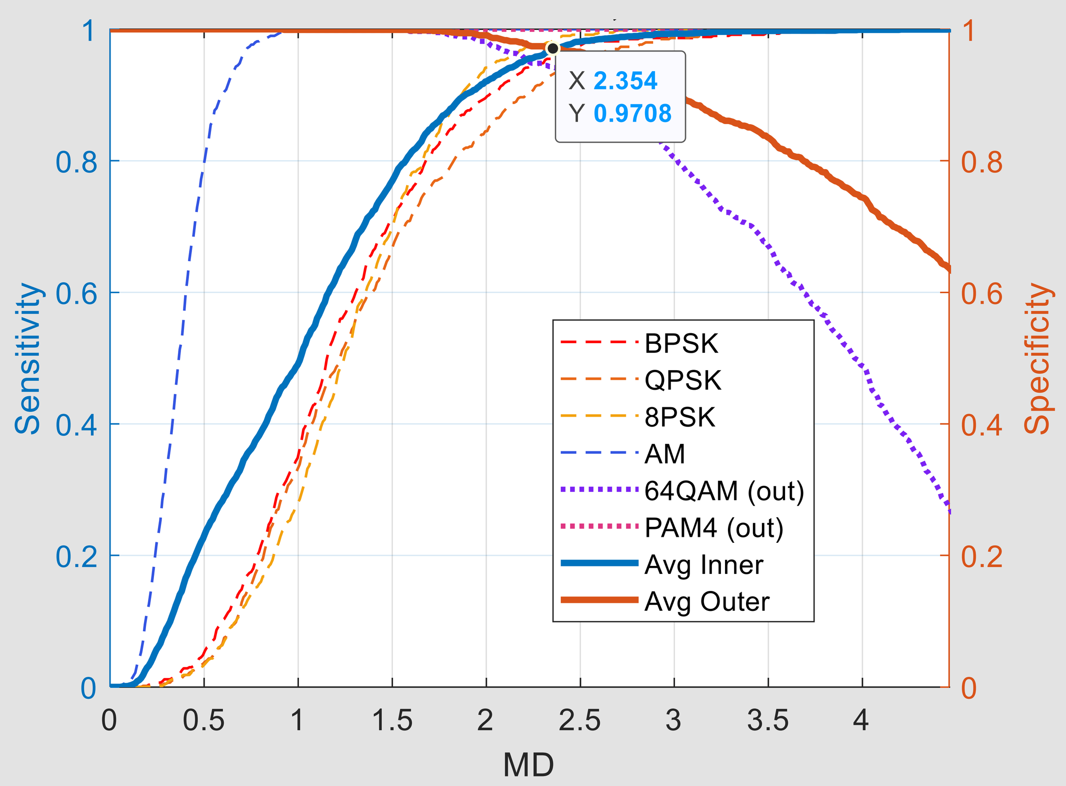
Inliers:

1	2	3	4
BPSK	QPSK	8PSK	AM

Outliers:

5	6
64QAM	PAM4





Step 1: Chose some features that possibly classify the outliers in training dataset.

Step 2: Find the feature center in hyper dimension for each known signal type.

Step 3: Calculate the distance for each test data.

Step 4: Hist the minimum Euclidean distance between the feature of test data and the closest feature cluster.

Step 5: Set a threshold γ based on the training dataset.

Simulation Results

Inlier signals: BPSK, QPSK, 8PSK, 16QAM, FSK, ABSSB-upper sideband (USB), AM-SSB-lower sideband (LSB), AM, and FM.

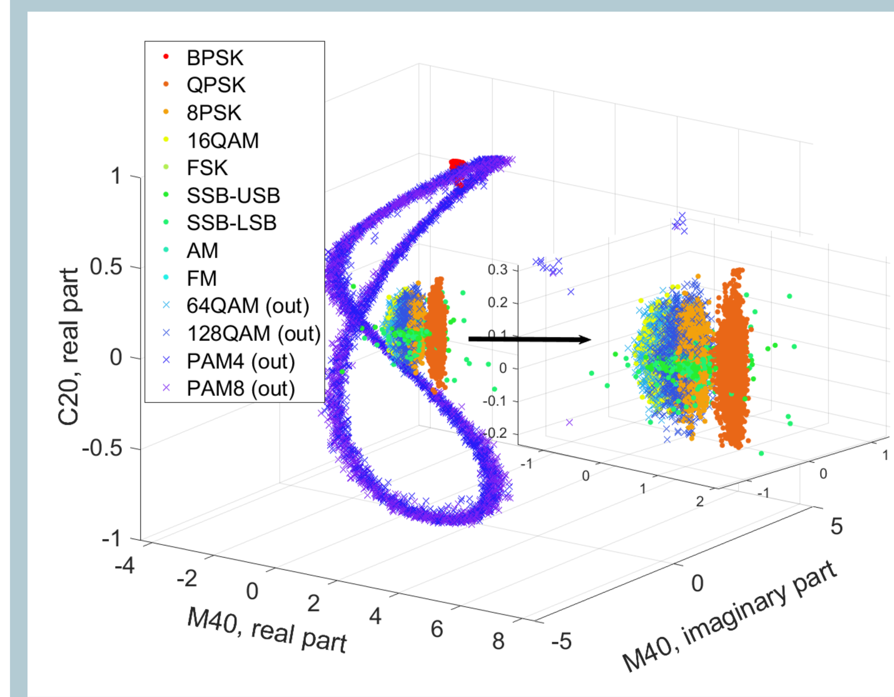
Outlier signals: 64QAM, 128QAM, PAM4, and PAM8.

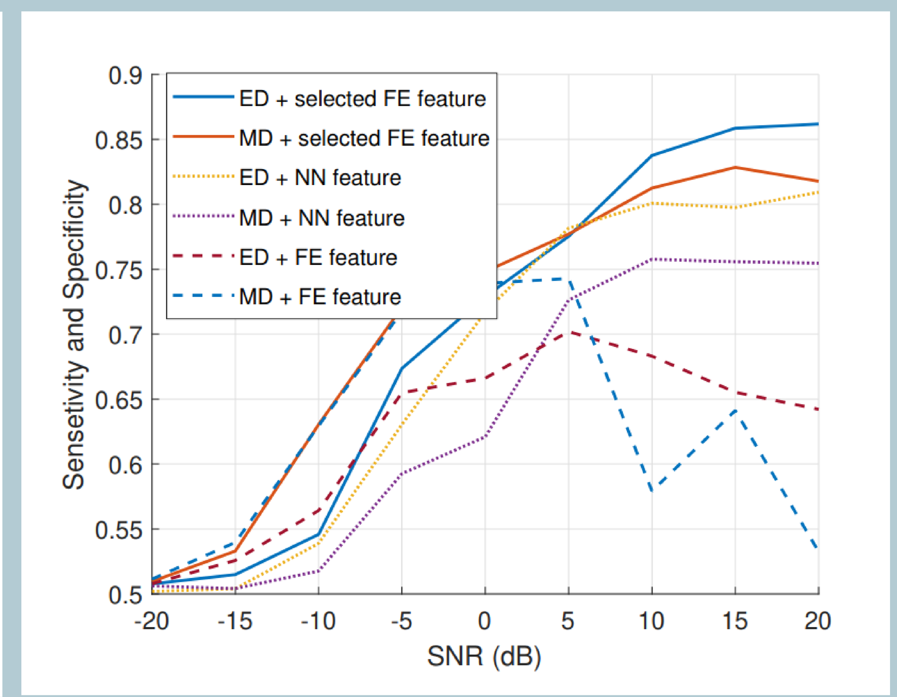
Data generalization [2]: 1024 points with SNR from -20dB to 20dB

Training : 80% of 3000 signals of each modulation

Testing: 20% of 3000 signals of each modulation.

Method 1:





Accuracy of selected feature with ED (%)

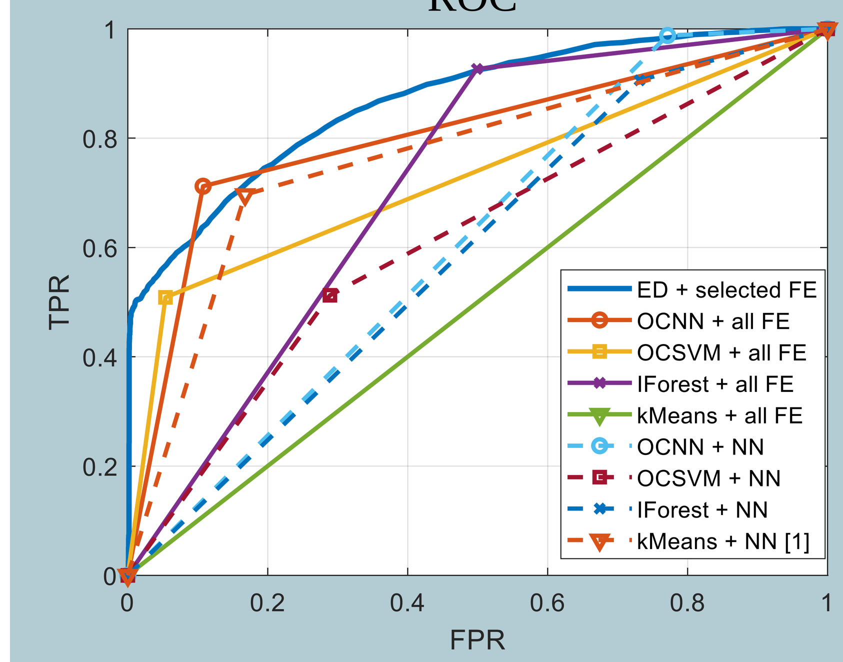
SNR (dB)	-10	-5	0	5	10	15	20
64QAM	51.0	52.5	59.5	68.0	76.9	80.3	81.3
128QAM	52.5	51.4	56.1	70.0	81.6	83.0	83.7
PAM4	58.7	84.7	95.6	99.0	99.5	99.7	99.8
PAM8	58.8	84.7	95.9	99.1	99.7	99.8	99.8
all outliers	54.6	67.4	72.9	77.5	83.8	85.8	86.2

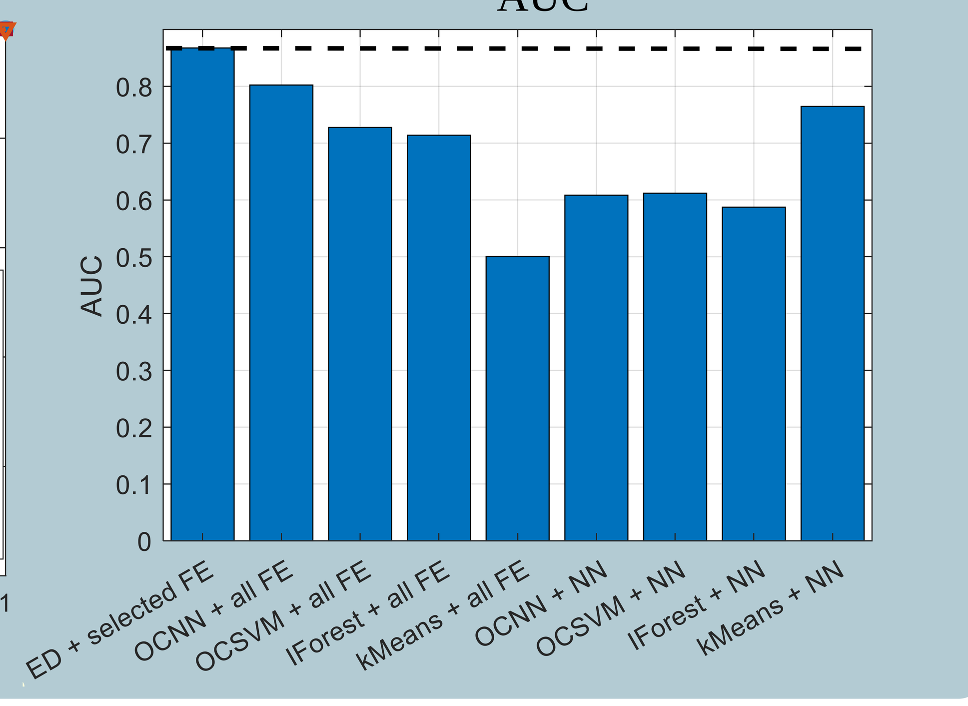
Accuracy of selected feature with MD (%)

SNR (dB)	-10	-5	0	5	10	15	20
64QAM	51.6	52.3	61.6	67.9	73.8	75.2	77.1
128QAM	51.1	52.3	60.2	70.8	78.5	80.7	79.5
PAM4	76.2	93.4	97.5	99.5	100.0	99.9	100.0
PAM8	75.5	93.8	97.8	99.6	100.0	99.9	100.0
all outliers	63.0	72.0	74.8	77.7	81.2	82.8	81.7

Method 2:

SNR=5dB





Conclusion

- Method 1: Selected features with distance-based discrimination.
- Method 2: Machine learning based features with binary classifiers.
- Results: 100% accuracy for mild confusers and 80% for the strong.

References

- [1] Y. Shi, et al, "Deep learning for RF signal classification in unknown and dynamic spectrum environments," in Proc. IEEE Int. Symp. on Dyn. Spec. Access Netw., pp. 1–10, 2019.
- [2] T. J. O'shea and N. West, "Radio machine learning dataset generation with GNU radio," in Proc. GNU Radio Conf., vol. 1, 2016.