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Supervised Learning for Physical Layer based Message Authentication in URLLC scenarios

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Abstract—PHYSEC based message authentication can, as an alternative to conventional security schemes, be applied within Ultra Reliable Low Latency Communication (URLLC) scenarios in order to meet the requirement of secure user data transmissions in the sense of authenticity and integrity. In this work, we investigate the performance of supervised learning classifiers for discriminating legitimate transmitters from illegimate ones in such scenarios. We further present our methodology of data collection using Software Defined Radio (SDR) platforms and the data processing pipeline including e.g. necessary preprocessing steps. Finally, the performance of the considered supervised learning schemes under different side conditions is presented.

I. INTRODUCTION

The upcoming demand for automation in our everydays life is increasing continuously. Many URLLC services, such as automated traffic systems, telesurgery and many more are not far from becoming a reality or already are. In order to meet the high requirements for this type of services, new approaches, especially whithin the field of information security, need to be considered. Beside authenticity, integrity and confidentiality of the data to be transmitted over wireless links have to be ensured in order to prohibit a wide range of passive and active cyber attacks. Confidentiality can be ensured by encryption of messages, e.g. using an Advanced Encryption Standard (AES) [1] cipher suite. This operation does not produce any overhead in message size (except zero padding). Whereas in case of message authenticity and integrity schemes some amount of overhead is generated in the sense of authentication tags, e.g. when a Message Authentication Code (MAC) is used or cryptographic certificates, which both need to be attached to a message respectively. E.g., the recommendation of the Internet Engineering Task Force is to either use a cipher based MAC (CMAC), e.g. based on a AES-128 block cipher, or a hash based MAC (HMAC) which is based on a cryptographic hash function. For AES-128 based CMAC a maximum shortening to 64 Bit is recommended [2], while for HMAC a minimum MAC size of 80 Bit is recommended [3]. If we now assume that the payload of a URLLC message in the uplink has a length of 400 Bit (the dimension of this assumption is e.g.

confirmed by [4] and [5]), then the overhead and with this the additional latency introduced in case of a AES-128 based CMAC of 64 Bit length would be 13.8%. Another important issue is, that key based schemes such as MAC are only able to protect the message payload from the mentioned attacks. An attacker is still able to perform attacks such as address spoofing, or even worse, record a message and replay it after a while (if counters are used to prohibit that, additional overhead is added as well). Due to these drawbacks, Physical Layer Security (PHYSEC) based message authentication can be used alternatively. Hereby, the physical properties of the radio link signal are taken into account in order to identify, by which user a message was originally transmitted and whether it was modified during the wireless transmission. As we focus on URLLC here, it can be assumed that frequent and periodic data transmissions (e.g. within the order of 10s of ms [4], [5]) and consequently channel estimation at the same rate is available. For experimental evaluation, we consider an Orthogonal Frequency Division Multiplexing (OFDM) system and based on the respective frequency domain channel estimations, we decide from which source a received data packet was transmitted.

The remainder of the work is organized as follows. In section II we give a short overview on related work with respect to previous considered approaches and in section III we describe the system model. The approach of Physical Layer (PHY) based message authentication is presented in section IV and the respective application of Machine Learning (ML) in section V. In section VI we present the results of our work in form of an experimental evaluation of the considered approach and section VII finally concludes the paper.

II. RELATED WORK

Several approaches on exploiting characteristics of the PHY in order to derive security functionalities (PHYSEC) have been investigated recently. In [6] an overview is given on PHYSEC functions derived from the wireless channel. While many works have focused on extracting secret keys (e.g. to be used for encryption and decryption of user data), such as [7], [8], [9], the focus of our work is to identify the original transmitter of data packets by exploiting the related PHY metadata.

First, statistical methods were used for PHYSEC based authentication, e.g. [10], where an approach based on hypothesis testing is presented for static scenarios. It is later

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extended to mobile and time-variant scenarios in [11]. Though the results of these works are plausible, they are obtained from simulations of the wireless channel only and therefore, it could not be proven, whether the methods also work for real world channels. Our work is in contrast considering measurements from real world wireless channels. Additionally, such testing methods require proper setting of the detection thresholds. In order to overcome this, ML based methods were proposed in recent years for PHYSEC based authentication as an alternative. In [12], two approaches based on Support Vector Machines and Linear Fisher Discriminant Analysis respectively, are presented that yielded acceptable results. A Gaussian Mixture Model based technique in combination with exploitation of the channel responses for different antenna modes is considered in [13]. Due to these promising results, the goal of our work is to further investigate ML based identification methods, especially such using supervised learning.

In previous works, various PHY features ranging from hardware characteristics such as Carrier Frequency Offset (CFO) to channel characteristics such as impulse or frequency responses have been used in order to identify the associated transmitters of data packets. E.g. the approach in [14] is based on time domain channel estimation within a single carrier system. In contrast to that, we will focus on multi carrier systems in our work as they are more common nowadays. The authors in [15] consider a cellular Internet-of-Things system and propose a scheme for channel based message authentication of nodes with the help of anchor nodes, which are assumed to have set up trust to the concentrator node before using Received Signal Strength Indicator (RSSI) values. Also, in [16] an RSSI based approach for body area networks is presented. As we only consider single links, a single and onedimensional feature might not be sufficient in order to reliable authenticate transmitters of the corresponding messages. Therefore, we will use the channel frequency response within OFDM systems in order to identify respective transmitters. The work in [17] considers a multilayer approach based on OFDM to guarantee authentication of Transmission Control Protocol (TCP) packets. In [18], a Multiple Input Multiple Output (MIMO) OFDM system is considered and a generalized likelihood ratio test is used as detection method. Further, the authors derive information theoretic bounds for the channel based detection problem. In [19] and [20] the authors use a Single Input Multiple Output (SIMO) system in order to detect the transmitter of data packets based on the respective Line of Sight (LOS) components. They further develop models in order to estimate the delays within message delivery in case of false alarms or misdetection and considere a variety of attack strategies, such as disassociation or sybil attacks.

III. SYSTEM MODEL

In this section, the system concept, as well as the channel estimation technique, which is used to derive the PHY metadata in our work, are introduced. Further, the attacker model is presented and we derive possible attack scenarios with respect to URLLC.

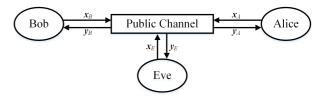


Fig. 1: System Model

Here, we consider a wireless (public) channel between two users, Alice and Bob, who want to exchange authenticated messages with each other over this channel. A third user Eve, who is an adversarial user, tries to inject illegal messages masqueraded as one of the legal users Alice or Bob. This can e.g. be done by reusing the radio ressources allocated to either Alice or Bob (in case of centralized Radio Resource Management (RRM)) or by spoofing their addresses (in case of competetive/decentralized RRM). Fig. 1 shows the possible message flows over the wireless channel for all considered users. Messages transmitted by users are denoted with x_u and messages received by users with y_u , where u denotes user Alice (u = A), Bob (u = B) or Eve (u = E).

A. Physical Layer Metadata

In PHYSEC schemes, PHY protocol metadata is used in order to provide lightweight security measures. This metadata can either originate from the transceiver hardware (e.g. radio fingerprints or clock skew) or can originate from characteristics of the wireless channel (e.g. RSSI or channel estimation data). In the first case, it is already challenging for an attacker to spoof these characteristics by using default hardware (offthe-shelf). On the other hand, this also requires an additional effort for the legitimate receiver in order to detect these characteristics and increases the receiver complexity and cost. For the second case, the respective data is typically available and accessible in any radio protocol. Therefore, in our work, we focus on channel based metadata and especially channel estimation data, which is e.g. computed at the receiver side in form of a frequency domain channel estimation (OFDM based systems). The received signal at a user u_i in such systems is

$$\boldsymbol{y}_{u_i} = \boldsymbol{H}_{u_i u_j} \boldsymbol{x}_{u_j} + \boldsymbol{n}_{u_i u_j} \tag{1}$$

with

$$\boldsymbol{H}_{u_i u_j} = [h_{u_j u_j}^0, \dots, h_{u_j u_j}^{M-1}]$$
(2)

being the *M*-dimensional channel matrix of the frequencyselective Single Input Single Output (SISO) fading channel between user u_i and u_j (transmitter) and $h_{u_iu_j}^{\ell}$ being the complex gain of the ℓ -th sample in frequency domain ($\ell = 0, \ldots, M - 1$). It can be estimated as

$$\dot{H}_{u_i u_j} = H_{u_i u_j} + \epsilon_{u_i u_j} \tag{3}$$

by user u_i . Due to noise $n_{u_i u_j}$ which is modelled as a gaussian random variable with zero mean and variance $\sigma_{n_{u_i u_j}}^2$ the channel estimation is not perfect and errors $\epsilon_{u_i u_j}$ occur.

B. Attacker Model

A typical scenario for an attacker Eve is, that he is at a spatially different location compared to Bob and Alice (we assume a distance of more than the wavelength of the transmitted signal respectively) and uses advanced equipment such as directed antennas and high sensitivity receivers in order to maximize the coverage to his benefits. We also assume perfect knowledge of the underlying communication protocol at Eve to run active attacks such as masquerade attacks, replay attacks or address spoofing attacks by introducing messages $x_{\rm E}$. It is not assumed that Eve is gaining physical access to Alice or Bob to accomplish invasive attacks such as hardware modification. Further, other active attacks such as Denial-of-Service attacks due to jamming are not considered as well. It is assumed, that the legal communicating participants Bob and Alice have already carried out initial user authentication to each other and have set up trust in a secure way by using cryptographic certificates or MACs. Attacks on the initial authentication stage are not considered. Further, we assume that Eve is, depending on the current attack strategy, spoofing on transmission slots which are actually allocated to Bob by using a higher transmit power in order to make Alice overhear Bobs transmissions. In order to successfully carry out attacks, the receive power of Eves transmissions has actually to be higher, compared to the receive power of Bobs transmissions at Alice.

IV. PHYSEC BASED MESSAGE AUTHENTICATION

One of the main characteristics, which can be exploited in PHYSEC based schemes, is the spatial decorrelation property of the wireless channel. It denotes, that channel characteristics are varying based on the location of a transceiver. This holds already true for small variations in the spatial domain which are in the order of the wavelength of the transmitted signal, due to positive and negative superposition of wireless signals, caused by e.g. reflection and scattering. In our case, let us assume, that Bob wants to transmit authenticated messages to Alice. Therfore, within a first step, Alice will estimate the channel as $\hat{H}_{AB}(k)$ when receiving message $y_A(k)$ at times k = 0, ..., T - 1 from user Bob (transmits $x_{\rm B}(k)$). In order to prohibit any spoofing attacks by Eve during time k = 0, ..., T - 1, the messages $x_{\rm B}(k)$ sent by Bob at times k = 0, ..., T - 1 need to contain cryptographic information from higher layers (e.g. certificates or authentication tags). Next, if Alice wants to authenticate Bob as the transmitter of further received messages $y_A(k)$ at time $k \ge T$, this can be achieved by comparing the new channel estimations $\hat{H}(k), k \geq T$ to the previous collected channel estimations $\hat{H}_{AB}(k), k = 0, ..., T - 1$. Based on these assumptions, there are two hypothesis about the origin of the respective estimated channel $\hat{H}(k), k \geq T$ and consequently the respective payload of it, either

$$\begin{aligned} \mathcal{H}_0 &: \hat{\boldsymbol{H}}(k) \text{ due to } \boldsymbol{x}_{\mathsf{B}}(k), \text{ or} \\ \mathcal{H}_1 &: \hat{\boldsymbol{H}}(k) \text{ due to } \boldsymbol{x}_{\mathsf{E}}(k). \end{aligned}$$

$$\tag{4}$$

In case of hypothesis \mathcal{H}_0

$$\boldsymbol{H}(k) = \boldsymbol{H}_{AB}(k) + \boldsymbol{\epsilon}_{AB}(k), \qquad (5)$$

and in case of hypothesis \mathcal{H}_1

$$\hat{\boldsymbol{H}}(k) = \boldsymbol{H}_{\text{EB}}(k) + \boldsymbol{\epsilon}_{\text{EB}}(k).$$
(6)

Due to temporal variations in wireless channels, e.g. due to doppler fading, the reference channel estimation used for comparison needs to be updated accordingly. Otherwise it is not possible to distinguish between channel variations and messages introduced by an attacker after some point. Therefore, the update interval should be below the channel coherence time T_c of the H_{AB} channel in order to catch up with these variations. Whereas in both cases, the temporal difference between two subsequent channel estimations should always be below T_c .

V. SUPERVISED LEARNING

This section introduces the concept of supervised ML based classification. Further, we introduce the necessary data processing steps (pipeline) including data prepocessing, the hyperparameter optimization strategy we applied and how the performance of classifiers for the PHYSEC based message authentication task can be evaluated.

A. ML based Classification

The ML classifiers that were applied to the problem of PHYSEC based authentication are introduced in detail in section VI including their hyperparameter spaces. In general in supervised learning based classification, the goal is to learn the function $f(x) = w^T x + b$ (or its parameters), which maps the input data $x = [x_1, ..., n_N], x_k \in \mathbb{R}^d$ to the outputs $x = [y_1, ..., y_N], y_k \in \{-1, 1\}$ (binary classification), the regularized training error

$$E(w,b) = \frac{1}{N} \sum_{k=1}^{N} L(y_k, f(x_k)) + \alpha R(w),$$
(7)

has to be minimized. Here, L is the loss function, R is the regularization or penalty term and $\alpha \in \mathbb{R}_0^+$ is a hyperparameter.

B. Data Processing Pipeline

Within this subsection, the processing pipeline including functionalities such as data pre-processing, hyperparameter optimization and finally testing the different ML models in order to evaluate their performance.

1) Preprocessing: The following preprocessing steps are applied to the validation and testing datasets respectively, in order to fit the classifiers. First, the magnitudes

$$\boldsymbol{F}(k) = \left| \boldsymbol{\hat{H}}(k) \right|, \ k = 0, \dots, N \tag{8}$$

of the complex channel gains are calculated for each data sample $\hat{H}(k)$. As it is in some cases necessary to reduce the dimensionality M of the the input feature in order to avoid overfitting or underfitting, we also add a preprocessing step for that purpose. This reduces the number of features of the original

sample from M = 48 to $M_{red} \in [1, 2, 3, 4, 6, 8, 12, 16, 24, 48]$ by either sampling the original feature vector at the respective rate yielding

$$\mathbf{F}_{red}(k,\ell^*) = \mathbf{F}(k,\frac{\ell^*M}{M_{red}}), \ \ell^* = 0,\dots,M_{red}-1,$$
 (9)

or by applying a mean function according to

$$\boldsymbol{F}_{red}(k,\ell^*) = \frac{M_{red}}{M} \sum_{j=\frac{\ell^*M}{M_{red}}}^{\frac{(\ell^*+1)M}{M_{red}}-1} \boldsymbol{F}(k,j), \ \ell^* = 0, \dots, M_{red}-1,$$
(10)

where ℓ^* denotes the index of the features in the new feature dimension M_{red} and ℓ the index in the original feature dimension.

The next steps involves a conversion of the time series data $F_{red}(k, \ell^*)$ into the a format that can be processed by a supervised classifier according to equation 7. A sample $F_{window}(k)$ at time k now consists of the original (reduced) sample $F_{red}(k)$, as well as the W previous samples, yielding

$$\boldsymbol{F}_{window}(k) = [\boldsymbol{F}_{red}(k), \boldsymbol{F}_{red}(k-1), \dots, \boldsymbol{F}_{red}(k-W)].$$
(11)

Next, the data sets are split into training and validation or testing sets, which are used to fit the classifiers (training) and validate (grid search) or test them (performance evaluation). The training set is given by

$$\boldsymbol{F}_{train} = [\boldsymbol{F}_{window}(0), \dots, \boldsymbol{F}_{window}(N_{train} - 1)], \quad (12)$$

and the remaining samples are used for validating or testing respectively. Finally, the training and validation/testing data is normalized. We calculate the mean and variance of the training set, then the training set is transformed to

$$\boldsymbol{F}_{train}^{norm} = \frac{\boldsymbol{F}_{train} - mean(\boldsymbol{F}_{train})}{std(\boldsymbol{F}_{train})},$$
(13)

whereas the validation set (and testing set respectively) is transformed according to

$$\boldsymbol{F}_{valid}^{norm} = \frac{\boldsymbol{F}_{valid} - mean(\boldsymbol{F}_{train})}{std(\boldsymbol{F}_{train})}.$$
 (14)

2) Grid Search: In order to find the optimal hyperparameters

$$\lambda^* = \underset{\lambda \in \Lambda}{\operatorname{argmin}} \underset{x_k^{(valid)}}{\operatorname{mean}} L(y_k^{(train)}, f_\lambda(x_k^{(train)})$$
(15)

to the given classification task, we use an exhaustive grid search. For each model, possible options for each hyperparameter are given as input and the respective models are fitted and validated on all combination of hyperparameters. For this, we only use a part of the overall $L_{total} = L_{valid} + L_{test}$ data sets, which we call the validation set. It consists of L_{valid} data sets. We use the accuracy metric in order to select the optimal hyperparameter set for each classifier, which is given by

$$\mathcal{P}_A = \frac{1}{N} \sum_{k=N_{train}}^{N-1} y_{pred}(k) - y_{true}(k), \qquad (16)$$

where y_{pred} is the label vector predicted by the respective classifier (user Bob or Eve is the transmitter) and y_{true} the true label vector.

3) Classifier Performance Testing: After deriving the optimal hyperparameters for each classifier, the remaining L_{test} data sets are used in order to evaluate their performance on the given classification task. For that purpose, beside the accuracy metric, e.g. other metrics such as Receiver Operating Characteristic (ROC) curves might be used.

VI. PERFORMANCE EVALUATION

In this section, we first describe the process of acquisition of channel estimation data and how the data is further processed in order to evaluate the introduced ML classifiers. We present the respective results and discuss them.

A. Data Acquisition

In order to obtain realistic channel estimation data, we used Universal Software Radio Peripheral (USRP) B210 SDR platforms and an OFDM based transmission systems by making use of the GNURadio [21] OFDM transmitter and receiver baseband processing blocks. These provide the functionality for channel estimation based on the Schmidl and Cox method [22] using the respective preamble symbols. An OFDM setup with an Fast Fourier Transform (FFT) size of 64 is considered with 48 active subcarriers. The cyclic prefix length is 16 samples, whereas the bandwidth is 10 MHz and the carrier frequency is 2.484 GHz. Each data packet consists of 2 preamble symbols, which are used for channel estimation and frequency offset estimation at the receiver and N data symbols. Here, packets are transmitted with a periodicity of 10ms, which yields us a vector of 48 complex symbols for each received OFDM packet (only the active subcarriers are considered for channel equalization). We consider a static setup where all participants do not move during transmitting and receiving. The environment is a mixed office/lab area with

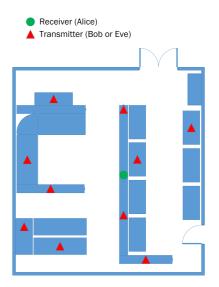


Fig. 2: Environment with different Bob and Eve positions

Model	Parameter	Options			
	loss	[hinge, log, modified_huber, squared_hinge, perceptron]			
	Penalty	[none, 12, 11, elasticnet]			
	alpha	$[10^{-6}, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}]$			
SGDClassifier	11_ratio	[0, 0.25, 0.5, 0.75, 1]			
	max_iter	[1, 10, 100, 1000, 10000]			
	tol	$[10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}]$			
	learning rate	[constant, optimal, invscaling, adaptive]			
	eta0	[0.25, 0.5, 0.75, 1]			
	penalty	[none, 12, 11, elasticnet]			
Perceptron	alpha	$[10^{-6}, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}]$			
Perceptron	max_iter	[1, 10, 100, 1000, 10000]			
	tol	$[10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}]$			
	С	[0.01, 0.1, 1, 10, 100]			
PassiveAgressiveClassifier	max_iter	[1, 10, 100, 1000, 10000]			
FassiveAgressiveClassifier	tol	$[10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}]$			
	Loss	[hinge, squared_hinge]			
	n_estimators	[1, 10, 100, 1000, 10000]			
	criterion	[gini, entropy]			
RandomForestClassifier	min_samples_split	[1, 2, 3, 4, 5]			
	min_samples_leaf	[1, 2, 3, 4, 5]			
	max_features	[none, auto, sqrt, log2]			
	n_neighbors	[2, 4, 6, 8, 10]			
KNeighborsClassifier	algorithm	[auto, ball_tree', 'kd_tree', 'brute']			
Kitelgilöörselassiiler	leaf_size	[10, 20, 30, 40, 50]			
	р	[1, 2, 3, 4, 5] [0.01, 0.1, 1, 10, 100]			
	С				
	kernel	[linear, poly, rbf, sigmoid]			
SVC	degree	[1, 2, 3, 4, 5]			
	tol	$[10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}]$			
	max_iter	[1, 10, 100, 1000, 10000]			
	solver	[svd, lsqr]			
LinearDiscriminantAnalysis	tol	$[10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}]$			
	shrinkage	[none, auto]			

TABLE I: Parameter space of all classifiers candidates

a lot of objects and metal walls. We record the respective data for several different locations of Bob and Eve respectively, yielding multiple different constellations of Bob-Alice and Eve-Alice pairs as depicted in fig. 2. In total, we acquire data from $L_{total} = 10$ different position constellations of the users. Further, the Attack Intensity (AI) of Eve P_{AI} denotes the amount of packets injected by Eve based on the total number of packets N = 100000 transmitted by Bob and Eve in addition. In case of a transmission of Eve, we assume, as mentioned in section III-B, that Bobs regular transmission is interfered by Eve (e.g. using a comparatively higher transmit power). Further, we assume that there is always at least one packet transmitted by each of the users within the N_{train} training samples.

B. Processing Pipeline

In order to finally derive the performance of the classifiers, their hyperparameters need to be selected first. In table I, an overview of the whole grid of hyperparameter options for all of the investigated classifiers is given. We execute the grid search step as introduced in section V-B2 on $L_{valid} = 2$ data sets in order to find the optimal hyperparameters λ^* for each classifier respectively. These are listed in table III. Finally, the classifiers are parameterized with these sets and we use $L_{test} = 8$ testing data sets in order to derive their classification performance for the task of PHYSEC based message authentication.

C. Results

Fig. 3 shows the performance of the classifier candidates depending on different side conditions. In fig. 4b, the AI was changed within a range between 5% and 25%. Some classifiers such as the Stochastic Gradient Descent Classifier (SGDC), Random Forest Classifier (RFC), Support Vector Classifier (SVC) and Linear Discriminant Analysis Classifier (LDAC) perform quite well under varying AIs, whereas the performance of the Gaussian Naive Bayes Classifier (GNBC) and K-Neighbors Classifier (K-NC) decrease with increasing AIs. Fig. 4c shows the performance of the classifier candidates under different feature dimension using the feature reduction scheme according to (10). Here, the SGDC and LDAC perform the best with an accuracy of 100% with at least 16 features.

TABLE II: Validation and testing parameters

Parameter	Variable	Value
No. of data sets	L_{total}	10
No. of validation data sets	L_{valid}	2
No. of testing data sets	L _{test}	8
original feature dimension	M	48
Reduction method	-	mean
No. of training samples	N _{train}	10
Window size	W	5
Attack intensity	P_{AI}	25%
No. of samples in each data set	N	100000

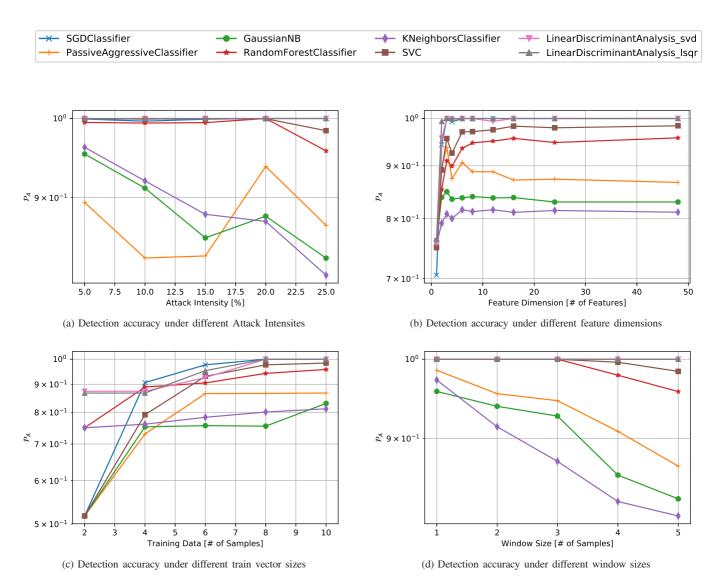


Fig. 3: Accuracy metrics for detection of the true transmitter for all classifiers under different side constraints

The performance of all other candidates saturates at specific limits, e.g. the K-NCs performance reaches a maximum of 81% accuracy from a feature dimension of 6. If a different amount for the training samples is considered, all candidates have a poor performance of below 90% when only 2 training data samples are used. The performance of each classifier increases, if more training data is used. E. g. the performance of the SGDC and LDAC both reach 100% accuracy, if 8 or more training samples are used, whereas the performance of the SVC does not further increase after 6 training samples and keeps constant at 86%. In fig. 4e, the dependence of the performance on different window sizes used within 11 is shown. Here, the performance of all classifiers does not increase, by taking more past samples into account. The performance of the SGDC and LDAC stays constant at 100%independent of the window size W, whereas the performance of the RFC and SVC keeps at that value at least until a window size of 3 and decreases for higher window sizes $W \ge 4$.

VII. CONCLUSION AND FUTURE WORK

Under specific scenarios, the application of supervised learning algorithms for channel based message authentication is a promising alternative to conventional security measures such as MAC. Especially within URLLC services, a considerable amount of radio resource overhead can be saved. Though the measured performance of some classifiers is comparable to the performance of conventional schemes in our scenario, it also needs to be validated for various other scenarios, such as e. g. mobile setups. Further, other features that are used in addition to channel estimates might yield more robust PHYSEC schemes in order to achieve the goal of message authentication and integrity checking. Another point for future work is to estimate Eves training data, as attackers might not be present yet during the initialization stage. Further, more advanced attacks strategies might be investigated in order to test the robustness of the detection schemes.

TABLE III: Optimal hyperparameters of each classifier	TABLE	E III:	Optimal	hyperparameters	of	each	classifier
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Model	Parameter	Options	
	loss	log	
	Penalty	elasticnet	
	alpha	10^{-2}	
SGDClassifier	11_ratio	1	
	max_iter	10000	
	tol	10^{-5}	
	learning_rate	adaptive	
	eta0	0.5	
	С	0.1	
Dessive A grassive Classifier	max_iter	1	
PassiveAgressiveClassifier	tol	10^{-5}	
	Loss	hinge	
	n_estimators	100	
	criterion	entropy	
RandomForestClassifier	min_samples_split	3	
	min_samples_leaf	1	
	max features	log2	
	n_neighbors	2	
KNeighborsClassifier	algorithm	auto	
Kiveighborsetassiner	leaf_size	10	
	р	2	
	С	0.1	
	kernel	linear	
SVC	degree	1	
	tol	10^{-5}	
	max_iter	10	
	solver	[svd, lsqr]	
LinearDiscriminantAnalysis	tol	10^{-5}	
	shrinkage	auto	

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