Real or Fake:
Mobile Device Drug Packaging Authentication

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content overview

Motivation [1]
Counterfeited products

2013: *5% counterfeited products on EU level → faked medicals are a threat for the patients and cause an economic loss.*

The Falsified Medicines Directive (FMD) should be implemented until 2018. The approached solution relies on product ***serialization*** *and tracking using unique numeric identifiers.*

Motivation [2]
Paper-based PUFs

Previous literature showed that the fibre structure of paper or packaging material is positional highly unique and enables to identify single instances.

Motivation [2]
Paper-based PUFs

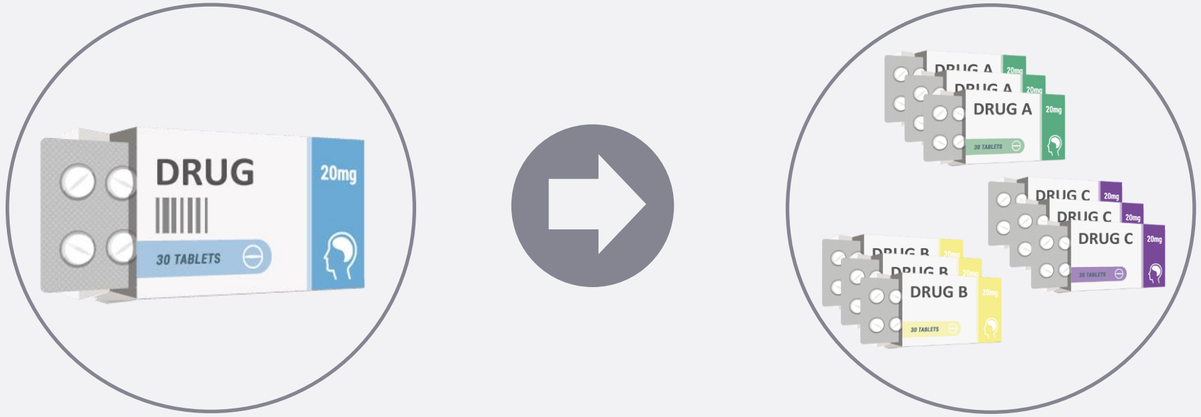
It is clear that the fibre-structure is locally unique.

Uniqueness

serialization

Individualize each instance of a product using unique identifiers or PUF-based approaches, e.g. fibre fingerprints

Basic idea
move from serialization to classification



serialization

Individualize each instance of a product using unique identifiers or PUF-based approaches, e.g. fibre fingerprints

classification

Use intrinsic or extrinsic features which are constant across all instances but different to features from other products.

Drug packaging authentication system
Basic concept

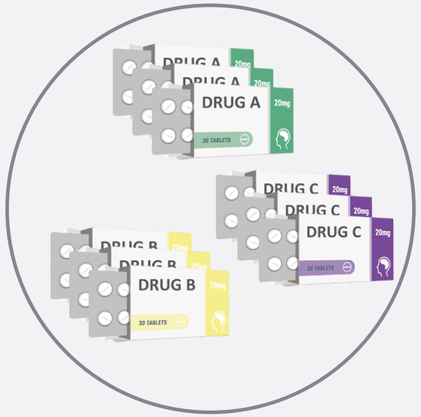
Capture packaging modalities:

CB = Cardboard
BB = Blister Bottom
BT = Blister Top

& the product code (PC)

WIFS’17

On the feasibility of classification-based product package authentication



classification

Use intrinsic or extrinsic features which are constant across all instances but different to features from other products.

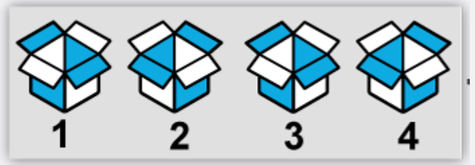
01

It is not clear

- If the fibre structure shows constant features across different regions and
- if those features are discriminative enough to distinguish between different types of paper or packagings.

Instance invariance

CLASS



$|1+2+3+4| = k$

?

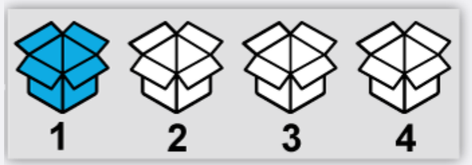
02

It is not clear

- how the texture and the computed features vary between different instances of a product.

Instance generalisation

PACKAGE



$|1|,|2|,|3|,|4| = k$

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WIFS'17
Results overview

01

02

	CLASS						PACKAGE					
	128×128			256×256			128×128			256×256		
CC	CB	BT	BB	CB	BT	BB	CB	BT	BB	CB	BT	BB
ONE-CLASS	*LTP* 0.83 ±7.9	*LTP* 0.9 ±6.2	*LTP* 0.92 ±5.8	*LTP* 0.91 ±4.4	*LTP* 0.85 ±13.6	*LBP* 0.87 ±13.5	*LBP* 0.81 ±8.7	*LBP* 0.86 ±6.3	*LTP* 0.84 ±11.3	*LTP* 0.85 ±9.1	*LBP* 0.88 ±5.0	*LBP* 0.85 ±7.1
BINARY	*LTP* 0.88 ±6.9	*LiLBP* 0.94 ±3.2	*LTP* 0.93 ±4.1	*LTP* 0.91 ±5.2	*LiLBP* 0.92 ±9.0	*LTP* 0.93 ±5.0	*LTP* 0.82 ±9.5	*LTP* 0.92 ±3.7	*LTP* 0.87 ±8.9	*LTP* 0.85 ±5.5	*LTP* 0.94 ±5.7	*LiLBP* 0.87 ±10.0
WSVM	*LTP* 0.86 ±7.6	*LTP* 0.93 ±4.1	*LTP* 0.93 ±4.3	*LiLBP* 0.88 ±6.0	*LTP* 0.88 ±7.6	*MFS* 0.88 ±9.1	*LTP* 0.85 ±8.2	*LTP* 0.91 ±4.2	*LiLBP* 0.85 ±9.2	*LiLBP* 0.83 ±8.5	*LTP* 0.89 ±8.7	*LiLBP* 0.84 ±10.1

CLASS results show high mean F-Measures over 0.9, indicating that textures from all three modalities show constant but highly discriminative features. This enables to recognize the same drug class and to distinguish it from others.

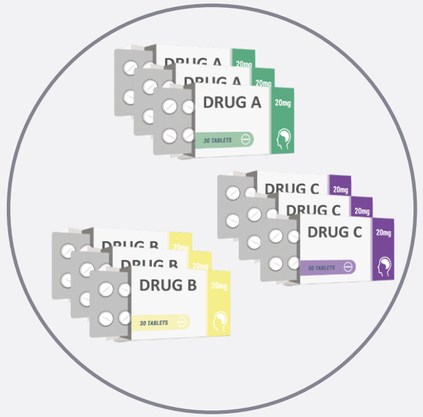
Instance invariance

PACKAGE results show that textural features are constant across different instances for all three modalities.
This is a basic requirement for a
classification-based authentication system.

Instance generalisation

IHMMSEC’18

Real or Fake: Mobile Device Drug Packaging Authentication



classification

Use intrinsic or extrinsic features which are constant across all instances but different to features from other products.

01

It is not clear:

- if mobile device cameras are applicable
- If data from different sensors can be utilized

DSLR vs. Mobile & Cross-sensor scenario

?

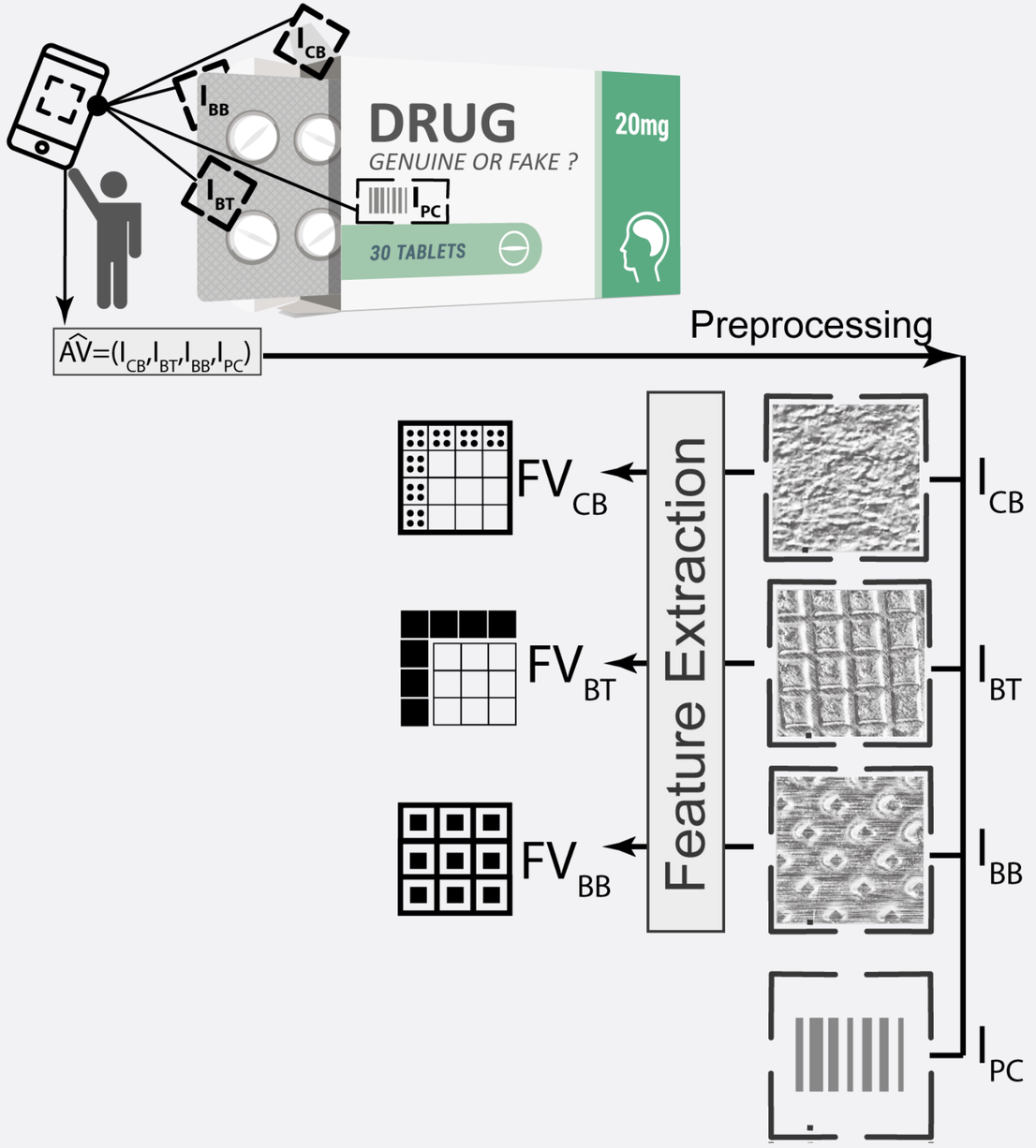
02

It is not clear:

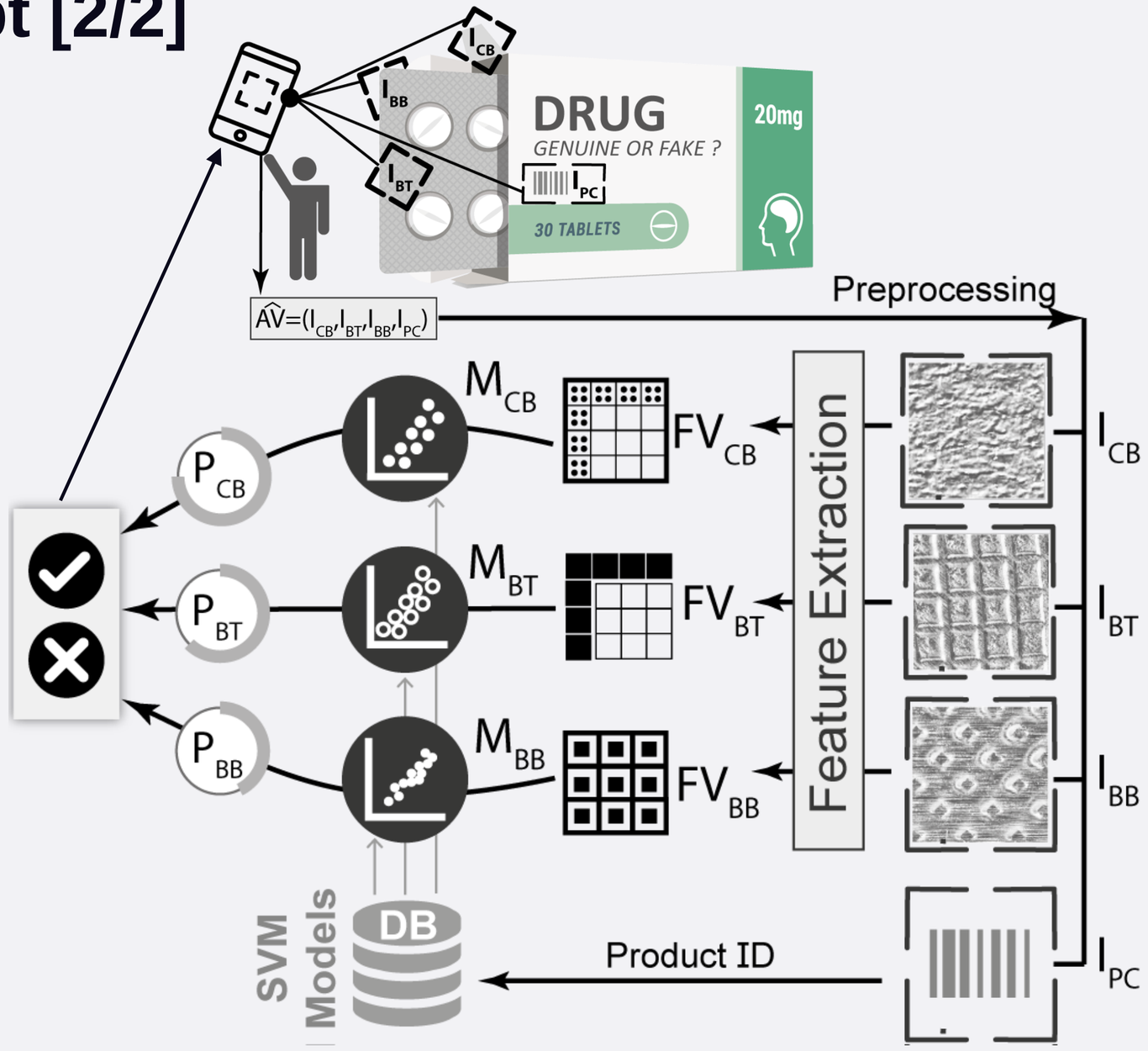
- If modality fusion can improve the classification performance

Modality Fusion

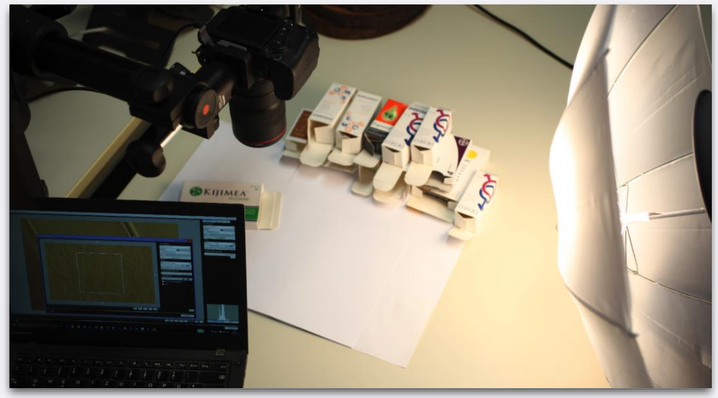
Drug packaging authentication system
Basic concept [1/2]



Drug packaging authentication system
Basic concept [2/2]



Drug packagings texture database
Acquisition details [1/2]



Sample collection

Packages were collected in different pharmacies in Salzburg.

Sorting & Labelling

All packages were sorted and each drug was assigned an identifier and the available instances were numbered.

- **Drugs #45**
- **Producers #28**
- **1 to 15 instances per drug**

Image Acquisition

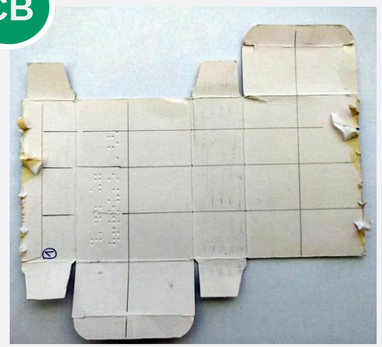
Images were captured in a controlled environment using a

- **DSLR camera** (Canon 70D with a 100 mm macro lens and a flashlight) .The image distance was approximately 28cm.
- **2 smartphone cameras:**
  - Samsung S5 Mini
  - IPhone S5

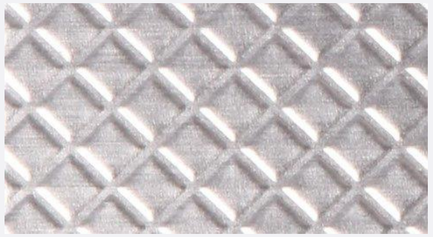
  with a macro-lens

Drug packagings texture database
Acquisition details [2/2]

CB



BT



BB

1

Non-overlapping

Capture non-overlapping sections of each instance and modality

2

Cropping

The final images are of arbitrary size and show textural information of the modality.

Classification pipeline
Sensors

Sensors

$$S = \{CANON = S1, SAMSUNG = S2, IPHONE = S3\}$$

Capturing device

Classification pipeline
Data selection

CLASS or PACKAGE

Keypoint selection:
k – image patches, with a predefined size, are selected for each modality and sensor.

Patch sizes:
256x256

Classification pipeline
Feature Extraction [1/2]

S1,S2,S3

Keypoint selection

Each selected patch is contrast enhanced (CLAHE) and a set of feature vectors are computed.

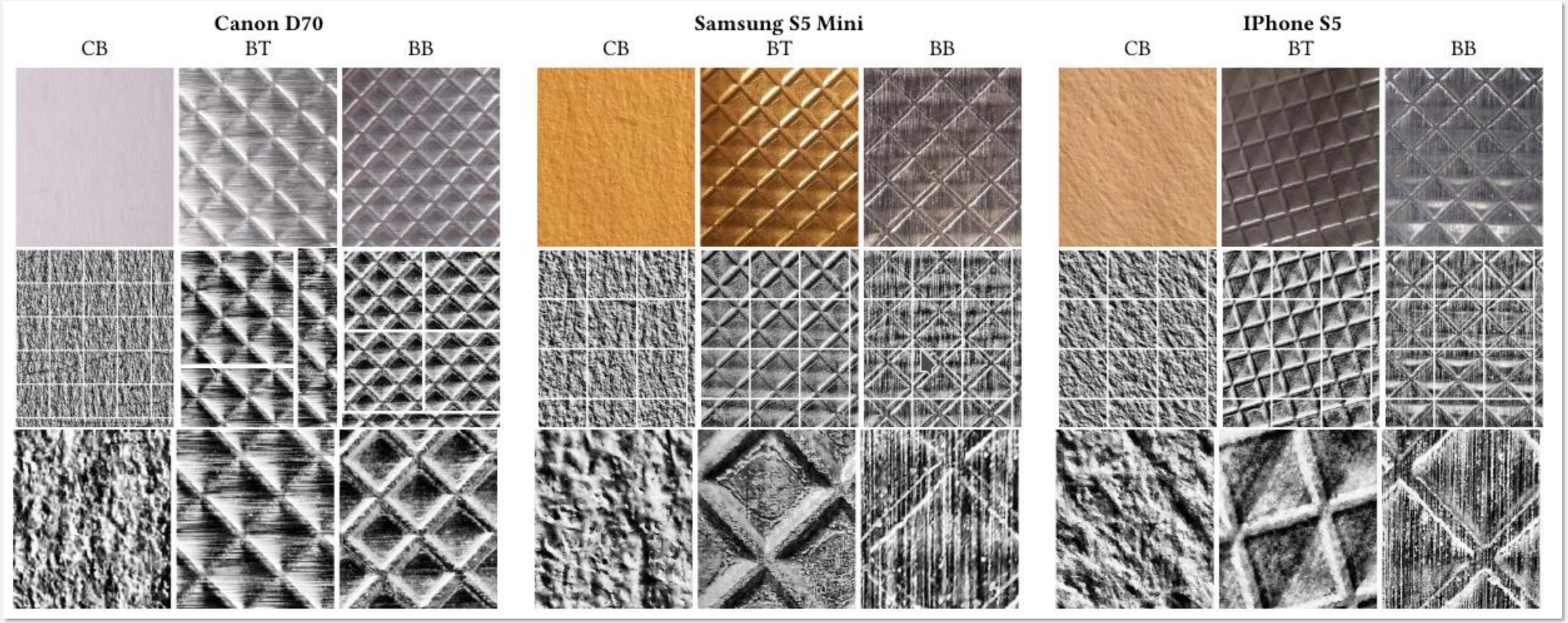
$$FE = \{LBP, LiLBP, LTP, SURF\}$$

Feature Extraction Approaches

$$FVE = \{NULL, FISHER\}$$

Feature Vector Encoding

Classification pipeline
Feature Extraction [2/2]



Classification pipeline
Classification approaches

CLASS or PACKAGE

Keypoint selection

Features

Applied SVMs:

- LIBSVM:
  - **BINARY RBF C-SVC**
  - **LINEAR**

Classification pipeline
Cross-fold validation [1/4]

CLASS or PACKAGE

Keypoint selection

Low-level features

Applied SVMs

- Data Partitioning,
- Hyperparameter optimization and evaluation

Classification pipeline
Cross-fold validation [2/4]

Scenario → Data → Feature Extraction → **Classification Approach** → **Cross Validation**

Parameters	
Target drugs out of #45 drugs	D = {d_1,…,d_{45}}
Sensors	S = {S1,S2,S3}
Packaging modality	M = {CB, BB, BT}
Feature Extraction	FE = {fe_1,…, fe_n}
Feature Vector Encoding	FVE = {NULL, FISHER}

Drugs with at least 5 instances were selected as **target drugs (d)**. The checkmark shows if the drug was captured with the corresponding sensor.

Manufacturer/Drug	#Samples		Camera		
	CB	BT&BB	Canon (S1)	IPhone (S2)	Samsung (S3)
(A) ratiopharm					
(A1) Danselle	10	10	✓	-	-
(A2) Danseo	9	9	✓	-	-
(A3) Mexalen	8	8	-	✓	✓
(F) Lannacher					
(F1) Thrombo ASS	5	5	✓	✓	✓
(I) Kwizda Pharma					
(I1) Liberel mite	15	15	✓	-	-
(I2) Delia	11	11	✓	✓	✓
(J) Rotexmedia					
(J1) Dexamethason	5	0	✓	-	-
(N) Gynial					
(N1) Bilinda	6	6	✓	✓	✓
(X) Pelpharma					
(X1) Peliette	17	17	✓	✓	✓

Classification pipeline
Cross-fold validation [3/4]

Scenario → Data → Feature Extraction → Classification Approach → Cross Validation

Parameters	
Target Drugs out of #45 drugs	D = {d_1,…,d_{45}}
Sensors	S = {S1,S2,S3}
Packaging modality	M = {CB, BB, BT}
Feature Extraction	FE = {fe_1,…, fe_n}
Feature Vector Encoding	FVE = {NULL, FISHER}

$$CC = (d \in D, m \in M, s \in S, fe \in FE\}$$

Classification Configuration

$$FV_{CC} = \{ FV_{(d_1,m,s,fe),\ldots,} FV_{(d_{45},m,s,fe)} \}$$

CC specific Feature Vector Sets

Nested cross-validation

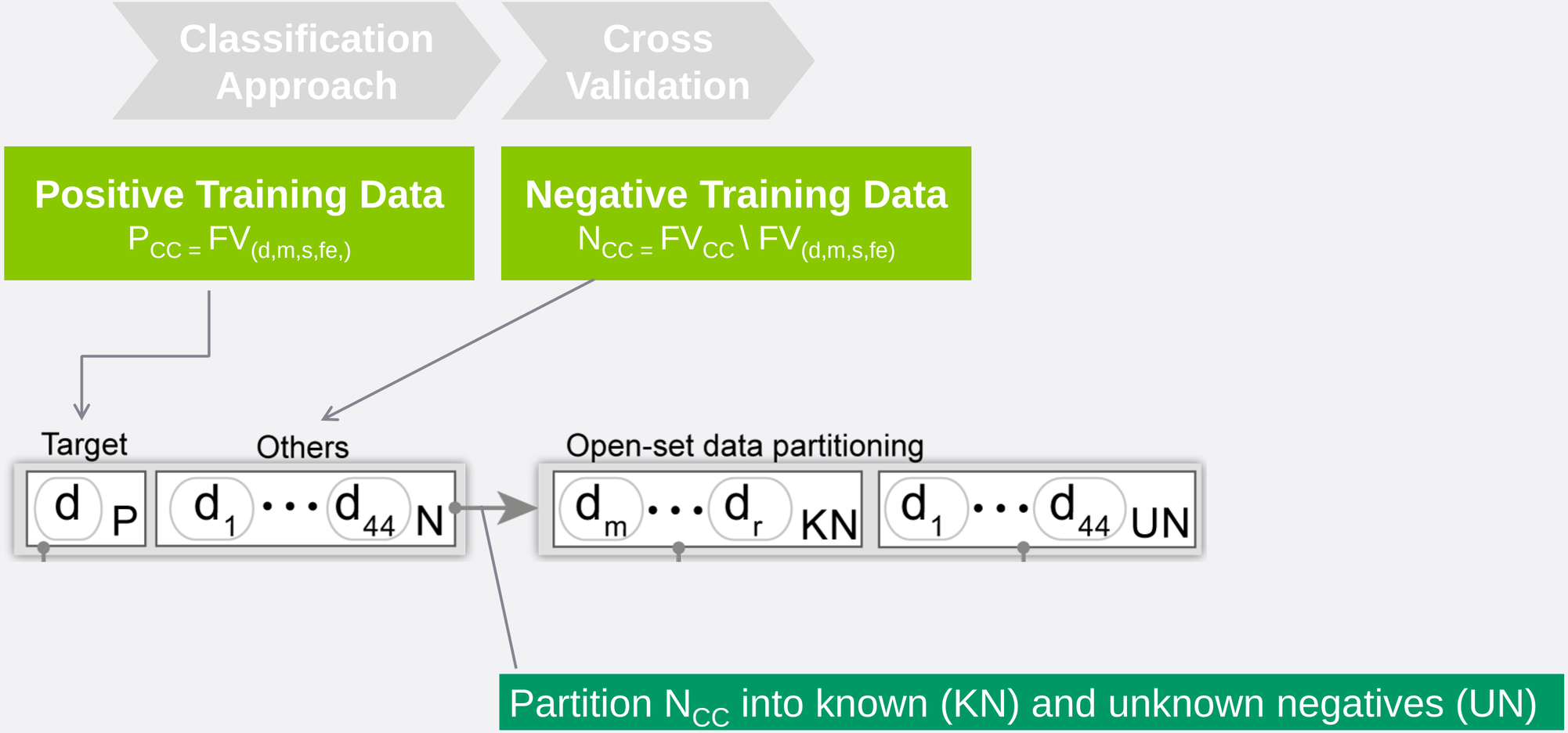
Positive Training Data

$P_{CC} = FV_{(d,m,s,fe)}$

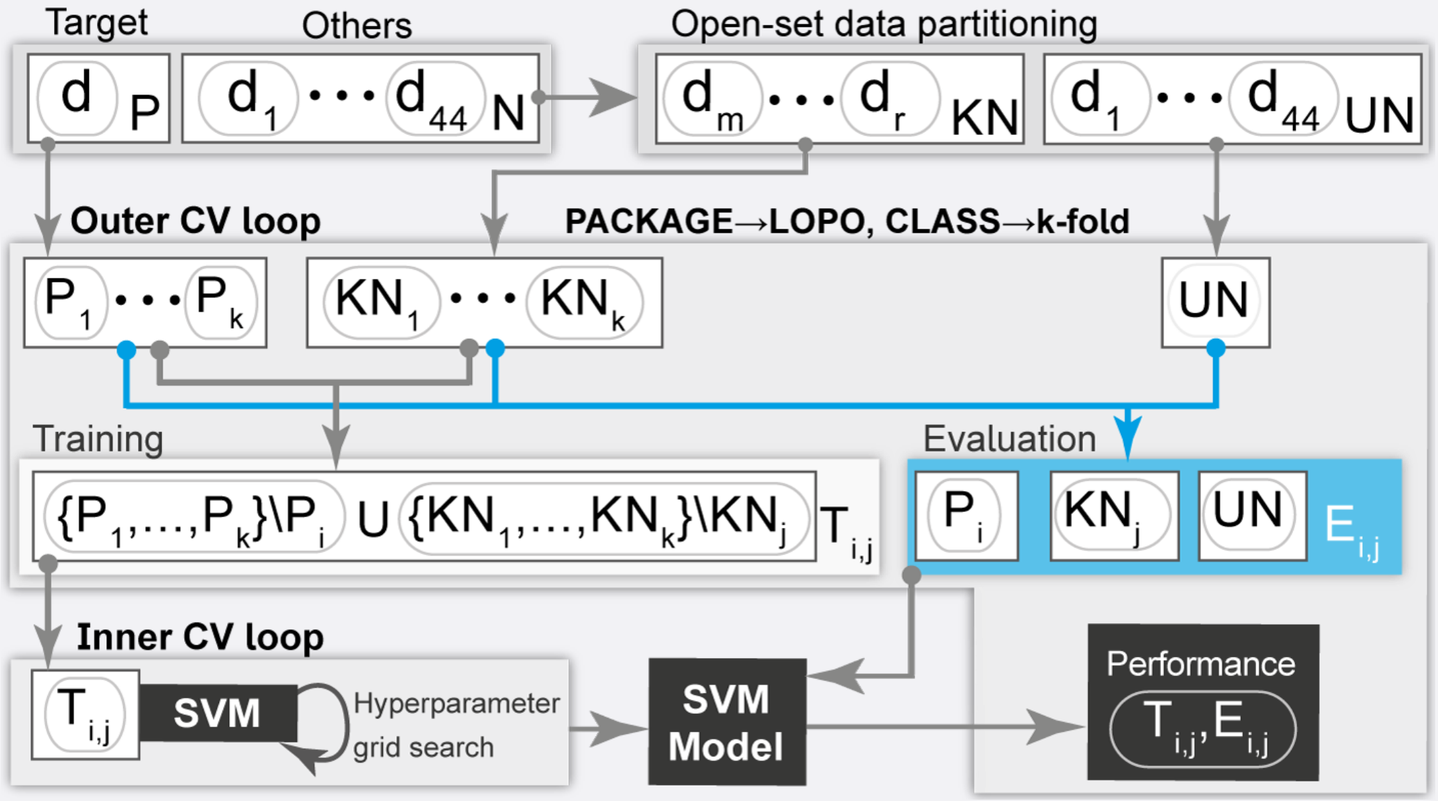
Negative Training Data

$N_{CC} = FV_{CC} \setminus FV_{(d,m,s,fe)}$

Classification pipeline
Cross-fold validation [4a/4]



Classification pipeline
Cross-fold validation [4b/4]



Optimize classifier using known negatives in the inner CV loop

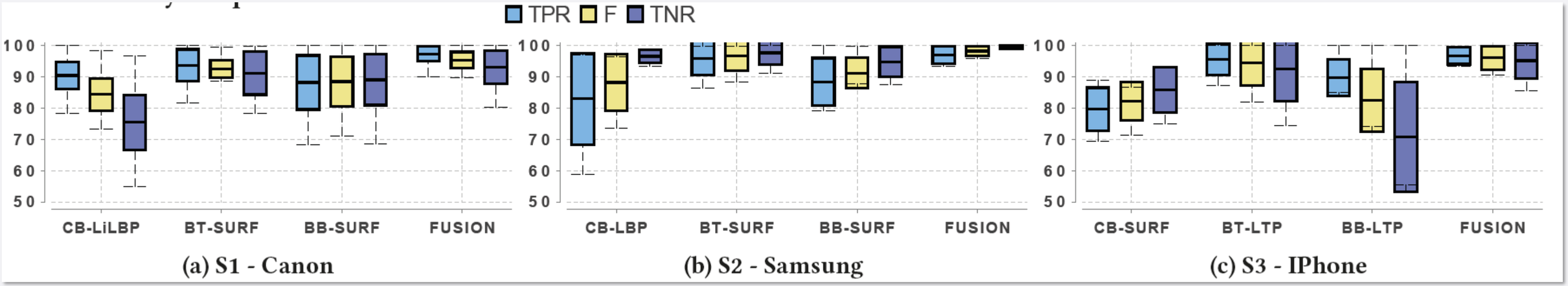
A subset of the known negatives is not used for training; i.e. only for evaluatuin in order to address the open-set problem in the inner CV loop. The SVM parameters and a probabilitay threshold achieving the highest F-Measure are determined.

Experiments
Single sensor results

CC		Canon - S1			Samsung - S2			IPhone - S3		
FVE	CA	CB	BT	BB	CB	BT	BB	CB	BT	BB
NULL	RBF-SVM	*LTP* 0.87 ±6.9	*LTP* 0.94 ±3.5	*LiLBP* 0.84 ±17.6	*LTP* 0.92 ±6.8	*LTP* 0.96 ±4.0	*LiLBP* 0.91 ±5.8	*LBP* 0.83 ±6.1	*LTP* 0.95 ±6.5	*LTP* 0.88 ±8.1
	L-SVM	*LTP* 0.87 ±7.4	*LBP* 0.92 ±4.7	*LiLBP* 0.83 ±13.5	*LTP* 0.92 ±6.3	*LTP* 0.94 ±4.1	*LiLBP* 0.9 ±5.6	*LBP* 0.83 ±6.9	*LTP* 0.95 ±6.2	*LTP* 0.8 ±12.6
A FISHER	L-SVM	*LiLBP* 0.84 ±7.4	*SURF* 0.93 ±3.8	*SURF* 0.89 ±10.6	*LBP* 0.88 ±9.3	*SURF* 0.97 ±4.8	*SURF* 0.91 ±4.9	*SURF* 0.82 ±6.3	*SURF* 0.95 ±7.9	*SURF* 0.84 ±12.0

- *No significant differences between the elaborated classifiers.*
- *Due to the amount of available evaluation data S2 and S3 reflect a closed-set scenario -> S1 with a high amount of unknown data (=real world) shows comparable results to S2 and S3.*
- *S2 and S3 results indicate the applicability of smartphone cameras for packaging classification.*

Experiments
A Single Sensor: Modality Fusion



For all sensors the performance (TPR,F,TNR) increases in case of modality fusion.

Class Accuracy / True Positive Rate:

$$TPR = \frac{TP}{TP + FN}$$

Others Accuracy / True Negative Rate

$$\mathrm{TNR} = \frac{TN}{TP + FP}$$

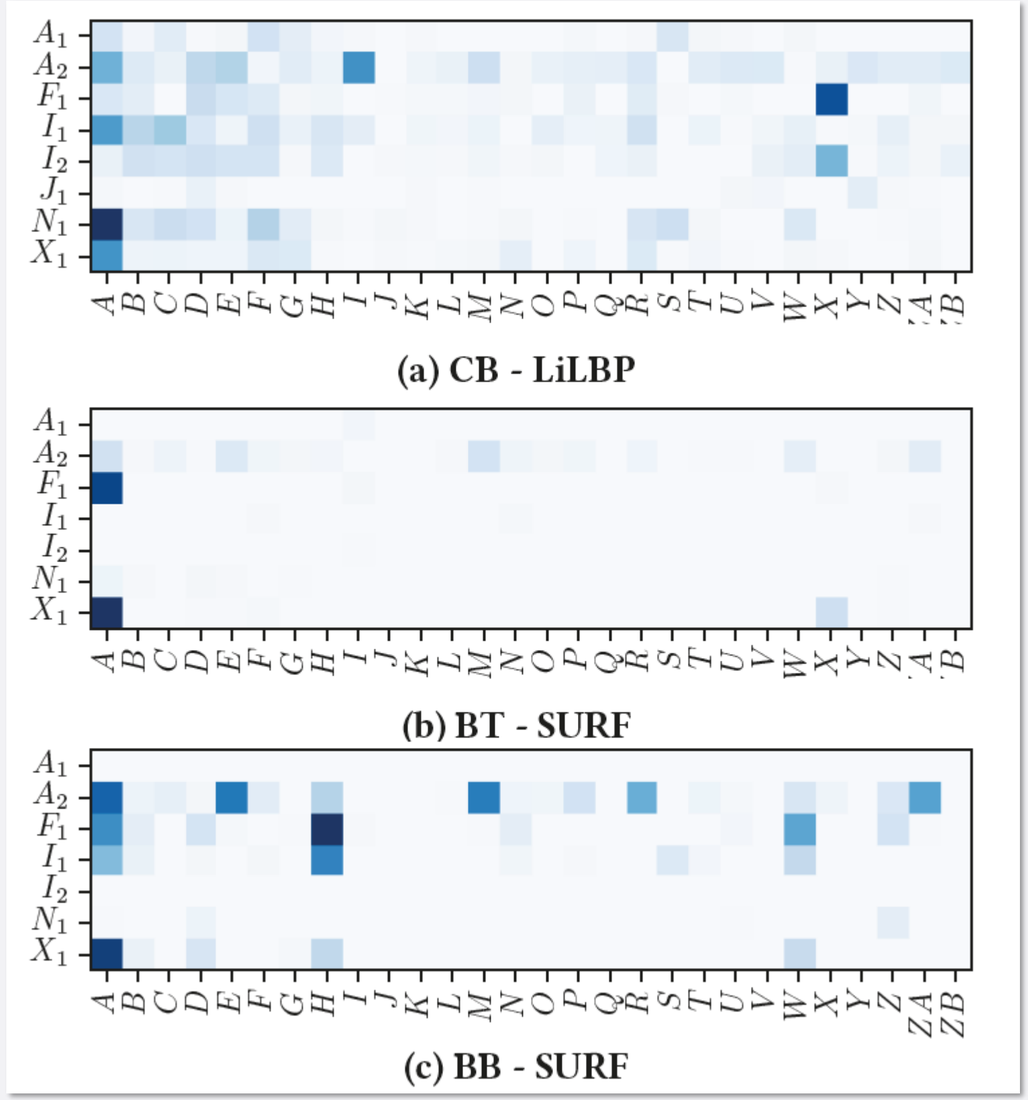
Experiments
Single-Sensor: Error matrices

Canon (S1) FISHER L-SVM:
FN+FP Error matrix for each modality

X-Axis: Producers from the evaluation data
Y-Axis: Target drugs

- The darker the cell, the higher is the classification error.

The most errors are visible in case of CB and BB and there are less errors for the BT textures.



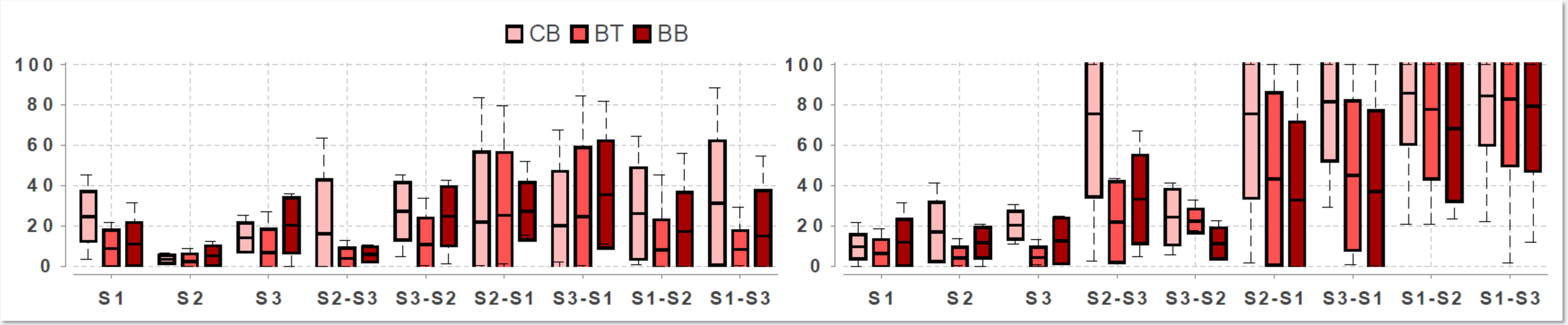
(a) CB - LiLBP

(b) BT - SURF

(c) BB - SURF

Experiments
FPR, FNR Error Plots

FISHER L-SVM (Best Features):
Y-Axis: Single sensor, Cross-sensor scenario



False Positive Rates: $FPR[\%] = \frac{FP}{TN+FP}$

False Negative Rates: $FNR[\%] = \frac{FN}{TP+FN}$

- *DSLR vs Mobile: Very high FNR‘s and FPR‘s*
- *Mobile cross-sensors error rates are better*
- *FNR worse than FPR: Easier to reject oter drugs than to detect the target drug captured with another sensor.*

Conclusions and Outlook

Modality fusion

Modality fusion improves the authentication performance.

Mobile-device based authentication

Images captured with mobile devices are suited for classification-based packaging authentication.

Cross-sensor scenario

Current approach is not suited for a real-word cross-sensor scenario