# Cross-Sensor Micro-Texture Material Classification and Smartphone Acquisition do not go well together

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## Abstract

Intrinsic, non-invasive product authentication is still an important topic as it does not generate additional costs during the production process. This topic is of specific interest for medical products as non-genuine products can directly effect the patients' health. This work investigates micro-texture classification as a mean of proving the authenticity of zircon oxide blocks (for dental implants). Samples of three different manufacturers were acquired using four smartphone devices with a clip-on macro lens. In addition, an existing drug packaging material database was utilized. While the intra-sensor micro-texture classification worked well, the cross-sensor classification results were less promising. In an attempt to track down the limiting factors, intrinsic sensor features usually used in device identification were investigated as well.

## Main Results

- Intra-Sensor Material Classification works well
- Cross-Sensor Material Classification does not work so well
- Sensor Classification works better than Material Classification
- Location dependent parts of PRNU are not the reason why sensor classification performance is better

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## Introduction

**Motivation**

- Counterfeit products are a significant problem: Causing economic damage to the manufacturers
- Especially in medical/health care applications have direct influence on patients' health
- Medical and health related products usually high priced - hence of higher interest for product forgers
- Different ways to establish the authenticity of products
  - Intrinsic: based on the product's properties, no external markers etc. needed
  - Extrinsic: based on QR codes, external markers, validated supply chains, etc.

**Goals of this work:**

- **Evaluate effect of scaling in cross sensor scenario for existing drug package database**
- Scope of existing database:
  - 3 capturing devices
  - 5-6 drug manufacturers
  - 3 modalities (cardboard, blister top, blister bottom)
- **Acquisition of zircon oxide block ceramic database**
  - zircon oxide blocks from 3 manufacturers
  - 4 smartphone devices
- **Can we classify ceramic manufacturers based on samples? (Intra-Sensor & Cross-Sensor)**

## Texture Classification Pipeline

- Different **feature extraction** schemes:
  - Dense SIFT (**SIFT**)
  - Dense Micro-block Difference (**DMD**)
  - Local Binary Pattern (**LBP**)
  - Local Phase Quantization (**LPQ**)
  - Weber Pattern (**WP**)
- Followed by a **PCA** based dimensionality reduction, a **Fisher vector encoding** and finally an **SVM** based classification

## Ceramic Data Acquisition Setup

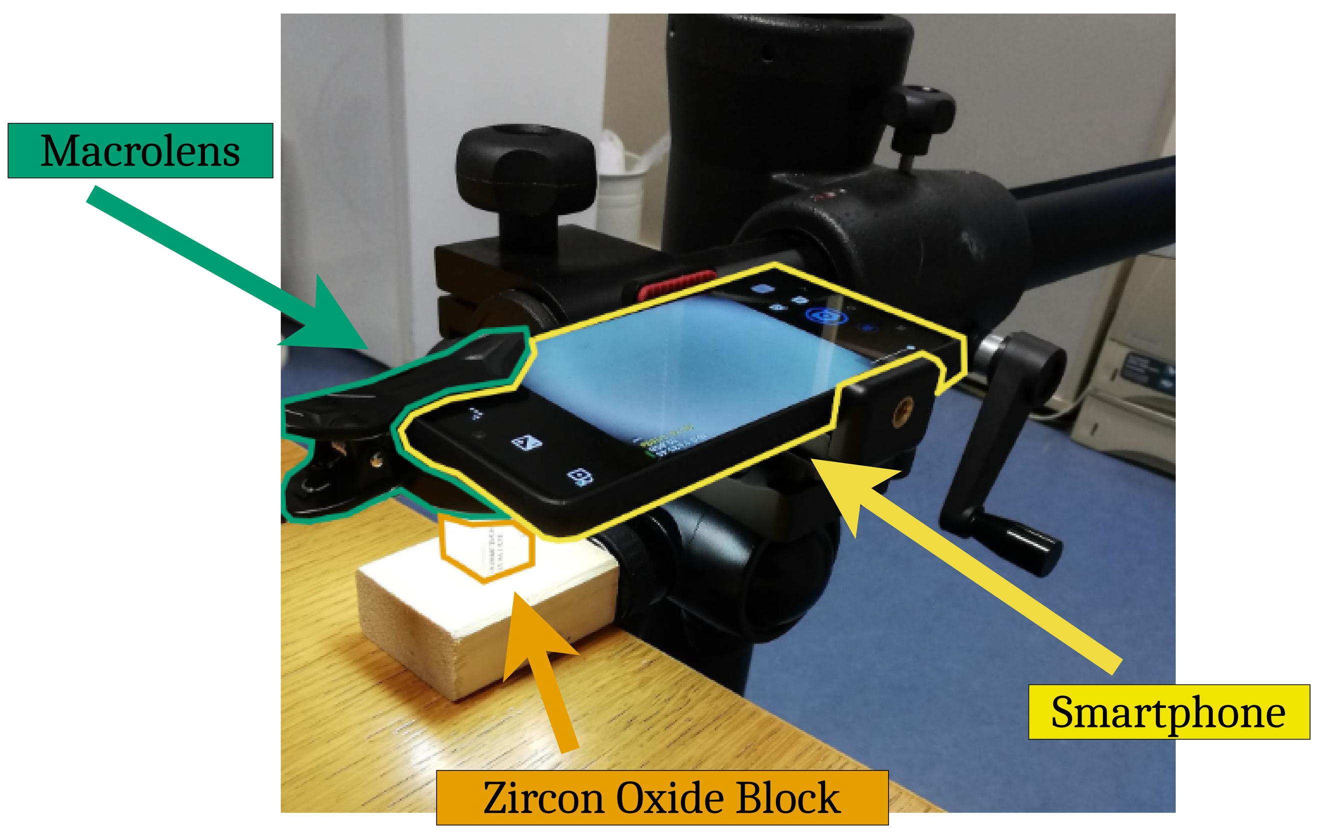



**Figure 1:** Image acquisition setup for zircon oxide blocks.

## Ceramic Data Patching

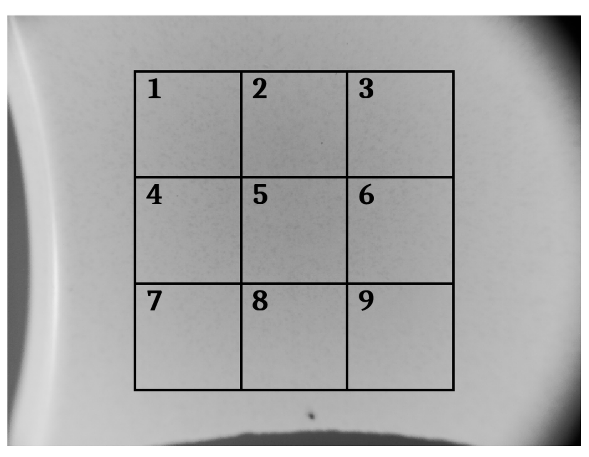



**Figure 2:** Acquired image with distortions & patching strategy.

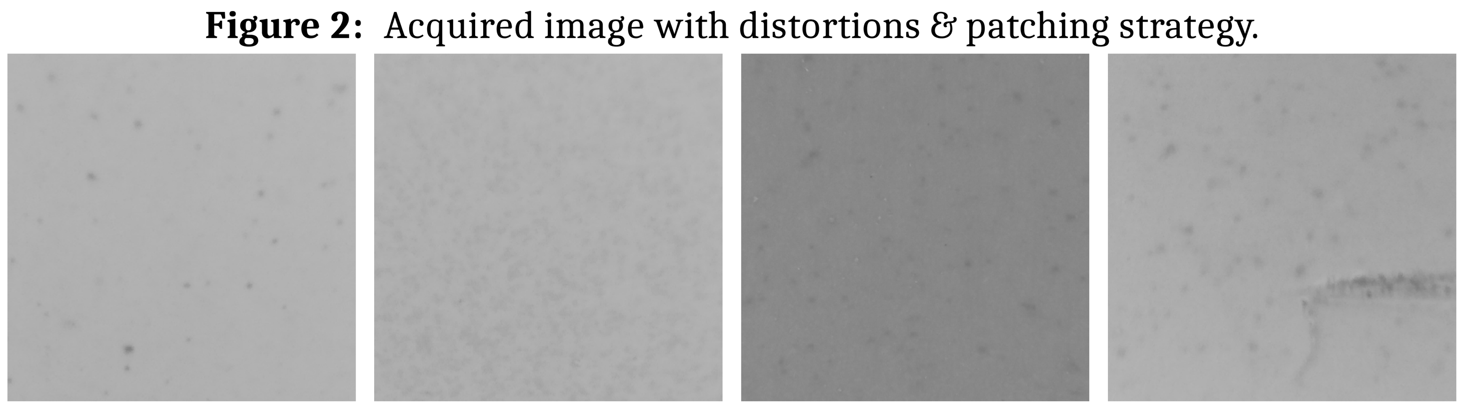


**Figure 3:** Ceramic data sample patches.

## Samples from (pre-existing) Drug Package Database

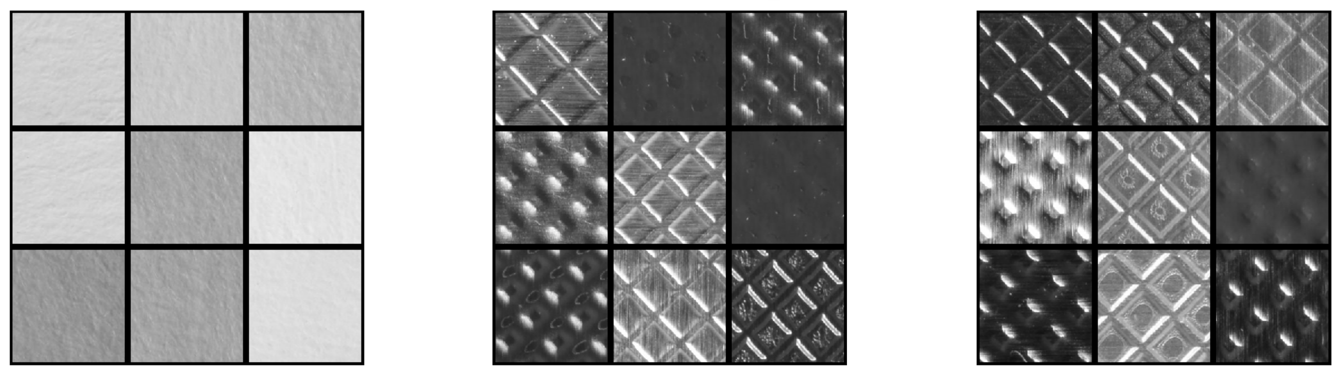



**Figure 4:** Drug data sample patches for different modalities.

## Experiment 1: Intra-Sensor Material Classification

| | SIFT | DMD | LBP | WP | LPQ |
|---|---|---|---|---|---|
| Cardboard | 90.18 | 90.14 | 70.21 | 61.09 | 31.78 |
| Blister Top | 99.89 | 99.30 | 89.98 | 74.17 | 38.48 |
| Blister Bottom | 99.36 | 97.88 | 69.92 | 56.12 | 24.26 |
| Ceramic | 98.88 | 97.46 | 72.90 | 71.04 | 51.60 |

**Table 1:** Intra-sensor material classification. Averaged accuracy.

## Experiment 2a: Cross-Sensor Ceramic Data Material Classification

| | SIFT | DMD | LBP | WP | LPQ |
|---|---|---|---|---|---|
| Ceramic | 68.60 | 60.74 | 36.17 | 55.65 | 31.13 |

**Table 2:** Leave-one-sensor-out ceramic material classification. Averaged accuracy.

## Experiment 2b: Cross-Sensor Drug Package Data Scaling

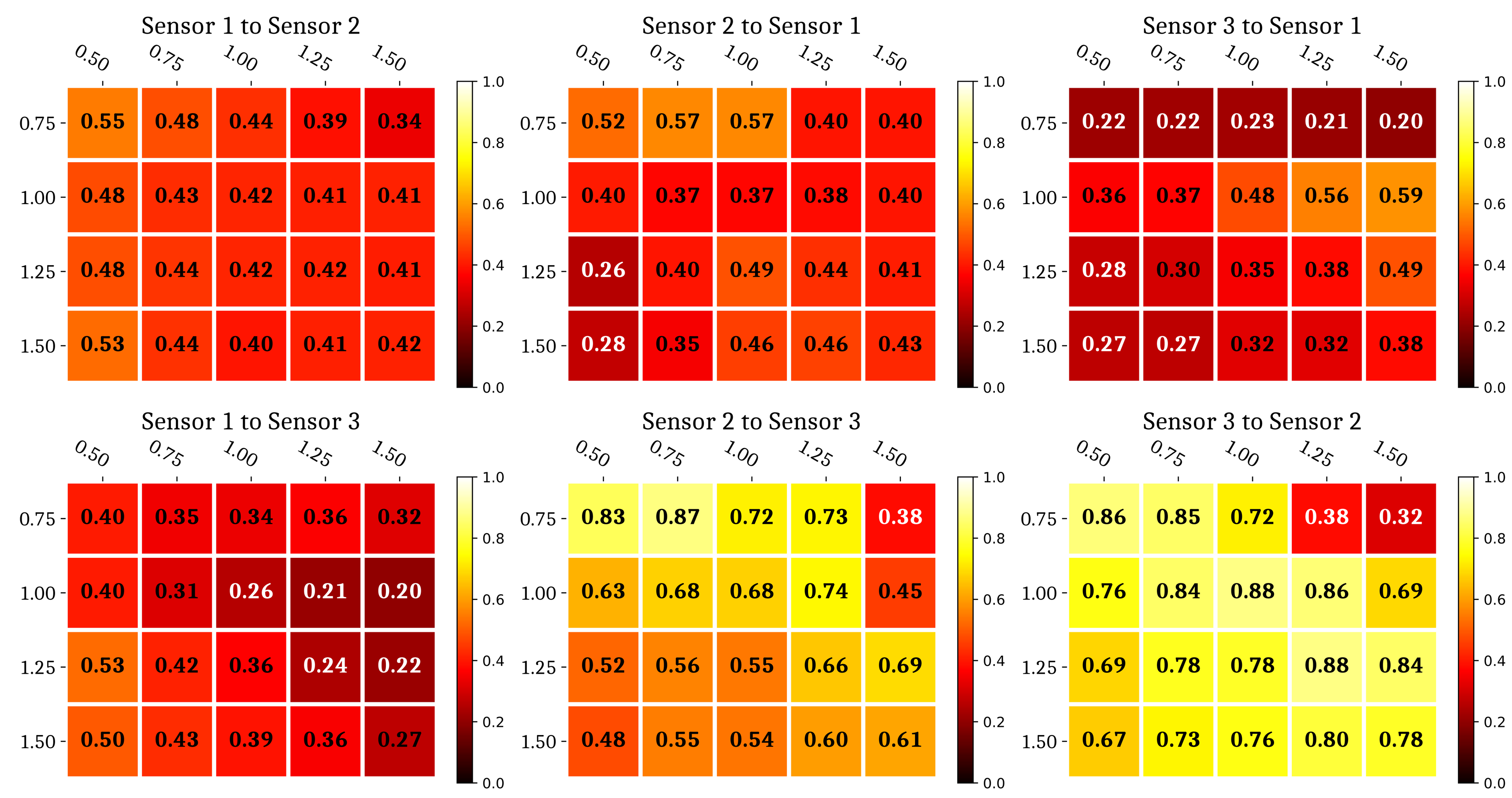


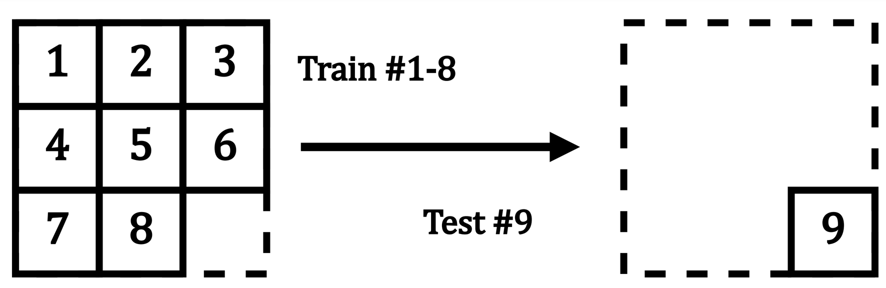

**Figure 5:** Different scale factors on the drug data (blister top-side) using SIFT.

## Experiment 3: Sensor Classification

| | SIFT | DMD | LBP | WP | LPQ |
|---|---|---|---|---|---|
| Cardboard | 100.0 | 100.0 | 99.75 | 99.41 | 75.48 |
| Blister Top | 99.42 | 99.29 | 81.01 | 92.95 | 81.86 |
| Blister Bottom | 98.66 | 98.63 | 69.66 | 86.15 | 73.08 |
| Ceramic | 100.0 | 99.92 | 98.66 | 92.44 | 83.55 |

**Table 3:** Switch classes (manufacturers) and devices = Sensor identification. Averaged accuracy.

## Experiment 4: Influence of PRNU




| | SIFT | DMD | LBP | WP | LPQ |
|---|---|---|---|---|---|
| Ceramic | 100.0 | 100.0 | 99.68 | 93.54 | 87.20 |

**Table 4:** Evaluation influence of PRNU, through testing a patch from location excluded in test data. Averaged accuracy.