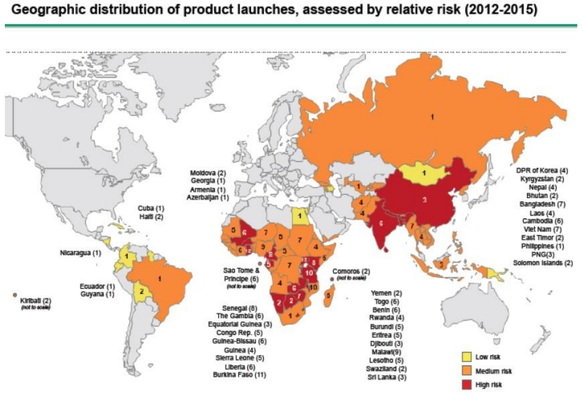
# Visual Recognition of Paper Analytical Device Images for Detection of Falsified Pharmaceuticals

**Sandipan Banerjee, James Sweet, Christopher Sweet and Marya Lieberman**
**University of Notre Dame**

## The Problem

**Counterfeit medicine:** has sub-therapeutic levels of an active ingredient or none at all. Some times it may contain harmful elements as well.


**Where**: South east Asia and Africa are high risk zones.




## Prior Approaches

Previous work focuses on the appearance of the drug - the color and the shape of the pill.
- e.g. [Hartl et al. 2011, Chen et al. 2012]

Other approaches use imprint information on the drug for identification purposes.
- e.g. [Lee et al. 2011, Chen et al. 2013, Yu et al. 2015]

These approaches work well in identifying pills but they fail to distinguish the fake medicine from its actual counterpart.

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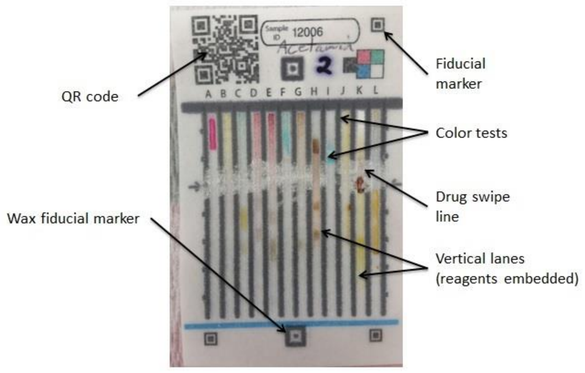
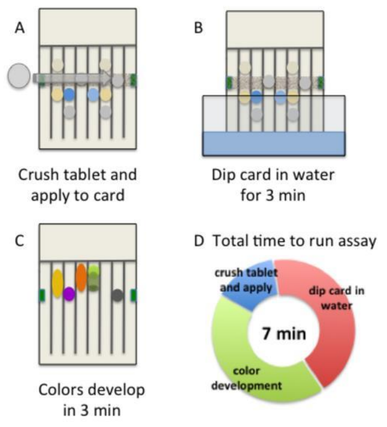
## PAD

**PAD cards**: PADs are inexpensive (under $1) cards that contain libraries of color tests to respond to the chemicals inside a pill.



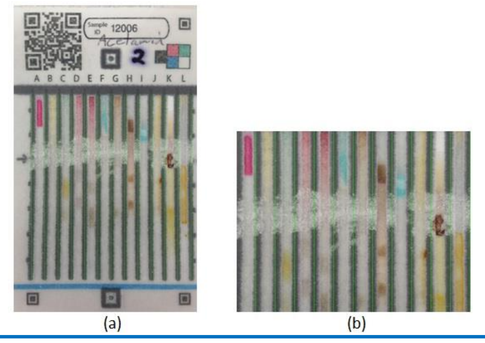

**PAD preparation**:




**Chemical fingerprint**: The chemical compounds present in the drug react with the reagents in the vertical lanes of the PAD. These reactions produce colors coming in contact with water and is unique for that drug.


## PAD Rectification

- We align, reposition and resize the raw PAD image using its fiducial markers and the PAD artwork.
- We crop out the salient region from the rectified image.




## Reagent Selection

**Drug selection**: We select 26 drug samples from the WHO list of essential medicine for our experiments.

**Reagent selection**
- matrix M of mean RGB values.
- **M = USV$^t$**.
- optimal reagent index from sorting columns of V.
- 9 unique optimal reagent + 2 from chemistry.

## Experiment

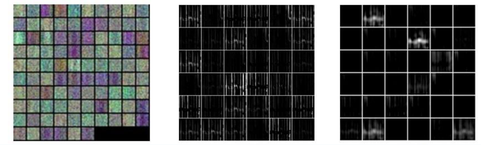
**Dataset**
- 520 salient regions for training (20 images/drug), 260 for testing (10 images/drug).
- 3-fold cross validation approach.

**Feature extraction**
- low level and high level features, ranging from the basic color histograms to image memorability features [Khosla et al. 2012].
- deep CNN features from Caffenet [Krizhevsky et al. 2012] and GoogLeNet [Szagedy et al. 2014].

**Classifier**
- a simple Euclidean distance based nearest neighbor approach (kNN, where k = 1).
- a support vector machine (SVM) with a radial basis kernel.
- for the CNN models, we use the softmax classifer in the pipeline

## Filter Response

**Caffenet features**



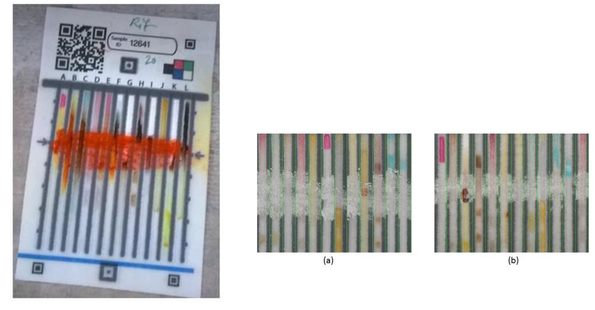
## Results

**Results (experiment 1)**:

| Method | Accuracy (%) |
|---|---|
| L*a*b* histogram with kNN | 138/260 (53.07%) |
| L*a*b* histogram with SVM | 172/260 (66.15%) |
| GIST with kNN | 216/260 (83.07%) |
| GIST with SVM | 230/260 (88.46%) |
| Color bank with kNN | 235/260 (90.38%) |
| Color bank with SVM | 231/260 (88.84%) |
| Dense SIFT with kNN | 200/260 (76.92%) |
| Dense SIFT with SVM | 233/260 (89.61%) |
| Color bank + dense SIFT with kNN | 238/260 (91.53%) |
| Color bank + dense SIFT with SVM | 240/260 (92.30%) |
| **Caffenet** | **245/260 (94.23%)** |
| GoogLeNet | 243/260 (93.46%) |

Clearly, high level features > low level features.

**Additional experiments**: We change the data in the following ways:
- use unrectified PAD images directly.
- perturb the vertical lane configuration randomly.




**Results (experiment 2)**:

| Method | Accuracy (%) |
|---|---|
| Unrectified images with Caffenet | 233/260 (89.61%) |
| Images with random lane order with Caffenet | 87/260 (33.46%) |

Blob patterns definitely matter on top of the color information.