Towards Drug Counterfeit Detection Using Package Paperboard Classification

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Abstract. Most approaches for product counterfeit detection are based on identification using some unique marks or properties implemented into each single product or its package. In this paper we investigate a classification approach involving existing packaging only in order to avoid higher production costs involved with marking each individual product. To detect counterfeit packages, images of the package's interior showing the plain structure of the paperboard are captured. Using various texture features and SVM classification we are able to distinguish drug packages coming from different manufacturers and also forged packages with high accuracy while a distinction between single packages of the same manufacturer is not possible.

Keywords: Drug Counterfeit Detection, Paper Structure Classification, Texture Classification

1 Introduction

Counterfeit products are a serious world wide issue affecting all industries. A recent OECD study [13] reports that in 2013 about 2.5% of the world wide traded products were faked ones. For the European Union (EU) a remarkably higher value of 5% for faked and imported products is reported.

In case of medical products counterfeit medicines and drugs lead to an economic loss and are all the worse a threat for the health of the consumers and patients. The International Medical Products Taskforce (IMPACT) of the World Health Organization (WHO) estimated a share of 1% of faked products in the developed countries and 10 to 30% in many developing countries [16]. Consequently, medical product authentication is becoming increasingly important. On European level the Falsified Medicines Directive (FMD) 2011/62/EU should be implemented until 2018. The overall aim is to improve patient safety stipulating an efficient anti-counterfighting system. Unique identifiers (2D barcodes) will be used to track and authenticate each medical package along the supply chain. A central repository system is required to enable authentication of each package. Such a system will not be available in developing countries. Furthermore, it suffers costs and is exposed to getting compromised by the forgers.

Another approach to verify the originality of a product is to use intrinsic features visible on the packaging or the product itself. For this work we focus on authentication of a medical product using intrinsic features from the packaging surface. Literature in this field relates to package fingerprinting based on the theory of physically uncloneable functions (PUFs). Paper PUFs use the fiber structure of paper as physical/intrinsic characteristic. The approaches presented in [10,1,3] show that the micro-structure in a certain region of a paper or package material is discriminative enough to identify it. Detailed investigations on paper identification, using a public available microstructure dataset [18], are presented in [5,4]. In [5] the authors explore the applicability of two approaches to overcome geometric distortions. The same approaches and a hybrid one are used to investigate package identification using mobile phones in [4]. Furthermore, in [6] a new feature descriptor for micro-structure identification using mobile phones is introduced. By comparing the performances for different PUFs the results in [20] indicate that the approach by [3] outperforms the approaches by [18,5,4] but it requires a commodity scanner. Thus, in [19] the authors showed that mobile devices and the camera built-in flash lights can also be used to capture images as required for [3].

As shown, research exclusively deals with identification of paper or packages. To the best of our knowledge no works which consider paper or package classification have been presented so far. Like in the work of [17] we assume that the fibre structure pattern of the packaging material is suited for classification, i.e. for a certain medical product the packaging fibre structure shows constant features. If so, one step for checking the authenticity of a medical product could be to assess if the packaging material is the same as used for the original product. To answer this question, we perform a preliminary study for nine different medical products from three different manufacturers and some forged packages for one medical product. The results of this work enable to draw conclusions which are a first step towards medical product authentication using the packaging material.

Section 2 introduces the basic concept of paper classification. The experimental setup and the data set acquisition are described in Section 3. Our experimental results together with a discussion of these results can be found in Section 4. Section 5 concludes this paper.

2 Paper Texture Classification

This section describes our proposed approach using paper texture classification for package counterfeit detection. The general procedure is the following: At first an image of the interior of the package is taken and several patches are extracted from random positions in the image. These patches are then preprocessed. Afterwards different features are extracted from the preprocessed patches. Based on these features a classifier returns a decision predicting the class a questioned image is belonging to (by utilizing a pre-trained SVM). The steps are explained in the following.

2.1 Image Acquisition

Several images of the package's interior are captured at different positions. For the image acquisition a Canon 70D (100mm lens and flash light), mounted on a tripod, was utilized. The flashlight was placed besides the package. The camera is set to the smallest possible distance from the package (about 30 cm) trying to capture as most as possible of the paper's fibre-structure. An image of the acquisition setup can be seen in figure 1 together with an acquired image from the interior of a sample package.

Fig. 1: Set-up for image acquisition of the fiber structure on the inside of a drug package (left) and acquired image sample (right).

2.2 Preprocessing

During preprocessing of the images a contrast limited adaptive histogram equalization (CLAHE) [21] is applied in order to improve contrast and enhance the paper structure. After this contrast enhancement all images are converted to grayscale and several patches are extracted from random positions in the images to reduce the computational effort and increase the amount of data that can be extracted from each package. Figure 2 shows the paper structure of different packages extracted from the random patches after preprocessing.

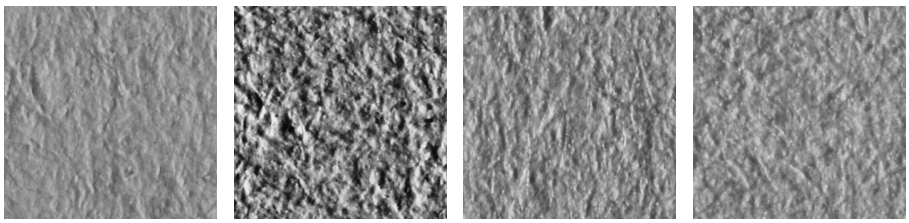

Fig. 2: Example preprocessed image patches

2.3 Feature Extraction Techniques

All techniques tested in this work are usually used for texture classification, image tampering detection and printer/paper identification and are applied on

the preprocessed images taken from the inside of the package. The techniques utilized in this work are briefly described in the following list, further information on the single techniques can be found in the corresponding papers.

- Histogram
  Gray-level histogram of all pixels as the extracted feature.
- LBP: Local Binary Patterns
  The local binary patterns (LBP) by Ojala *et al.* [14] observe the variations of pixels in a local neighbourhood and are represented in a histogram.
- DMD: Dense Micro-block Difference
  Texture classification approach by Metha *et al.* [9] which captures the local structure from the image patches at high scales, but instead of the pixels small blocks which capture the micro-structure of the image are processed.
- RI-LPQ: Rotation-Invariant Local Phase Quantization
  The rotation-invariant local phase quantization (RI-LPQ) by Ojansivu *et al.* [15] consists of two stages: Estimation of the local characteristic orientation for a given image patch and directed descriptor extraction.
- Dense SIFT: Dense Scale Invariant Feature Transform
  Lowe [8] proposed a technique used in object recognition which is commonly known as scale invariant feature transform (SIFT). This technique is invariant to image scale and rotation and robust against various affine distortions, addition of noise, illumination changes and changes of the viewpoint.
- GLCM: Gray-level Co-occurence Matrix
  Mikkilineni *et al.* proposed to use gray-level co-occurence features for printer identification in [11]. The features model the spatial relationships among the pixels of an image to represent its texture information.
- WP: Weber Pattern
  In [12] Muhammad proposed a multi-scale local texture descriptor which was applied as part of an image forgery framework.
- BSIF: Binarized Statistical Image Features
  The Binarized Statistical Image Features (BSIF) proposed by Kannala *et al.* in [7] rely on pre-computed local image descriptors which efficiently encode texture information.
- LSB+JD: Least Significant Bitplane + Jaccard Distance
  Extraction of the images least significant bitplane (LSB-plane) and calculate the Jaccard distance between the LSB-planes of two images.

2.4 Classification Approach

The features extracted with the techniques described in the previous section are used to classify the images of the various kinds of drug packages.

The classifier is designed according to the improved Fisher vector (IFV) SVM classifier in [2]. The features are soft-quantized using a Gaussian mixture model (GMM), decorrelated and dimensionality reduced by PCA to obtain a Fisher vector (FV) encoding. A pre-trained linear SVM is then used to classify the IFV encoded features. The SVM is trained using a subset of the package's images which is subsequently not used for the testing (evaluation) step.

3 Experimental Settings

The following section describes the dataset used in this work, which contains images showing the paper structure of different forged and original drug packages. Furthermore a description of the two different dataset splits and our evaluation methodology to avoid overlapping between training and testing data is given.

3.1 Dataset

Table 1: Number of genuine (G) and forged (F) packages in the data set with drug name, corresponding ID and manufacturer (MF).

ID	Name	# G	# F	MF
1	Levitra	3	4	A
2	Kijimea Reizdarm	2	0	B
3	Kijimea Immun	1	0	B
4	Kijimea Derma	2	0	B
5	Narumed	3	0	B
6	Deseo	4	0	B
7	Signasol	2	0	B
8	Neradin	4	2	B
9	Unistop	2	0	C

Unfortunately, only a limited number of drug packages was available for our work. In particular we have packages of 9 different kinds of drugs from 3 different manufacturers denoted by A, B and C.

For all 9 kinds of drugs we have genuine packages and for 2 of them we also have forged packages. The forged packages for the *Levitra* drug (ID 1) are real counterfeits confiscated by customs, while the forged packages for the *Neradin* drug (ID 8) have been purpose-made by the manufacturer of the drug.

Table 1 lists the number of genuine and forged packages for each kind of drug (ID 1...9). We acquired 10 to 20 slightly shifted and overlapping images from each of the packages' interiors from which 5 patches of 512×512 pixels are extracted at random position within each image. The extracted patches correspond to a section of approximately $4.1 \times 4.1mm$, or $16.81mm^2$, of the package. From this data we generated two distinct data sets to analyze two different issues using the paper structure of the packages:

1. Is it possible to distinguish different packages of the same manufacturer?
2. Is it possible to distinguish packages of different manufacturers?

The first data set, *SMDP* (Same Manufacturer Different Packages), contains images from packages of the same manufacturer, which correspond to the manufacturer B in table 1. We only considered packages of this manufacturer since it is the only one from which we had more than one different type of drug package.

The second data set, *FGDM* (Forged and Genuine Different Manufacturers), contains images from all the packages, genuine and forged, from all manufacturers in table 1.

3.2 Evaluation Methodology

To investigate the two questions of section 3.1, we split the evaluation according to the two data sets SMDP and FGDM.

For the SMDP data set, where we want to find out if it is possible to distinguish between different types of drug packages from the same manufacturer, images having the same drug ID are defined as corresponding to the same class. A class thus can contain images from different packages of the same drug. Forged and genuine packages are furthermore split into different classes. This yields 8 different classes, because we have 7 different types of drug packages for manufacturer B and for one drug we also have 2 packages, which have been forged by the manufacturer.

To find out if it is possible to distinguish packages of different manufacturers (FGDM data set), images having the same manufacturer ID are defined as corresponding to the same class. Forged and genuine packages are again split into different classes for the *Levitra* drug produced by manufacturer A, but not for the *Neradin* drug of manufactuer B because these forgeries have been produced by the manufacturer and use the same material as the genuine packages. The different classes for the SMDP and FGDM data set are summarized in table 2.

Table 2: Evaluation classes and corresponding IDs with number of packages

Name	# Packages	SMDP Class ID	FGDM Class ID
Levitra forged	4	-	1
Levitra genuine	3	-	2
Kijimea Reizdarm genuine	2	1	3
Kijimea Immun genuine	1	2	3
Kijimea Derma genuine	2	3	3
Narumed genuine	3	4	3
Deseo genuine	4	5	3
Signasol genuine	2	6	3
Neradin forged	2	7	3
Neradin genuine	4	8	3
Unistop genuine	2	-	4

The acquired images of the drug packages are slightly overlapping, this might lead to patches of the same image belonging to both, the training and the testing subset. Hence we used leave one package out (LOPO) for the selection of the training and testing images/patches: Training is done with randomly selected patches from all images except the images from one specific package. The patches for the testing subset are then randomly selected only out of images from this package. If there is only a single package in a class, like for the class with ID 2 in the case of the SMDP data set, the patches for this class are only used to train the classifier. Thus, no intra-class comparisons for this class exist and the average precision is not calculated and shown as 0 in the plots. By using the LOPO approach for the evaluation, the slight overlap of images from the same package does not introduce any bias to the results.

4 Experimental Results

This section presents the results of the conducted experiments and the conclusions made from those. We analysed the two cases, at first the separation according to manufacturer (FGDM) and second the separation of packages all from the same manufacturer (SMDP).

Table 3: Mean accuracies (mAcc) and mean average precisions (mAP)

Data set	FGDM		SMDP	
Method	mAcc	mAP	mAcc	mAP
BSIF	0.428	0.403	0.138	0.171
DMD	0.97	1	0.328	0.423
DenseSIFT	0.91	1	0.37	0.476
GLCM	0.953	0.964	0.14	0.18
Histogram	0.603	0.662	0.145	0.176
LBP	0.758	0.863	0.265	0.272
LSB	0.71	0.818	0.113	0.182
RI-LPQ	0.842	0.888	0.158	0.226
WP	0.861	0.896	0.158	0.197

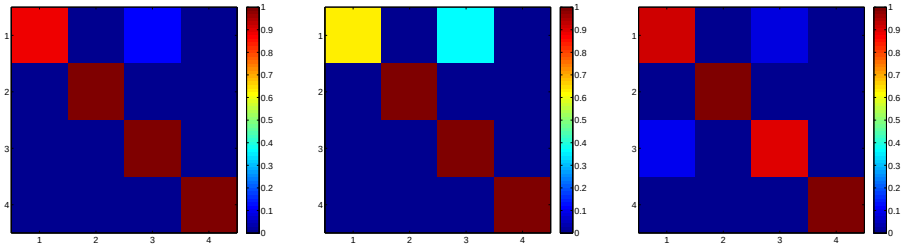

Fig. 3: Confusion matrix for DMD, DenseSIFT and GLCM in the FGDM case

Table 3 lists the mean accuracies (mAcc) and mean average precisions (mAP) for both cases. The mean accuracy corresponds to the mean of the values of the confusion matrix diagonal. It can be seen that for FGDM the results for DenseSIFT and DMD are close to 100% meaning that almost a perfect classification of the paper and thus the manufacturer is possible. Consequently, the true forgeries (corresponding to class 1) can be seperated from the other classes well.

Some example confusion matrices using a heat map for selected feature types (DMD, DenseSIFT and GLCM) can be seen in figure 3 and figure 5 for the FGDM and SMDP case, respectively. The numbers on the axes denote the classes according to table 2, which shows the correspondence of the class labels to the drug packages. Figures 4 and 6 show the corresponding average precision plots for FGDM and SMDP, respectively. These confirm that the recognition works well if the split is done according to different manufacturers and does not work if the split is done according to different drugs all from the same manufacturer.

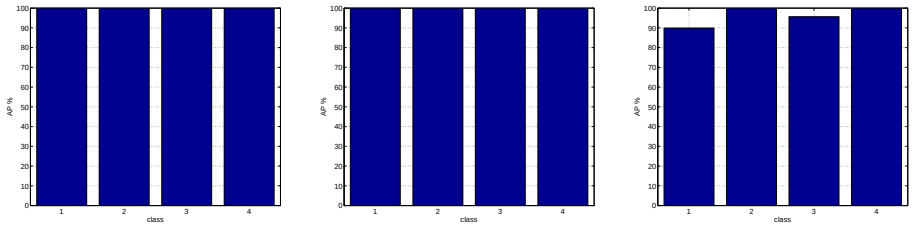

Fig. 4: Average precision for DMD, DenseSIFT and GLCM in the FGDM case

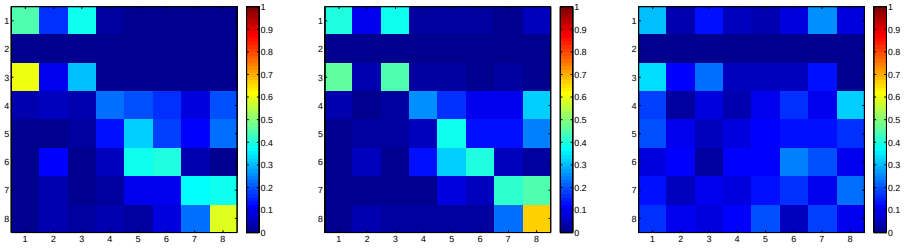

Fig. 5: Confusion matrix for DMD, DenseSIFT and GLCM in the SMDP case

We do not have any information about which kind of paper is used for the different drug packages. But the experimental results suggest (distinction between different types of drugs from the same manufacturer was not possible) that one manufacturer uses the same kind of paper and the same printing facility/printing process for his drug packages. As long as the forgers do not have access to the same kind of printing facility the genuine manufacturers utilizes, drug counterfeit detection is feasible using our proposed approach.

5 Conclusion

In this paper we investigated whether counterfeit drug package detection using texture classification based on the intrinsic paper texture is possible. The available data was split to investigate two different issues.

In the SMDP case (same manufacturer) a distinction between single packages of the same manufacturer was not possible. We concluded that this is not

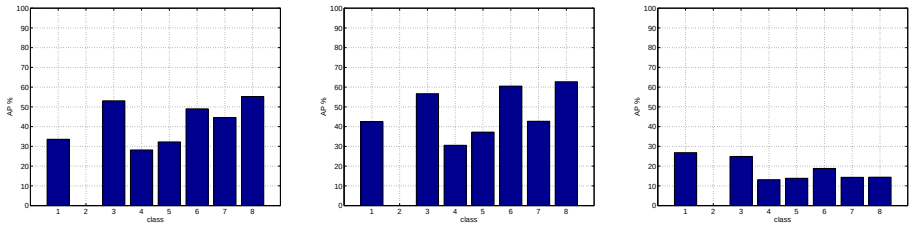

Fig. 6: Average precision for DMD, DenseSIFT and GLCM in the SMDP case

possible because all packages have very likely been produced using the same manufacturing process and therefore share a very similar paper structure.

In the FGDM case (different manufacturers) it was indeed possible to classify different genuine and forged packages with high accuracy. This indicates that it is possible to identify counterfeit packages not produced by the original manufacturer, since they are most likely being produced in a different manufacturing facility and hence do not share a similar paper structure. The class containing the forged packages and the classes containing genuine packages could all be clearly separated in this case.

This promising results however have to be taken with a grain of salt because of the small data set size and the availability of only a few real counterfeit packages. Hence the first step of our future work is the acquisition of more test data, i.e. a higher number of distinct types of drug packages and even more important more counterfeit and genuine packages of the same type of drug. In addition we want to acquire further information about the printing and manufacturing process of the packages.

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References

1. J. Buchanon, R. Cowburn, A.-V. Jausovec, S. Petit, D., G. P., Xiong, D. Atkinson, K. Fenton, D. Allwood, and T. Bryan. Forgery: Fingerprinting documents and packaging. *Nature*, 436:475, 2005.
2. M. Cimpoi, S. Maji, I. Kokkinos, S. Mohamed, and A. Vedaldi. Describing textures in the wild. In *Proceedings of the IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2014.
3. W. Clarkson, T. Weyrich, A. Finkelstein, N. Heninger, J. Halderman, and E. Felten. Fingerprinting blank paper using commodity scanners. In *Proceedings of the 30th IEEE Symposium on Security and Privacy*, pages 301–314, 2009.
4. M. Diephuis, F. Beekhof, S. Voloshynovskiy, T. Holotyak, N. Standardo, and B. Keel. A framework for fast and secure packaging identification on mobile phones. In *Proceedings of SPIE Photonics West, Electronic Imaging, Media Forensics and Security V*, San Francisco, USA, January, 23 2014.
5. M. Diephuis, S. Voloshynovskiy, and F. Beekhof. Physical object identification based on famos microstructure fingerprinting: comparison of templates versus invariant features. In *8th International Symposium on Image and Signal Processing and Analysis*, Trieste, Italy, September, 4-6 2013.
6. M. Diephuis, S. Voloshynovskiy, and T. Holotyak. Sketchprint: Physical object micro-structure identification using mobile phones. In *European Signal Processing Conference (EUSIPCO)*, Nice, France, 31 August - 4 September 2015.
7. J. Kannala and E. Rahtu. BSIF: binarized statistical image features. In *Proceedings of the 21st International Conference on Pattern Recognition, ICPR 2012, Tsukuba, Japan, November 11-15, 2012*, pages 1363–1366, 2012.

8. D. G. Lowe. Distinctive image features from scale-invariant keypoints. *Int. J. Comput. Vision*, 60(2):91–110, Nov. 2004.
9. R. Mehta and K. Egiazarian. *Texture Classification Using Dense Micro-block Difference (DMD)*, pages 643–658. Lecture Notes in Computer Science. Springer-Verlag, Berlin, 2015.
10. E. Metois, P. Yarin, N. Salzman, and J. Smith. Fiberfingerprint identification. In *Proceedings of the 3rd Workshop on Automatic Identification*, New York City, USA, 2002.
11. A. K. Mikkilineni, P.-J. Chiang, G. N. Ali, G. T. C. Chiu, J. P. Allebach, and E. J. Delp III. Printer identification based on graylevel co-occurrence features for security and forensic applications. volume 5681, pages 430–440, 2005.
12. G. Muhammad. Multi-scale local texture descriptor for image forgery detection. In *Industrial Technology (ICIT), 2013 IEEE International Conference on*, pages 1146–1151, 2013.
13. OECD and EUIPO. Trade in counterfeit and pirated goods. *OECD Publishing*, page 138, 2016.
14. T. Ojala, M. Pietikainen, and D. Harwood. Performance evaluation of texture measures with classification based on kullback discrimination of distributions. In *Proceedings of the 12th IAPR International Conference on Pattern Recognition*, volume 1, pages 582 –585 vol.1, Oct. 1994.
15. V. Ojansivu, E. Rahtu, and J. Heikkila. Rotation invariant local phase quantization for blur insensitive texture analysis. In *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*, pages 1–4, Dec 2008.
16. W. H. Organization. International medical products taskforce - brochure. `http://apps.who.int/impact/FinalBrochureWHA2008a.pdf?ua=1`[last accessed: 29.04.16].
17. M. Varma and A. Zisserman. A statistical approach to material classification using image patch exemplars. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(11):2032–2047, Nov 2009.
18. S. Voloshynovskiy, M. Diephuis, F. Beekhof, O. Koval, and B. Keel. Towards reproducible results in authentication based on physical non-cloneable functions: The forensic authentication microstructure optical set (famos). In *Proceedings of IEEE International Workshop on Information Forensics and Security*, Tenerife, Spain, December 2–5 2012.
19. C. W. Wong and M. Wu. Counterfeit detection using paper puf and mobile cameras. In *Information Forensics and Security (WIFS), 2015 IEEE International Workshop on*, pages 1–6, Nov 2015.
20. C. W. Wong and M. Wu. A study on puf characteristics for counterfeit detection. In *Image Processing (ICIP), 2015 IEEE International Conference on*, pages 1643–1647, Sept 2015.
21. K. Zuiderveld. Graphics gems iv. chapter Contrast Limited Adaptive Histogram Equalization, pages 474–485. Academic Press Professional, Inc., San Diego, CA, USA, 1994.