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ENHANCING FAKE PRODUCT DETECTION USING DEEP LEARNING OBJECT DETECTION MODELS

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ABSTRACT

ResearchAndMarkets wrote in their report on May 15, 2018, that up to 1.2 Trillion USD in 2017 of products are counterfeited goods. The report estimated this damage globally at 1.82 Trillion USD in 2020. This paper does not consider copyright infringement, digital piracy, counterfeiting or fraudulent documents, but rather examines the prevention of counterfeiting on a technological basis. The presence of counterfeit products on the European and US markets increase, the intervention of inspection bodies and authorities alone is obviously not sufficient, but consumers could make their contribution and improve the situation. In this paper, we research the possibility to reduce counterfeit products using machine learning-based technology. Image and text recognition, and classification based on machine learning have the potential to become the key technology in the fight against counterfeiting. Image recognition and classification of product information empowers the end customer to identify counterfeits accurately and efficiently by comparing them with trained models. The goal of this paper is to create an easy, simple, and elegant application, which empowers the end-users to identify counterfeit products and as such contribute to the fight against product piracy.

KEYWORDS

Anti-Counterfeiting, Deep Learning, Image Recognition, Object Classification, Transfer Learning

1. INTRODUCTION AND CURRENT PROBLEM

Detection of counterfeit products is in certain cases a challenge for the consumers and can sometimes be dangerous when it comes to medical products or toys for children, for example. ResearchAndMarkets wrote in their report on May 15, 2018, that up to 1.2 Trillion USD in 2017 of products are counterfeited goods. The report estimated this damage globally at 1.82 Trillion USD in 2020 (Research and Markets, 2018).

Even though these markets are protected by inspection bodies and authorities, the presence of counterfeit products on the European and US markets are increasing (OECD/EUIPO, 2016) & (Homeland Security- Office of Strategy, Policy & Plans, 2020), impressively demonstrating that these protection mechanisms and approaches alone are not sufficient. Since its launch in 2003, the EU's Rapid Alert System has been providing EU member States with a network and communication tools to publicize counterfeit products. The system stabilizes at regular intervals, about 50 alerts are published each week on the European Commission's website, with slightly more than 2,000 alerts released each year. (Directorate-General for Justice and Consumers (European Commission), 2018). The number of counterfeits reported products is extremely low in relation to the number of counterfeit products imported into the EU. The OECD wrote in their report 2016 that up to 5% of imports are counterfeited goods. The report quantified this damage at EUR 85 billion (OECD/EUIPO, 2016). A major problem of such governmental instruments is that the end-consumers are not involved, if at all, in the detection process of counterfeiting. In contrast, the low production costs and easy access to millions of potential customers and listing near well-known brands provides a highly profitable and easy way to sell counterfeits and pirated goods through e-commerce (Homeland Security- Office of Strategy, Policy & Plans, 2020).

The market surveillance authorities require generally that a product must pass through and prove certain regulations and standards before it can be imported and sold in the internal market. This verification can be provided either by a self-declaration by the manufacturer, supported by appropriate tests, or by certification of an independent third party from the certification industry. The approached solution in this paper focuses on those products which have falsified certification or and quality marks because:

- The quality of the certificate on the product significantly increases the probability of purchase by five and the willingness to pay by 15 percentage points. Even 36% of consumers mistakenly classify TÜV SÜD as a government testing institute. (SPLENDID RESEARCH GmbH, 2020).
- The market surveillance authorities require that a product must pass through and prove certain regulations and standards before it can be imported and sold in the country. This verification can be provided either by a self-declaration by the manufacturer, supported by appropriate tests, or by certification by an independent third party from the certification industry (TIC Council, Anti-Counterfeiting Committee., 2020).

In the next section, we will highlight the subject of counterfeit domains and focus on the area where the use of IT technology can make a positive contribution. After introducing the related works, we will outline the solution concept and technical architecture, then we will focus on the implementation and evaluation of such solutions and their challenges. Finally, we will review the results of our work and consider the outlook for the future.

2. RELATED WORKS

The term "**counterfeit**" has been associated to different categories of goods, which has been copied, modified or re-branded in different ways. There are various categories of counterfeit goods in different domains and a precise taxonomy for each domain is out of the scope of this work, but we will provide an example from the electronic products market sectors, which are heavily impacted by the counterfeit problem. A potential taxonomy of the different counterfeit electronic products has been presented in (Guin, et al., February 2014) and it reused here:

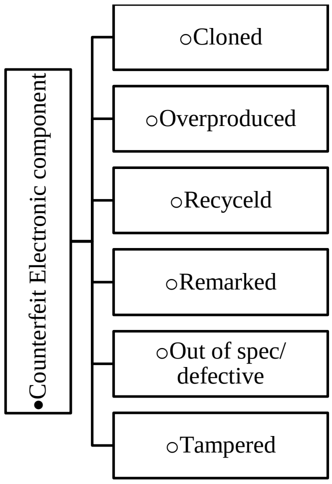

Figure 1. A taxonomy of the counterfeit electronic products adapted from Guin, et al. 2014)

Where the different categories are described to: **Cloned:** cloning can be done by a) reverse engineering, and, b) by obtaining intellectual property (IP) illegally. **Overproduced:** due to globalization, design houses outsource their designs for fabrication and packaging to companies all around the world, mainly to reduce the manufacturing cost. Overproduction occurs when foundries and packaging companies sell components outside of contract with the design house (Tran, 2017). Note that this category does not include overproduced goods, which have identical components and design of valid goods. In this case, this is considered a contract policing issue. This category is related to overproduced goods, which have different components or materials (often of lower quality). **Out-of-Spec/Defective:** a part is considered defective if it produces an incorrect response to post-manufacturing tests. These parts should be destroyed, downgraded, or otherwise properly disposed of. However, if they instead are sold on the open markets, either knowingly by an untrusted entity or by a third party who has stolen them, there will be an unknown increase in the risk of failure. **Recycled:** it refers to an electronic component that is reclaimed/recovered from a system and then modified to be misrepresented as a new component of the proper manufacturer. Recycled components can be declared counterfeit if they are not declared as such and they are instead sold as genuine/new components. **Remarked:** most legitimate components contain markings on their packages that indicate manufacturer, trademark, part number, grade, lot code, etc. If a company is remarked to indicate another model or category, it can be considered counterfeit. **Tampered:** components that are tampered can have dangerous consequences for the systems that incorporate them for security and safety. In this case, a good can be considered counterfeit when it has been tampered to replace internal components.

In our work we focus according to (Guin, et al., February 2014) on the categories **Overproduced, Out-of-Spec/Defective, Remarked and Tampered**

After having defined the term “counterfeited product”, anti-counterfeiting technologies should provide an end consumer-friendly approach to detect counterfeited products. The challenge here is to keep a balance between ensuring the businesses from the financial point of view and terms of reputation. According to (Li, 2013) these technologies usually have four main features:

- difficult to duplicate or forge,
- easily identifiable visually without the need of special equipment,
- hard to re-label or reuse, and
- easily noticeable when tampered with.

From a product standpoint, there are three common categories for anti-counterfeiting: **overt**, **covert**, and **track and trace**, shown in Figure 2. **Overt** technologies focused on the packaging of the products. Color-shifting inks, watermarks and holograms are some of the technologies that can be used in this category. End consumers need to be briefed in advance so that they interpret these technologies correctly to verify the fake products. **Covert technologies** like ultraviolet (electromagnetic radiation) and bi-fluorescent are also applied to the product itself but are not identifiable without special equipment. Digital watermarks, hidden printed messages and pen-reactive ink are also part of the covert technologies.

The final category is **track and trace**. Radio Frequency Identification (RFID) tags, Electronic Product Codes (EPCs) and barcodes are the main technologies in this category. The possibility of a holistic tracking and tracing approach contributes to the overall goal to reduce counterfeit products. Consumers and retailers scan the code already implemented by suppliers and manufacturers to verify the authenticity of the product or to trace the overall supply chain process.

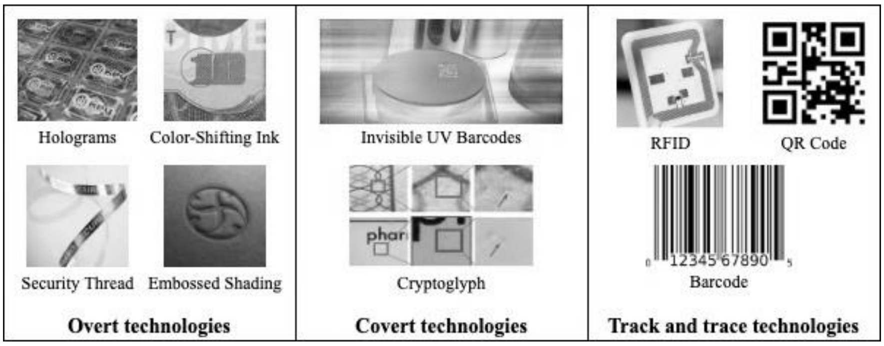

Figure 2 Anti-counterfeiting technologies

There are other approaches based on improved communication between companies and organizations with the interest to reduce counterfeiting on the market - an example is React. React is a not-for-profit organization providing a market, and online and customs enforcement professional services (React, 2020). Professional services approaches have a big advantage concerning accuracy, but still work with the manual process and need manpower. All three technologies mentioned in Figure 2 Anti-counterfeiting technologies have disadvantages and limitations. In previous work, we have addressed the subject in detail but with the use of blockchain technologies (Daoud & Gaedke, 2019) and we found also a lot of limitations in the related work. Counterfeiters are becoming more and more professional and sophisticated. They are always developing approaches to better package counterfeit products and bring them to the market undetected (Shields & Deshmukh, 2020). Consequently, **overt** and **covert** technologies can be easily imitated. It is difficult for the average end-consumer to distinguish between a convincing imitation and the real product. Besides, **covert** technologies are required special devices to identify counterfeited products so that customers are neither able to detect nor verify their products. The **track and trace** technologies with its encoding and security feature can be used in combination to improve this situation but it leads to another major issue: overhead cost. As an effect, the price of a product continuously increases, which in certain cases eventually encourages the end user to seek out counterfeit products (Li, 2013).

Based on these findings, this paper proposes a low-cost and user-friendly solution by relying on machine learning-based technology, which enables end-consumers to identify and to verify products without any special equipment. By using image and text recognition, this approach aims to improve fake product detection. It can also be combined with Track and Trace technologies to help combat counterfeiting even more efficient and effective. In the next section, we will introduce the concept behind the solution and the corresponding technical architecture.

3. CONCEPT AND TECHNICAL ARCHITECTURE

According to the report of (Statista, 2019), the current number of mobile phone users in the world is 4.78 billion, of which 3.5 billion are smartphone users. Today, with a low price, users can easily own a smartphone with a built-in digital camera and internet access. Based on that, our proposed solution will allow the end-consumers to use their phones as equipment to detect products with fake certification marks/logos.

Figure 4 shows two typical use cases of our solution. For detection, the end-consumer takes pictures of a product packaging, which contains product text information, logos, and certification marks/logos. These pictures will be sent in a request to the server for processing and verifying. Afterwards, the detection result will be returned to the end-consumer to make a further decision. In the case of fake product detection, the end-consumer could report this counterfeit product to the government system, such as the Safety Gate© - EU's Rapid Alert System. Thereby, our proposed solution could make the detection more accessible and convenient for end consumers, as well as connect quickly with authority people for reporting counterfeited products.

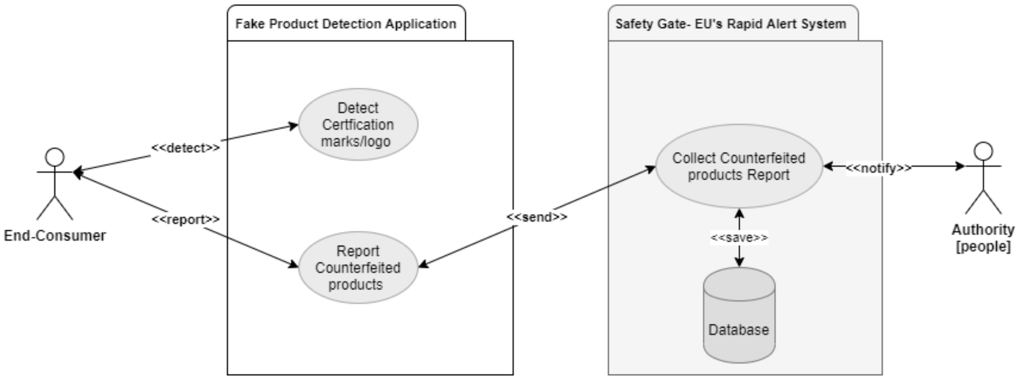

Figure 3. The typical use case of detection and reporting

An overall concept of this approach is shown in Figure 4. In the Fake Product Detection Application, there are two main components: a web server and a Deep Learning application. The web server will be acted as the middle layer. It receives requests (pictures and metadata) from the end-users (the client-side) and forwards this request information to the Deep Learning application for detection. Afterwards, the web server receives the detection result and sends the response back to the client. Also, the server also performs several operations, such as storing detection results, data statistics, or allowing users to report counterfeit products.

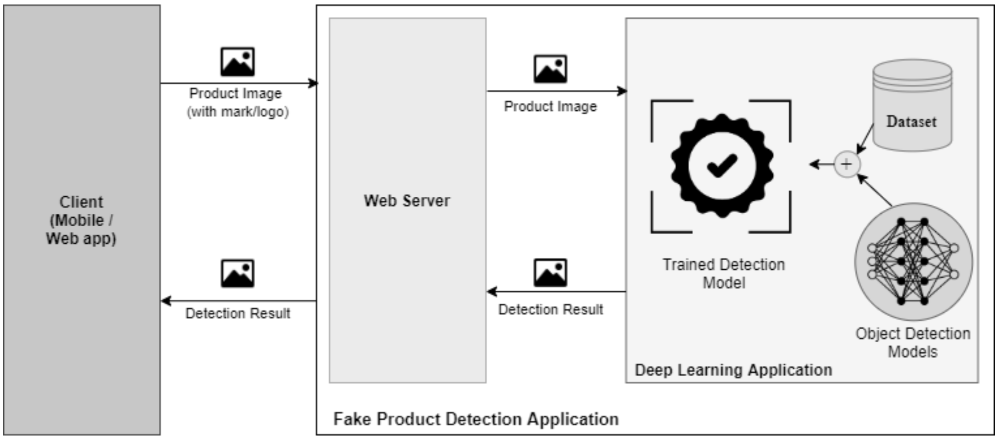

Figure 4. Overall Concept of Fake Product Detection Application

The second component- Deep Learning application- is the main contribution of our paper. It uses computer technology, called Object Detection, to detect and verify the certification mark/logo in the product images. To doing so, the application needs three main parts: **Dataset**, **Object detection models**, and **Trained detection model**. A good quality dataset is a fundament to achieve an efficient Deep Learning application. The dataset represents the related entities with their values, and it has two types: training dataset and test dataset. In our application, the dataset is a collection of the valid logo or/and mark.

Next, we need the Object detection models- the functions/algorithms which perform certain operations on the given input (product images with mark/logo) and procedure the suitable output (detection result). In our application, we use several pre-trained Deep Learning Object detection models with different object detectors (e.g., SSD (Liu, et al., 2016) and Faster R-CNN (Ren, et al., 2016)) and feature extractors (e.g., Restnet, Inception, Mobilenet), which will be discussed in detail in section 4.

Lastly, to create our trained detection model, we do a transfer learning by training the pre-trained Object detection models with our input dataset. As a result, our trained model will be used to verify the validity of the mark/logo.

To challenge the concept and the proposed solution is the first Deep Learning application, mainly concentrating on detecting fake products. We implement the solution in the next section and training the model with the certification body logo and the mark of TÜV SÜD AG. There are many reasons to assume, and based on the (OECD/EUIPO, 2016), that many counterfeiters use the certification agency logo to gain better access to the EU market.

4. IMPLEMENTATION

Based on the mentioned overall concept in section 3, two primary components need to be implemented. For the Web server, we build a web application by using Flask- a lightweight Python web application framework. This web application focuses on handling requests from the client (mobile/web browser application), which includes the digital product images with the mark/logo. In the backend, the images will be sent to the second component- our Deep Learning application, which is built with the Google Tensorflow library. This application runs the algorithms to identify the location of the mark/logo in the digital image (localization) and then classifies whether the mark/logo is valid or not (classification). At the end of this process, the detection result will be sent back to the Web server and then to the end-user.

In the rest of this section, we will focus on discussing in detail our Deep Learning application. Figure 5 shows a detailed implementation, which consists of 2 steps: **training model** and **detecting images**.

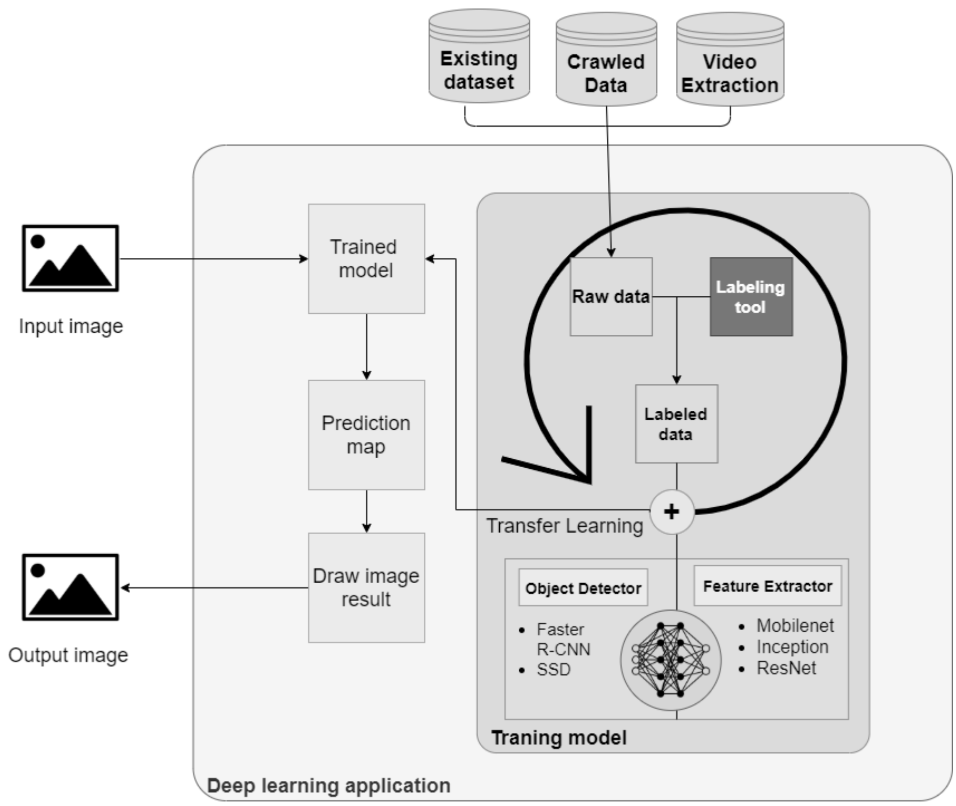

Figure 5. Implementation of Deep Learning application

4.1 Training Model

As the first step, the training model depicts a way we prepare dataset and select the Deep Learning pre-trained detection models.

4.1.1 Dataset Preparation

As the first step, we need to collect the authentic certification marks/logos as raw data and then do a labelling process. It is the most time-consuming step. For demonstration, we gather more than 2000 marks/logos of the Testing, Inspection, and Certification members (TÜV SÜD AG, Dekra, and Bureau Veritas) from our existing dataset and the crawled data (using web scraping tools). Moreover, to make our dataset more diverse and avoid overfitting, we also apply another technique to extract the certification marks and logos from video frames. Afterwards, we label our raw data by using annotation tools (i.e., LabelImg) and divide them into a training set (80%) and test set (20%). The collecting-labelling is not a one-time process. We operate it iteratively so that the Deep learning detection model could gain the ability to generalize and return more precisely outcome.

4.1.2 Selecting the Deep Learning Pre-Trained Object Detection Models

In our implementation, instead of investing time and effort to build our trained model from scratch, we use Transfer Learning. This optimization allows us to achieve a reliable performance quickly from the existing Deep Learning pre-trained Object Detection models. Hence, the next step is selecting suitable models that can fulfil the requirement of our solution. After an analysis phase, there are two main aspects that we consider are Object detectors for localization and Feature extractors for classification.

For **Object detectors**, there are two common meta-architectures: Region-based family detectors and Regression/Classification family detectors. On the one hand, the Region-based family detectors consist of 2 stages: region proposal and region classification. This family detector includes several versions, e.g., R-CNN (Region-based Convolutional Neural Networks) (R. Girshick, J. Donahue, T. Darrell and J. Malik, 2014), Fast R-CNN (Girshick, 2015), and Faster R-CNN (S. Ren, K. He, R. Girshick and J. Sun, 2017). In general, two first versions use an advanced technique, namely, Selection search (K. E. A. van de Sande, J. R. R. Uijlings, T. Gevers and A. W. M. Smeulders, 2011). This technique generates small segments from the image base on these different similarities: color, texture, size, fill, etc. Then it merges them repeatedly into large ones until the whole process becomes a single region. Since the images are divided into various small fragments based on its quality, the process of identity object inside these fragments are faster and more effective. In the next version- Faster R-CNN, the selective search is replaced by an advanced technique Region Proposal Network (RPN), which can adequately find the region which contains object by using different anchors boxes. In our implementation, we considered selecting Faster R-CNN because it can improve the speed of training and detection as well as ensures accuracy (same or even better) in comparison to the other versions.

On the other hand, the Regression/Classification family detectors need only one stage to fulfil the same request, which is also called single shot detectors. Two meta models in this object detector family are YOLO (you only look once) and SSD (single-shot detector). In YOLO, we divide an image into a grid of different sizes. Each grid and the confidence, which reflect the chance of the object if it appears on the box. In the final step, all the boxes are treated as a single input into the Convolution Neural Network (CNN). The advantage of Yolo is efficient in detecting image in high frame rate or real-time detector. However, it has more localization errors and struggles at finding the small object. The concept of SSD is the same as Yolo, which aim to use the various different size bounding box to find the most suitable box for objects. Both Yolo and SSD use a convolutional layer to extract features and a convolutional filter to make a decision. For selecting one of them in our implementation, both models are evaluated and compared, deciding for SSD in the end because of its higher accuracy.

Feature extractor aims to extract features from raw data sources (region output of object detector) and return output as a class label. Any state-of-the-art feature extraction model is built based on CNN, which is a breakthrough in computer vision since this deep neural network beats all previous approaches in image recognition. Different variations of CNN models are provided and improved from time to time, with higher accuracy and better detecting speed. Some of the outstanding models can be mentioned as Inception Network (C. Szegedy et al, 2015), ResNet (K. He, X. Zhang, S. Ren and J. Sun, 2016), and MobileNet (AG. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, H. Adam, 2017). It is worth noting that each mentioned model has different versions with iterative improvement from the previous one. While Resnet is a deep and complicated network - which focuses on improving accuracy, Inception is a shallower network and runs faster with decent accuracy. MobileNet, which requires less computation power to train or detect objects, is efficient for mobile and embedded vision applications (low resource devices). In our approach, we consider using four versions of the listed model, which include Inception Network, ResNet50, ResNet101, and MobileNet.

4.2 Detecting Image

As a result of the training model step, we now have the trained model, which is ready for detection. When an image is passed through our trained model, a prediction map will be returned to classify and localize the certification mark/logo we need to detect. To visualize the detection result for the end-user, the prediction bounding box, and the class label for each certificate mark are drawn on the uploaded, shown in Figure 6.

With the combination of different object detection models and feature extractors, this would result in diversity outcomes. Table 1 compares various detection models that are used in our paper.

Table 1. Comparison of different object detection models

Name	SSD Mobilenet v1	SSD Inception v2	SSD ResNet 50	Faster R-CNN Inception V2	Faster R-CNN ResNet 101
Object Detector	SSD	SSD	SSD	Faster R-CNN	Faster R-CNN
Feature Extractor	Mobilenet	Inception v2	Resnet 50	Inception v2	Resnet 101
Paramerter	3m	10m	23m	110m	42m
Focus	speed	speed	speed	accuracy	accuracy
Transfer dataset	coco	coco	coco	coco	coco
Batch size	24	24	64	1	1
FPS	22	20	11	9	5
MAP	21	24	35	25	32
Speed (ms)	30	42	76	79	106

As can be seen in Table 1, SSD MobileNet is the fastest model which archive at 22 frame per second (FPS) and only take 30 milliseconds to perform detection task. SSD ResNet 50 and Faster R-CNN ResNet 101 have highest accuracy, with the mean average precision (mAP) peaked at 35 and 32 respectively. For demonstration, the current version of our Fake Product Detection Application is now integrated into the CertificateOK platform, which can be found at https://app.certificateok.de/. In the following section, we will discuss the challenges of our approach before we headline the summary and an outlook on our work.

5. EVALUATION AND CHALLENGES

The approached solution has several improvements for the current anti-counterfeiting technologies. Firstly, it can be verified by average end-users, which can add a new protection layer to combat counterfeiting products. In comparison to the track and trace technologies mentioned in section 2, our solution provides a low-cost implementation, which is appropriate when the market is scaling up.

In addition, unlike overt technology, end-consumer does not need any special device to use our solution they only need a typical consumer mobile device for running the application and internet access to verify the genuineness of certification logo/marks. The detection result from our demonstration reveals the potential of machine learning-based technology to fight against counterfeiting. Our solution archives 97% precision at 3.1 seconds/certificate mark, on 400 tested data. As the result in Figure 6, the sophisticated forged marks can be detected, e.g. minor change in color, missing or incorrect text.

Figure 6. Tested results on TÜV SÜD AG certification mark

Similar to any other anti-counterfeiting technologies, issues and challenges arise for our machine learning-based approach. One of the challenges is the limitation of data for the training process. The amount of needed data to combat counterfeiting products is huge, but the existing data sources are limited. Furthermore, crawling data from the Internet and manually annotating consumes a lot of time. The more data we have, the more accuracy we can provide. Last but not least, 3.1 seconds for single certification mark detection is not efficient in real-time application. Hence, there is still room for improvement, e.g., considering other faster algorithms like YOLO (Redmon & Farhadi, 2019) but with the trade-off of accuracy. After highlighting the challenges, we headline a summary and an outlook on our work.

6. CONCLUSION AND OUTLOOK

This paper presents a new approach for an anti-counterfeiting machine learning-based solution to detect fake product. The machine learning-based approach used in core deep learning and neural network technologies. The conclusions we can derive from the new approach are that the implementation of the system should be deeper researched, from the point of view of collecting more training data and annotation/labelling service. The main focus is on how the implementation might have a positive impact on anti-counterfeiting of products and the adoption of machine learning-based detection depends on how the consumer can easily and simply interact with the system. By using image recognition, this approach can improve fake product detection. It can also be combined with over, covert and/or track and trace technologies to help combat counterfeiting more efficient and effective.

In future work, we plan to explore and research more in the direction of faster machine learning algorithms to classify marks and logos and to detect text with the help of OCR. In addition, we need to extend our web crawler to have the possibility to gather more web information, especially from the eCommerce world to find fake products with help of detecting logo, marks and text. This would combine three state-of-the-art technologies, machine learning, Text recognition and web searching in one application. That will bring great convenience and a better experience for users. However, we trust that using machine learning-based technology will change the role and empower the consumer to drive the market for more transparency and safety.

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