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X-RAY BAGGER BASED SECURITY ON AIRPORT USING DEEP LEARNING ALGORITHM

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ABSTRACT: Luggage screening is a very important part of the airport security risk assessment and clearance process. Automating the threat objects detection from x-ray scans of passengers' luggage can speed-up and increase the efficiency of the whole security procedure. We consider the use of CNN with transfer learning for the image classification and detection problems posed within the context of X-ray baggage security imagery. The use of the CNN approach requires large amounts of data to facilitate a complex end-to-end feature extraction and classification process. In particular, we focus on identifying harmful objects like knife, blades etc., as threat objects, being the main part of the weapon needed for deflagration. For this purpose, we use a dataset of 22k double view x-ray scans, containing a mixture of benign and threat objects. In the proposed system we employ deep learning techniques (Convolutional Neural Networks and VGG16) for the classification task. Furthermore, we validate our findings on a second dataset of double view x-ray scans. We report and critically discuss the results of the comparison on both models, showing the accuracy of our approach.

Keywords: *Deep learning, Convolutional Neural Networks and VGG16.*

1. INTRODUCTION

Security screening of X-ray baggage is majorly used to maintain security in transport, primarily in aviation and provides valuable image-based investigating operation for human admins reviewing immense, disorganized and immensely varying contents in baggage within a limited period [1]. Result of elevated consumers turnout in the universal traveling network and the increased attention on wider extension principles on national security, resulting in a challenged automated timeous classification of images task. The database images are the inputs that have been provided for checking it where it goes on to the pre-processing stage to analyze its width, height and many other features. After that, the next process that comes on to the stage is Convolutional Neural Network (CNN), where the image classification process occurs that is split up into class I and class II, where the first-class identifies the hazardous objects and the other class identifies the non-hazardous objects. For this methodology, YOLO

v3 (which is one type of CNN architecture) is applied for the X-ray image classification process. The problems that arise in automatic visualization X-ray baggage imagery can be treated as typical image classification issues [2]. In the following paragraph use of CNN in image classification is discussed. Further, the outline of a wide generalized background for CNN and an explanation of our approach in the application of these processes to object classification of X-ray baggage are described.

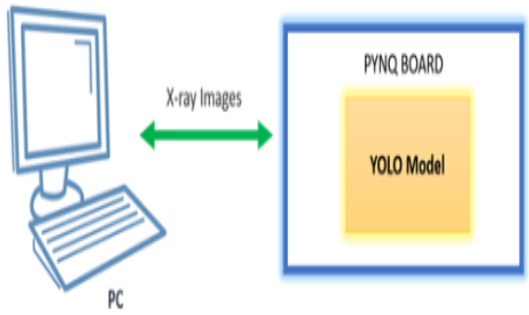

Fig.1: hazardous and Nonhazardous objects detector in X-ray images

And its inspiration by the outcome, the width of the network is entirely explored using the comparable area of the networks with dynamic width. By this, the study of the importance of networking core on classification accuracy by stacking convolutional layered parts with minor receptive fields is possible. The use of smaller receptive filters not only increases the non-linearity but also lowers down entire parameters. It has been shown that layers of convolutional kernels inside a network with dynamic depth can significantly improve the process. Duo stacked convolutional parts are used to feed the input. Later they are combined with the output. At last, the application of non-linearity is made. This process is repeated multiple times. For networks that are deep, filter factorization is carried out.

2. LITERATURE REVIEW

Towards Automatic Threat Detection: A Survey of Advances of Deep Learning within X-ray Security Imaging

X-ray security screening is widely used to maintain aviation/transport security, and its significance poses a particular interest in automated screening systems. This paper aims to review computerised X-ray security imaging algorithms by taxonomising the field into conventional machine learning and contemporary deep learning applications. The first part briefly discusses the classical machine learning approaches utilised within X-ray security imaging, while the latter part thoroughly investigates the use of modern deep learning algorithms. The proposed taxonomy sub-categorises the use of deep learning approaches into supervised and unsupervised learning, with a particular focus on object classification, detection, segmentation and anomaly detection tasks. The paper further explores well-established X-ray datasets and provides a performance benchmark. Based on the current and future trends in deep learning, the paper finally presents a discussion and future directions for X-ray security imagery

Transfer learning using convolutional neural networks for object classification within x-ray baggage security imagery

We consider the use of transfer learning, via the use of deep Convolutional Neural Networks (CNN) for the image classification problem posed within the context of X-ray baggage security screening. The use of a deep multi-layer CNN approach, traditionally

requires large amounts of training data, in order to facilitate construction of a complex complete endto-end feature extraction, representation and classification process. Within the context of X-ray security screening, limited availability of training for particular items of interest can thus pose a problem. To overcome this issue, we employ a transfer learning paradigm such that a pre-trained CNN, primarily trained for generalized image classification tasks where sufficient training data exists, can be specifically optimized as a later secondary process that targets specific this application domain. For the classical handgun detection problem we achieve 98.92% detection accuracy outperforming prior work in the field and furthermore extend our evaluation to a multiple object classification task within this context.

Driver Distraction Apprehension using Face Perception

Recognizing prohibited items automatically is of great significance for intelligent X-ray baggage security screening. Convolutional neural networks (CNNs), with the support of big training data, have been verified as the powerful models capable of reliably detecting the expected objects in images. Therefore, building a specific CNN model working reliably on prohibited item detection also requires large amounts of labeled item image data. Unfortunately, the current X-ray baggage image database is not big enough in count and diversity for CNN model training. In this paper, we propose a novel method for X-ray prohibited item data augmentation using generative adversarial networks (GANs). The prohibited items are first extracted from X-ray baggage images using a K-nearest neighbor matting scheme. Then, the poses of the obtained item images are estimated using a space rectangular coordinate system and categorized into four or eight classes for constructing a training database. For generating the realistic samples reliably, different GAN models are evaluated using Frechet Inception Distance scores, and some important tips of handling GAN training in X-ray prohibited item image generation are reported. Finally, to verify whether the generated images belong to its corresponding class or not, a cross-validation scheme based on a CNN model is implemented. The experimental results show that most of the generated images can be classified correctly by the CNN model. This implies that the generated prohibited item images can be used as the extended samples to augment an X-ray image database.

Occluded Prohibited Items Detection: an X-ray Security Inspection Benchmark and De-occlusion Attention Module

Security inspection often deals with a piece of baggage or suitcase where objects are heavily overlapped with each other, resulting in an unsatisfactory performance for prohibited items detection in X-ray images. In the literature, there have been rare studies and datasets touching this important topic. In this work, we contribute the first high-quality object detection dataset for security inspection, named Occluded Prohibited Items X-ray (OPIXray) image benchmark. OPIXray focused on the widely-occurred prohibited item "cutter", annotated manually by professional inspectors from the international airport. The test set is further divided into three occlusion levels to better understand the performance of detectors. Furthermore, to deal with the occlusion in X-ray images detection, we propose the De-occlusion Attention Module (DOAM), a plug-and-play module

that can be easily inserted into and thus promote most popular detectors. Despite the heavy occlusion in X-ray imaging, shape appearance of objects can be preserved well, and meanwhile different materials visually appear with different colors and textures. Motivated by these observations, our DOAM simultaneously leverages the different appearance information of the prohibited item to generate the attention map, which helps refine feature maps for the general detectors. We comprehensively evaluate our module on the OPIXray dataset, and demonstrate that our module can consistently improve the performance of the state-of-the-art detection methods such as SSD, FCOS, etc, and significantly outperforms several widely-used attention mechanisms. In particular, the advantages of DOAM are more significant in the scenarios with higher levels of occlusion, which demonstrates its potential application in real-world inspections.

3. IMPLEMENTATION

Luggage screening is a very important part of the airport security risk assessment and clearance process. Automating the threat objects detection from x-ray scans of passengers' luggage can speed-up and increase the efficiency of the whole security procedure. In this paper we investigate and compare several algorithms for detection of firearm parts in x-ray images of travellers' baggage. In particular, we focus on identifying steel barrel bores as threat objects, being the main part of the weapon needed for deflagration. For this purpose, we use a dataset of 22k double view x-ray scans, containing a mixture of benign and threat objects.

In the preprocessing stage we apply standard filtering techniques to remove noisy and ambiguous images (i.e., smoothing, black and white thresholding, edge detection, etc.) and subsequently employ deep learning techniques (Convolutional Neural Networks and Stacked Autoencoders) for the classification task. For comparison purposes we also train and simulate shallow Neural Networks and Random Forests algorithms for the objects detection. Furthermore, we validate our findings on a second dataset of double view x-ray scans of courier parcels. We report and critically discuss the results of the comparison on both datasets, showing the advantages of our approach.

DISADVANTAGES;

- Accuracy is low.
- These segmentation have shortcomings
- Feature extraction is not accurate
- Accuracy will be low Computation load very high.

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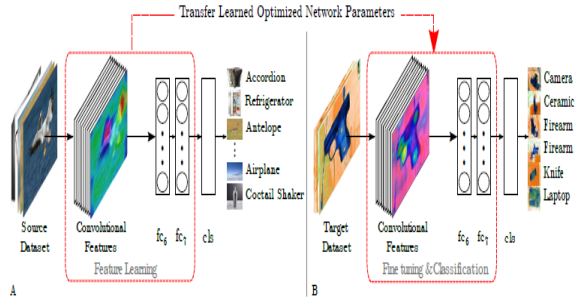

Fig.2: System architecture

ADVANTAGES:

- Speed and very low complexity, which makes it very well suited to operate on real scenarios.
- Computation load needed for image processing purpose is much reduced, combined with very simple classifiers.
- Ability to learn and extract complex image features.

MODULES:

1. Data Collection X-ray baggage security screening is widely used to maintain aviation and transport security, itself posing a significant image-based screening task for human operators reviewing compact, cluttered and highly varying baggage contents within limited time-scales.
2. Image Preprocessing:- Image processing is divided into analogue image processing and digital image processing. Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analogue image processing.
3. Data Augmentation Since the image classes are heavily imbalanced, we augment the training data to get balanced distribution among the classes.
4. Splitting of data After cleaning the data, data is normalized in training and testing the model. When data is spitted then we train algorithm on the training data set and keep test data set aside. This training process will produce the training model based on logic and algorithms and values of the feature in training data.
5. Classification: When data has been ready we apply Deep Learning Technique. We use different classification and ensemble techniques, to predict mental illness. The methods applied on brain MRI dataset. Main objective to apply Deep Learning Techniques to analyze the performance of these methods and find accuracy of them, and also been able to figure out the responsible/important feature which play a major role in prediction.

4. ALGORITHM

CNN:

In the past few decades, Deep Learning has proved to be a very powerful tool because of its ability to handle large amounts of data. The interest to use hidden layers has surpassed traditional techniques, especially in pattern recognition. One of the most popular deep neural networks is Convolutional Neural Networks.

CNN's were first developed and used around the 1980s. The most that a CNN could do at that time was recognize handwritten digits. It was mostly used

in the postal sectors to read zip codes, pin codes, etc. The important thing to remember about any deep learning model is that it requires a large amount of data to train and also requires a lot of computing resources. This was a major drawback for CNNs at that period and hence CNNs were only limited to the postal sectors and it failed to enter the world of machine learning.

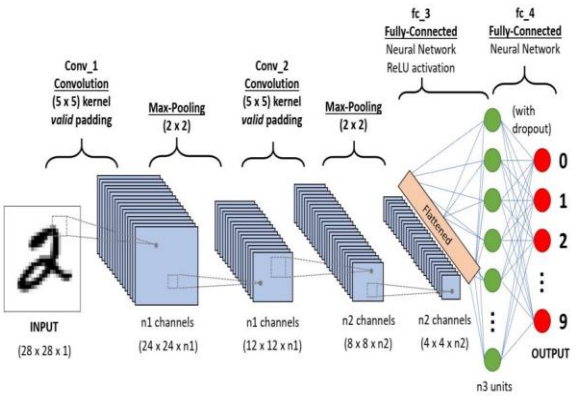

Fig.3: CNN model

Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and outputs an activation value. When you input an image in a ConvNet, each layer generates several activation functions that are passed on to the next layer.

VGG-16:

The ImageNet Large Scale Visual Recognition Challenge is an annual computer vision competition. Each year, teams compete on two tasks. The first is to detect objects within an image coming from 200 classes, which is called object localization. The second is to classify images, each labeled with one of 1000 categories, which is called image classification. VGG 16 was proposed by Karen Simonyan and Andrew Zisserman of the Visual Geometry Group Lab of Oxford University.

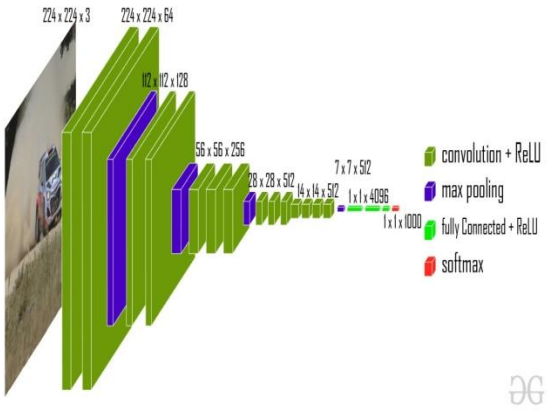

Fig.4: VGG16 model

5. EXPERIMENTAL RESULTS

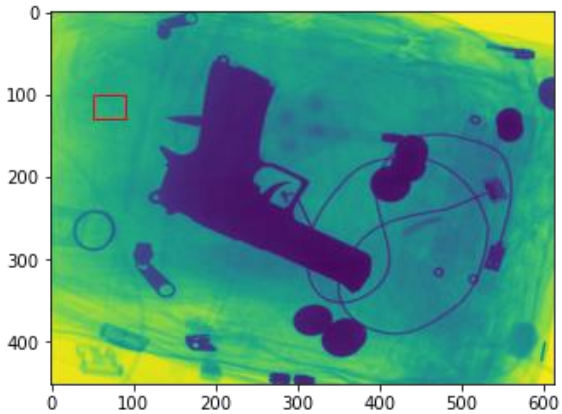

Fig.4: output

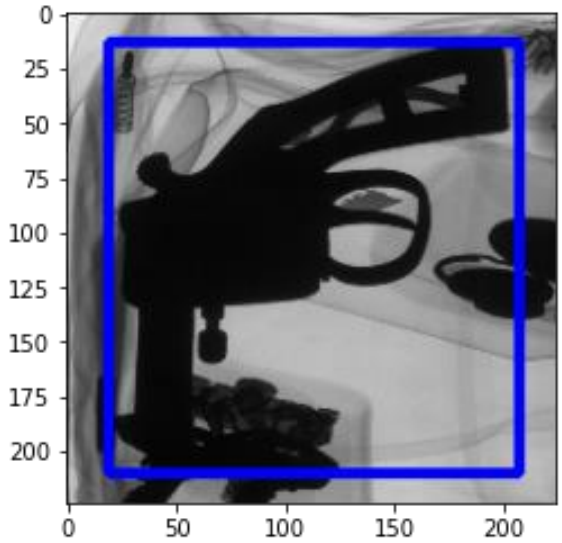

Fig.5: Output

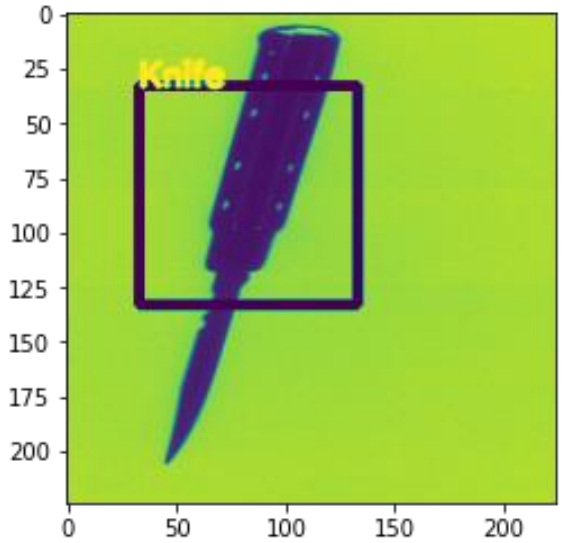

Fig.6: Output

6. CONCLUSION

The inspection of X-ray images is a challenging visual search task akin to finding a needle in a haystack. The majority of images that an operator is tasked with inspecting do not contain an abnormal, thus wasting time and money. In this report, we presented a modular framework based on modern machine vision and learning techniques that aims to assist security officers by partially automating the inspection process. By automatically sifting through large numbers of images, the proposed system would enable security officers to focus their attention on images that are likely to be anomalous, thus easing the inspection time constraint and making sure that the security infrastructure can be scaled-up as necessary with the ever-increasing volume of commerce. We demonstrated state-of-the-art performance for three tasks: i) gun detection, ii) knife detection and iii) 'small metallic threat' detection. In order to achieve these results, it was necessary to introduce several new methods such as location-specific appearance learning by providing the classifier with window coordinates, and threat image projection for the generation of de-novo synthetic training examples. To our knowledge, the proposed 'small metallic threat' detection module is the first application of convolutional neural networks to X-ray images.

REFERENCES

[1] S. Michel, S. M. Koller, J. C. de Ruiter, R. Moerland, M. Hogervorst and A. Schwaninger, "Computer-based training increases efficiency in X-ray image interpretation by aviation security screeners," in 41st Annual IEEE International Carnahan Conference on Security Technology, 2007.

[2] V. Riffo and D. Mery, "Active X-ray testing of complex objects," Insight-Non-Destructive Testing and Condition Monitoring, vol. 54, no. 1, pp. 28-35, 2012.

[3] D. Mery, V. Riffo, U. Zscherpel, G. Mondragon, I. Lillo, I. Zuccar, H. Lobel and M. Carrasco, "The database of X-ray images for nondestructive testing,"

Journal of Nondestructive Evaluation, vol. 34, no. 4, pp. 1-12, 2015.

[4] D. Mery, V. Riffo, I. Zuccar and C. Pieringer, "Automated X-ray object recognition using an efficient search algorithm in multiple views," in IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2013.

[5] G. Flitton, A. Mouton and T. Breckon, "Object classification in 3D baggage security computed tomography imagery using visual codebooks," Pattern Recognition, vol. 48, no. 8, pp. 2489-2499, 2015.

[6] N. Jaccard, T. W. Rogers, E. J. Morton and L. D. Griffin, "Tackling the X-ray cargo inspection challenge using machine learning," in Anomaly Detection and Imaging with X-Rays (ADIX), 2016.

[7] T. W. Rogers, N. Jaccard and L. D. Griffin, "A deep learning framework for the automated inspection of complex dual-energy xray cargo imagery," in Anomaly Detection and Imaging with X-Rays (ADIX) II, 2017.

[8] G. Li and Y. Yu, "Contrast-oriented deep neural networks for salient object detection," IEEE transactions on neural networks and learning systems, vol. 29, no. 1, pp. 6038-6051, 2018.

[9] Y. Shen, R. Ji, C. Wang, X. Li and X. Li, "Weakly supervised object detection via object-specific pixel gradient," IEEE transactions on neural networks and learning systems, vol. 29, no. 1, pp. 5960-5970, 2018.