Analysis on airport security of baggage screening using deep learning

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Abstract. Airports are the places where landings and take offs of the flights take place. In general, airports are preferred for traveling over large distances. While traveling in flights we carry our baggage which consists of various items, but the items that are prohibited in the baggage are scissors, knives, gun, and the electronic devices which cannot be switched off. Carrying dangerous items may lead to hijacking of flights and it even led to unusual situations in the airport. To prevent public from threat, airports generally have security inspection in which you will be required to pass your luggage through an X-ray machine where it will be checked for dangerous items. This analysis deals with software side of the security inspection and it is a brief study on various state-of-art proposed deep learning intended methods that are used to detect threat in baggage screening, advantages of their methodology, limitations, and gaps to be implemented.

Keywords: Airport Inspection, Threat Items, Hijacking, X-ray machine, Deep Learning.

1. Introduction

People prefer air transportation over large distances. People travelling with baggage should handover them to the cargo holdings. There are certain restrictions that a baggage should be within the required size and weight. Baggage's are often checked at airline systems to detect the threat items such as knife, gun, blade, and explosive devices etc., The baggage is transferred through the panel to check x-ray screening. The panel recognizes the threat items through imaging. The service agents will check the threat presence in the baggage through imaging from the panel and print the details of the passenger on a tag which will be notified as checked baggage. The research papers in the references had brought a new state-of-art methodologies in detecting the threat items in the baggage screening through Deep Learning (DL). The detection may be a masked image or may be the confidence percent in bounding box representation. The researchers use some custom datasets like either X-ray images or videos and custom models to build the state-of-art models.

2. Literature survey

There are many existing works for detecting the threat items and classifying the information with various datasets. In this survey, the state-of-art models of much research will be discussed. Taimur Hassan et al., proposed an unsupervised anomaly localization. They made a one-staged encoder-decoder utilization network to train the dataset at a time. The further testing was made, and they

achieved mean AP for five publicly available datasets individually. They scored 0.85 on GDXray which performs best on their proposed model [1]. The researchers presented a Hierarchical CNN model to the custom dataset which is named as ASS-BD which have video clips as datasets. The clips were taken at the airport baggage checking recording scenes. At last, they succeeded in increasing their mean AP for their custom dataset [2]. The author Wei Zhang et al., introduced a detection model through an automated mode for threat items based on depth wise and combination of three pretrained models. One of the best parts of this model is high detection accuracy, fast computational speed [3]. Priscilla Steno et al., made research which aims to the improvement of faster R-CNN. The researchers made an improved regional based proposal of faster R-CNN. Therefore, the proposed model shown a 15% of improvement to their existing method on localizing the threat items [4]. The researchers made a frequency resolution increase on the input images that are being used. They have employed a multi-scale convolution neural network (CNN) for identifying the material class based on the Dual Energy X-ray scans (DEXS) data which is limited to six fixed classes [5]. Hyo-young et al., proposed learning-based image synthesis for hazardous object detection. They have use average precision (AP) and mean AP for object detection performance. Finally, the proposed method improves performance of various object detection [6]. Xianglong Liu et al proposed an over-sampling de-occlusion attention network (DOAM-O).This model improves the rate of performance of some famous object detection models like SSD, YOLOv3. The models also achieved an impressive result [7]. The researchers used DL based models and CV algorithms to combine large number of x-ray images. They have categorized the threat items as knives, blade, gun, and shuriken. After the evaluation of each category, they have obtained mean AP precisely [8]. This paper tackles the problem through the pixel-based approach. Since the pixels in X-Ray images shows the radiation energy and thus signifies that the darker or denser the pixel regions are the higher the chance of being overlapped objects. The authors also noted that Mask RCNN method is more accurate (93%) than Faster RCNN where the most items exhibit dense material properties [9]. The authors Boying Wang et al proposed Real-world Prohibited Item Detection. The datasets they have used for this work are PIDray dataset. They have use AP, AR, and IOU metrics. Finally, they show that this model will help to evaluate the prohibited items recognition in real applications [10]. The authors Taimur Hassan et al presented a single-staged instance segmentation framework and it is only the framework that has been validated on combined grayscale and colored scans. Mean AP obtained by using the proposed method on GDXray is 96.72 [11]. The authors of this paper proposed a novel detection strategy called as Cascaded Structure Tensor (CST) is to identify obstructed or overlapped objects. This scheme works on any grayscale or colored X-ray scan for recognizing the potential threats [12]. The authors hyo-young Kim et al., proposed detail restoration and tone mapping networks. Generally, there is no publicly available dataset we have constructed a synthetic dataset. Finally, they show that proposed method achieves visually compelling images with improved details [13]. The authors Bangzhong Gu et al., proposed Automatic and robust object detection in X-ray baggage inspection. The datasets they have used for this work are Xdb1 and Xdb2 datasets. The automation work achieved as best when compared with existing models [14]. Neelanjan Bhowmik et al made a Transfer Learning which focuses on the automated screening approaches. They have considered 2D x-ray images to localize the threat items. They have used automated faster R-CNN to be classifying and determining. The results produce better accuracy [15]. Qing Ma et al proposed a DL model which is named as Unfolding Spatiospectral Super-Resolution Network (US3RN). They stated that the model reduces the parameters to extremely small. They have named this method as two-step method. The achieved PSNR is 32.90 and SSIM is 0.9416 [16].

Sonali et al proposed a technique which filters the noisy area and low contrast areas and creates sharpened images that highlight the object area in an image. The proposed model is known as CLAHE. The model exceeded PSNR improvement by 7.85% and SSIM improvement by 1.19% [17].

2.1. Hierarchical diagram
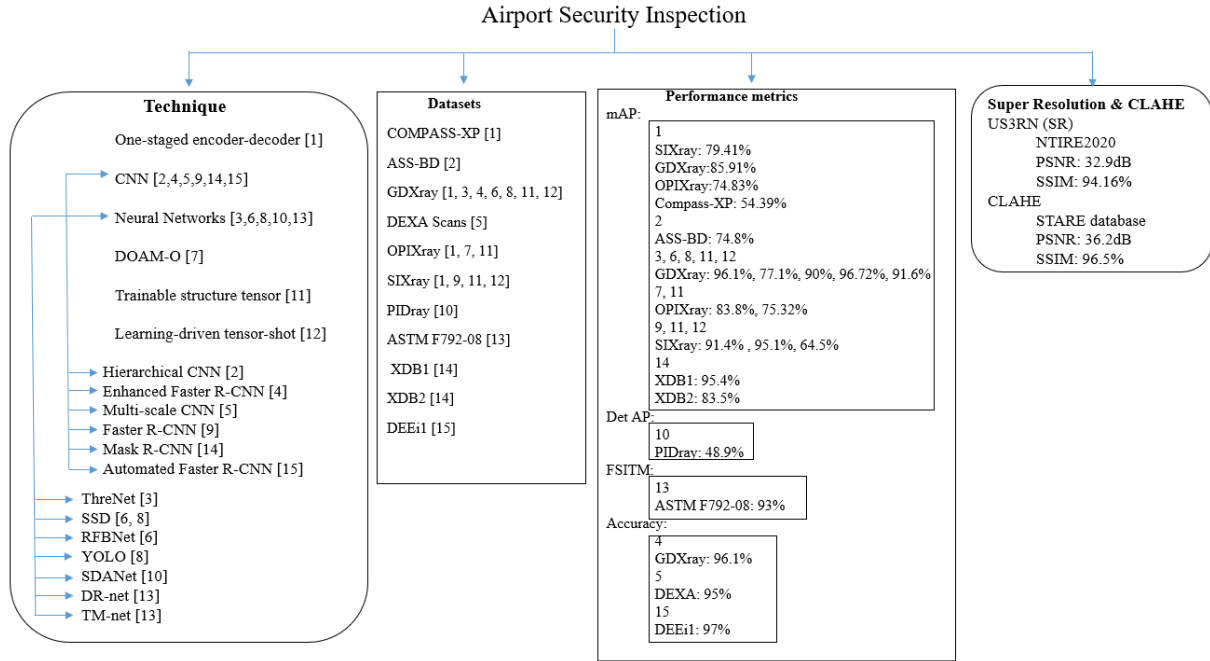The hierarchical diagram is a representation made from the related works.

Figure 1. A Hierarchical view of technique, Datasets, and their respective evaluations.

The **figure 1** represents the techniques of the corresponding references and stated as numbers. The datasets which are used in all the references are also stated as numbers. The evaluations of the techniques through the datasets in the figure are classified as mAP, Det AP, FSITM, and Accuracy.

3. Analysis on existing methodologies

The analysis is made in a tabular representation, consisting of author' names, technical details, advantages of their proposed work, limitations in their work, and gaps or future scope.

3.1. Comparison table

Table 1 (a). Comparison table of related works which consists of techniques, advantages, limitations, and gaps.

	Year	Technique	Advantages	Limitations	Results	Gaps
1	2021	Encoder-decoder	It is one-staged unsupervised approach which consists encoder-decoder network. This approach reduces time and gives best.	The working of SIXray dataset is the largest and most challenging. The model trained without supervision.	mAP=85.9%	Overlapping object detection.
2	2021	Hierarchical CNN	The model has strong versatility when applied inspection task of appearance. It also solves motion blur, and deformation.	Difficult frames for detecting such as part occlusion, rare pose when the operator is placing baggage, tying baggage tags.	mAP=74.8%	JETSON TX2 is used for efficient computing.
3	2021	ThreNet	The model has faster computation speed and bounding boxes can cover threat object perfectly.	The detection depends on some specific region rather than the entire image. The model loss some information in detection.	mAP=96.1%	Anchor-free detection
4	2021	Enhanced Faster R-CNN	The enhance faster R-CNN with improved region proposal network. Improved RPN produces better quality feature map.	The proposed model is only trained to detect the pistols in the screening. It cannot detect other objects.	Accuracy=77%	Train model with larger dataset

Table 1 (b).

	Year	Technique	Advantages	Limitations	Results	Gaps
5	2021	Multi CNN	Less training time, less parameters and a multi scaled model which is useful for different level feature extraction.	It is limited for classification of six fixed classes of object materials and prone to noise.	Accuracy=95% Recall=96%	Work on noisy images
6	2021	Learning - based image synthesis	The model shows the improvement in performance of various objects compared to previous image synthesis.	The model is a conventional method and failed in detecting occluded objects, although cause false alarms by test set.	mAP=77.1%	More hard training samples to be taken.
7	2021	DOAM-O	Effective in collecting edge and region information to improve feature representation in occluded objects.	Extra computational cost compared with existing methods. Difficulty in dealing with high-level occlusions.	mAP=83.8%	Integrated with any other model.
8	2021	YOLOv3	The idea of the work is to show how to use known object detection strategies in baggage inspection, rather than new.	The subset of test set contains same categories but different images from training set. Thus, it is challenging for detection.	mAP=90%	Superimposition of simulated targets
9	2021	Faster R-CNN	High prediction confidence on true positives and consistent on false positives. Supress any potentially wrong detections.	When most of the objects are overlapped then this model has a time detecting since the baggage has more denser materials.	mAP=91.4%	Need to improve of finding wrench and pliers
10	2021	Selective dense attention network	SDANet achieves best performance in terms of all subsets in PIDray dataset.	Detecting prohibited items hidden in messy objects is one of the most significant challenges in security inspection.	Det AP=48.9%	Include more images in dataset.
11	2020	Trainable structure tensor	Ability to suppress the boundaries of normal baggage content as it is tested on multiple datasets and robust in detecting.	The proposed framework is leveraged on pixel-wise recognition, some pixels are classified as false negatives.	mAP=95.1%	Extended for 3D printed objects
12	2020	Learning-driven tensor-shot	Works on any grey scale or coloured scan for recognising threat objects. The model can detect even for overlapped objects.	Misses some extremely dull and occluded objects. Inability of the model to accurately differentiate the low contrasted objects within the low-energy tensor.	mAP=91.62% F1-score=95%	Backbone should be more biased.
13	2020	TM-Net and DR-Net	Tone Mapping is simple, fast and preserve intensity. Finally, they show that proposed method achieves visually compelling images with improved details.	There is no publicly available dataset for TM of X-ray images. we constructed synthetic dataset to simulate X-ray images for target applications.	FSITM=93%	Further improve performance in terms of visibility of images.
14	2020	Mask R-CNN	The proposed method proves that it is more accurate and robust when dealing with densely cluttered backgrounds during X-ray baggage inspection.	X-ray object detection is still a challenge for them with characteristics and densely cluttered background.	mAP=95.4%	Discriminating the false alarms.
15	2019	Automated faster R-CNN	Here they present a deep learning enabled approach to address the challenges of threat concealment detection within consumer electronics items via a generalized approach to anomaly, rather than explicit threat, detection	The dataset consists of disparate models and shapes of electronics items, where the inserted anomaly/threat concealment might be challenging to identify.	Accuracy=97% Precision=95%	Targeting on more varied electronic items

Table 1 (c).

|	Year	Technique	Advantages	Limitations	Results	Gaps
16	2022	UnifoldS3RN	The design of the US3RN provides a fast spatial global operation to accelerate the spatial SR network.	The training of NTIRE2020 database made a challenge for them to make spectral reconstruction for RGB images.	PSNR=32.9dB SSIM=94.16%	Extensive ablation study will be made.
17	2019	CLAHE	It is proved that the proposed technique removes noise and enhances contrast in fundus images effectively. The results of the model are quite impressive.	The image enhancement for RGB images shown a quite challenging one because the model has filter each of the RGB component and de-noise the region and then merge the RGB components.	PSNR=36.2dB SSIM=96.5%	Applied to another medical images.

4. Results
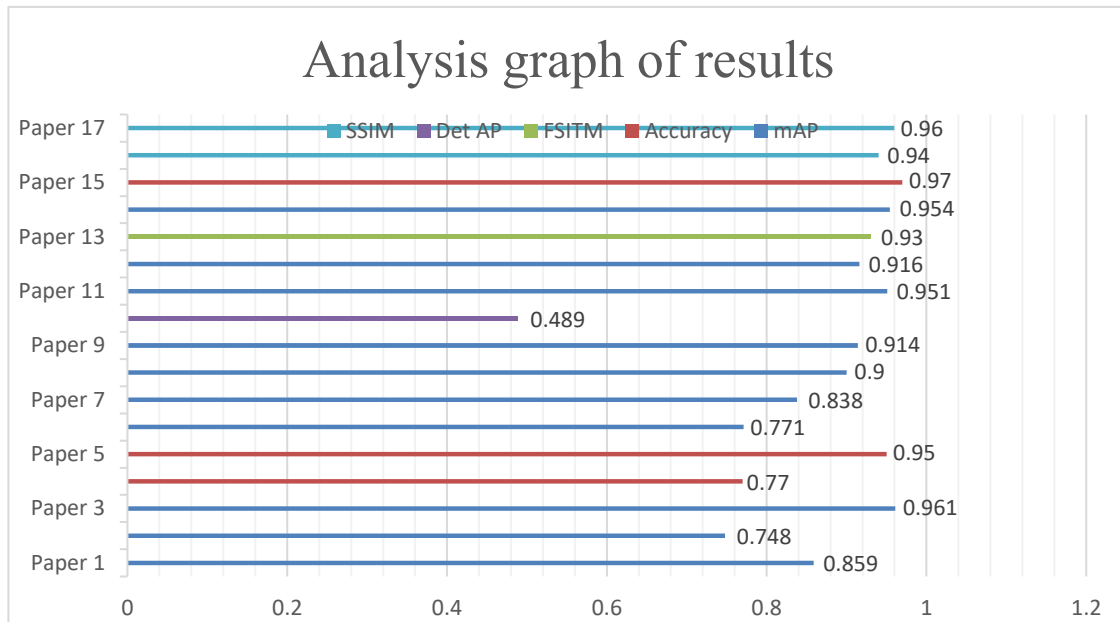
Figure 2. Graph for evaluations metrics (SSIM, Det AP, FSITM, Accuracy, mAP).

The **Figure 2** graph shows that the significant improvement on their state-of-art models via some performance metrics such as SSIM, Detection AP, FSITM, Accuracy, and Mean AP.

5. Conclusion

This paper gives the overview of the various of state-of-art models and a detailed comparison table to identify the advantages of their methodologies, limitations of their work, and future works which will be implemented. The analysis of the most of the reference's states that the detection of threat items is done through mask generation and bounding box prediction.

6. Future Scope

After analysing all the reference papers, some gaps are identified on the main theme i.e., airport security screening through DL [18]. Obviously, the major thing of any research is to improve the rate of performance and stability of their model [19]. To improve the detection rate, we have two theories to propose. These theories based on Computer Vision (CV). We have also analysed the papers 16, 17

for our theories. The dataset which will be trained can be pre-processed [20]. The CV algorithms like Enhance Super Resolution (ESR), and Image Enhancement (IE) can be used to increase the detection rate and bounding box prediction [21]. The dataset will be generated as normal images, ESR images, and IE images. Later, we can use some object detection models to confront our theories with the performance of their results.

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