Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 8s (2025)
https://www.jneonatalsurg.com

Airport Screening for Threat Detection Via Super Resulted and Sharpened Data

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Cite this paper as: Aravind Karrothu, A Ravi Kishore, Shalini D, Ramachandro Majji, (2025) Airport Screening for Threat Detection Via Super Resulted and Sharpened Data. *Journal of Neonatal Surgery*, 14 (8s), 460-469.

ABSTRACT

People basically prefer a runway for air transportation through airports. These are the places where airplanes land and gets take offs. This transportation prefers for large distance travelling. The baggage's are the basic necessity for the passengers. If the passengers carry some dangerous items like pin, screw, knife, gun, blade, spring, shuriken, and other metal items and some electronic gadgets which don't have authorizations. This all leads to scarce situation and bizarre state in airports. Therefore, the airport screening should be must involve in thorough scanning. The proposal of this project is that if embed the detection model in the scanner of the machine, it alerts the nearby security agents when a threat item is detected. The work deals with software side of the security inspection. To train and test for the detection of the threat, we gather the X-ray images related to the airport baggage. The development of our proposed model is done through Deep Learning (DL) and Computer Vision (CV) algorithms to detect the threat items. The algorithms enlarge the images and analyzes the area of threat items.

Keywords: *Air Transportation, Security Inspection, Threat Items, Deep Learning, X-ray Images, Computer Vision.*

1. INTRODUCTION

The process of relocating someone or something is known as transportation. People prefer transportation over large distances. There are so many transportation systems all over the world. Some of them are rail transport, bus transport, and airport transport etc., The fastest transportation is the air travel transportation system.

People travelling with luggage should handover the luggage that would need to go into the cargo holdings. There are certain restrictions that luggage should be within the required size and weight. After the destination is reached people need to pick up any bags that are checked.

Baggage's are often checked at airline systems to recognize the threat items such as knife, gun, blade, and explosive devices etc., the luggage is transferred through the panel to check x-ray screening. The panel recognizes the threat items through imaging. The service agents will weigh the baggage and print the details of the passenger on a tag which will be attached to the checked luggage.

Taimur Hassan et al., [1] works on various publicly available datasets on the problem statement. They followed a one-staged approach i.e., (encoder-decoder network) to determine the threat items in the baggage content. They proceeded with an unsupervised approach for anomaly recognition. Eventually they achieved mean AP for various datasets. This approach generates a patch for anomaly mask and anomaly localization. Apart from the patch generation, this model faces a challenge for overlapping object detection. So, we required to overcome such type of challenges with various new enhancements.

To improve the detection rate of threat items, a new methodology has been proposed with two preprocessing techniques of CV and several object detection algorithms of DL are to be tested to prove the theory. The CV algorithms are Super-Resolution (SR) and Image-Enhancement (IE). The input is fed by the dataset i.e., GDXray. The outputs of this stages represent high quality and sharpened images. This is further fed to the DL object detection model. At last, the performance of the threat item detection will be measured according to module wise outputs of module 1 (Super-Resolution) and 2 (Image-Enhancement).

2. LITERATURE SURVEY

There are few existing works to detect the threat items in airport security screening. The existing works contains various state-of-art models to identify the threat regarding to its dimensions and angles.

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].

QINGJI GAO et al introduced a novel method for airline baggage appearance. They presented a Hierarchical CNN model to the custom dataset which is named as ASS-BD. They have worked on video clips as datasets. Most the clips were taken at the airport baggage checking recording scenes. This approach provides a real time inspection. Eventually they are succeeded in increasing their mean AP for their custom dataset [2].

The author's Wei Zhang et al introduced a detection model which is automated for threat objects localization based on depth wise separable convolution. The best advantage of this model is, it is not only able to not only categorize the threat objects but also locate it simultaneously. One of the best parts of this model is high detection accuracy, fast computational speed. Mean AP obtained by using this model is 95.33%. The further works could explore the integration of different kinds of deep learning features [3].

Priscilla Steno et al made research which aims to the improvement of faster R-CNN. They stated that DL model for security inspection has not been implemented effectively. But 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 some image processing methods like object detection, or a frequency resolution increase are being used. In general, many X-ray scanners label material (object) classes by assigning four or six main colors based on the material like light organic, heavy organic, non-organic, metal, heavy metal. 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 however is limited to six fixed classes of materials and sometimes faces the problem in differentiating light organics and light metals. As given in this paper apart from this architecture VGG is stated to be most efficient one by providing 88% accuracy [5].

Hyo-young Kim et al proposed learning-based image synthesis for hazardous object detection. The datasets they have used for this work are GDX-ray which contain five object categories. They have use average precision (AP) and mean (AP) for object detection performance. Finally, they show that proposed method improves performance of various object detection compared to previous image synthesis [6].

Xianglong Liu et al proposed an over-sampling de-occlusion attention network (DOAM-O). This model improves the performance of famous detection models like SSD, YOLOv3. Dataset used to train the proposed model is OPIXray, the main purpose of using this dataset is exploiting images in high quality. Mean AP obtained by using DOAM-O is 74.57 which is better when compared to other existing methods. In future works the proposed model could be beneficial to promote the development of prohibited items detection in noisy X-ray images [7].

The researchers made an DL based method to determine the threat images from x-ray images. They have used 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. Taking object separation as an important aspect this paper implemented Image Segmentation and at later stage threat object detection is done through various models like Faster RCNN and Single shot detector on SIX-Ray data set. The authors also noted that Mask RCNN method is more accurate (93%) compared to Faster RCNN in cases where the most items exhibit high density material properties. Further this paper states that the SIX-Ray data set consists of about one percentage mislabeled negative samples, which may be considered small but affects the real-world applications which need to be as accurate as possible for threat identification [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 will help to establish a platform for evaluating the prohibited item detection towards 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. Evaluation metrics that are presented in this paper is, Dice Coefficient and Intersection-over-Union, Mean Average Precision. Mean AP obtained by using the proposed method on GDXray is 96.72 which is the best when compared to the other datasets. In future works the proposed framework can be used to detect the 3D printed objects within the luggage [11].

The authors of this paper proposed a novel detection strategy called as Cascaded Structure Tensor (CST) is to identify obstructed or overlapped objects since it requires more stages to identify them as they probably blend into the background. This paper follows the framework of meta-transfer learning-driven tensor-shot detector that converts the input scan images into dual-energy tensors that amplifies the edges and implements a meta-one-shot classification backbone to recognize baggage threats. This scheme works on any grayscale or colored X-ray scan for recognizing the potential threats and hence implemented on both SIX-Ray and GDX-Ray datasets [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. They have use EME, PixDist, TMQI, FSITM and HDR-VDP for object performance. 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. They have use AP, mAP, and IOU metrics. Finally, the proposed methods achieve better performance than comparative methods and more effective than existing [14].

YUE ZHU et-al proposed Data Augmentation of X-Ray images in Baggage Inspection. The datasets they have used for this work are X-Ray prohibited item image dataset and X-Ray security checking image dataset. They have used Average Precision and Mean Average Precision as metrics for evaluating detection performance. In this detection results when we compare for Mean Average precision (MAP) the Real+Synthetic Database got more accuracy than Real Database. Finally, this method can impressively achieve data augmentation for the X-Ray security checking [15].

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 [16].

The researchers stated that the crimes will be eventually affects the baggage screening inspection. They made a Transfer-Learning (TL) approach for test the theory of faster R-CNN and YOLOv2. They have made a progress which leads to categorizing the threat items. Eventually they have achieved accuracy of 98% for faster R-CNN and 97% for YOLOv2. They also stated that the model is capable of automate screening process [17].

In this paper the researchers proposed Anomaly instance localization in X-ray Security Images. The datasets they have used for this work are X-ray images. They have use AUC (Area Under the Curve) for accuracy and performance. Finally, they show that there is good potential to achieve better performance [18].

In this paper, the authors Samet Akcay et al designed a transfer learning paradigm by which we address the task by using convolutional neural networks. The performance is calculated by comparison of True Positive Rate and False Positive Rate together with Precision and accuracy. Among all the trained models CNN+SVM gives the best accuracy and precision. In this paper we exhaustively explore the use of CNN in classification of images. Accuracy obtained by using this model is 99.4. In future works we consider X-ray security imagery in end-to-end design [19].

The authors Aydin et al believed a new approach for threat object detection i.e., Faster R-CNN with ROI pooling. The ROI pooling possess the nature of classifier and regressor. The results of their model were compared with traditional computer vision algorithms which satisfies them with better results [20].

Many important medical and scientific problems require the collection of high-resolution data over large fields of view. One approach to overcoming this problem is to acquire a large FoV at low resolution (LR) and interpolate it to obtain a higher resolution image of sufficient quality. Advances in Deep Neural Networks have many methods for this task. This paper states that among them, SRGAN (Super Resolution Generative Adversarial Neural Network), which processes the images by adversarial training and perceptual loss, is one of the efficient preprocessing techniques and is currently in evolution [21].

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. They have considered various analysis methods to determine the performance of the model. The achieved PSNR is 32.90 and SSIM is 0.9416 [22].

The authors, Joon Young Ahn et al proposed a new search method for Single Image Super Resolution which can decrease the overall design time by applying a weight-sharing scheme. SISR is the task that restores the high-resolution image from a low-resolution observation. The proposed method comparably performs better to the conventional hand-crafted structures and other NAS networks [23].

QUAN DO et al proposed an effective and dependability Framework for accelerated Super-Resolution Microscopy. This model is MUSICAL, a multivariate super-resolution technique for comprehensive fluorescence microscopy. The authors improved its low computational performance by using high-performance computing libraries. The outcome shows that the new improved parallel MUSICAL algorithm achieves an acceleration up to 30.36x on a commodity machine with 32 cores with an efficiency of 94.88% [24].

The authors Rohit Gupta et al proposed a Generative Adversarial network architecture which is used to generate lifelike images, in this deep learning model, two neural networks race with each other to improve themselves. The main advantage of this approach is that it had proved to outperform many standard deep learning models are indistinguishable from target images. This model acquires high accuracy when compared to before. In future this approach can be useful for MRI datasets [25].

The researchers stated that the DL models plays a vital role in in Medical Image Segmentation (MIS). They combined two traditional methods and produced a new model named as BoostNet. They divided the entire model into four phases. Finally, they have combined ChampNet and CLAHE models and achieved 95.88% of accuracy [26].

In diagnosis of multiple sclerosis (MS), measurements of the volume of brain structures plays a key role in obtaining reproducible measurements for these several automated brain structure segmentation methods are implemented. The authors have introduced a combined two label fusion methods for segmentation which is applied on MR images of Brain where disease causing plaques appear as low signal intensity areas. These areas are like the white matter areas around the scans which leads to errors. This issue is resolved by implementing pre-processing to the MR image by correcting in-homogeneous areas and normalizing their intensity and so that pre-processing would help in preventing false positives [27].

Viacheslav Voronin et-al proposed 3-d block-rooting scheme with application to medical image enhancement. The datasets they have used for this work are NYU, fastMRI, Chest x-ray. They have used Pearson correlation coefficient (PCC) and (SD) for accuracy and performance. Finally, they show that achieves good performance and can prevent noise increasing during sharpening of image details [28].

KHAIRUL MUNADI et al proposed Image Enhancement for Tuberculosis Detection. The dataset they have used for this work are Shenzhen Public Dataset. The have used HEF, UM, CLAHE methods for Image Enhancement. In this validation accuracy the HEF method has more efficiency than others. Finally, when compared the results of previous works, the proposed idea accomplishes better results [29].

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 evaluation metrics for this model was used are PSNR, SSIM which is same for the Image Super-Resolution (ISR). The model exceeded PSNR improvement by 7.85% and SSIM improvement by 1.19% of the existing model [30].

3. METHODOLOGY

3.1. Proposed Architecture

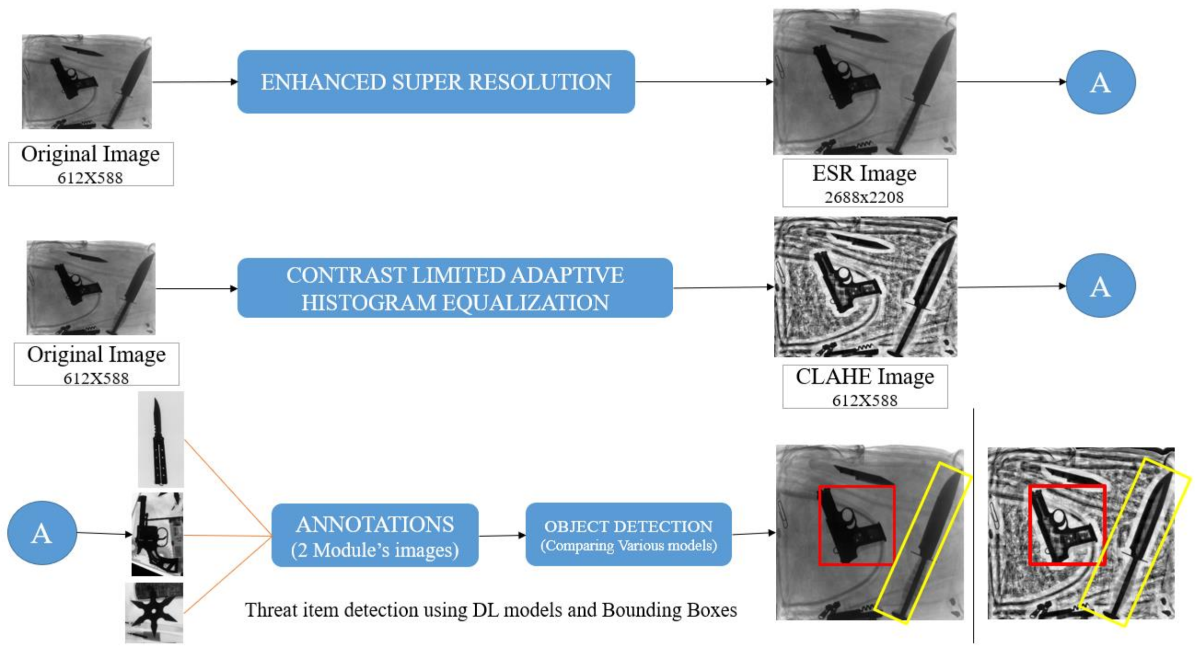


Figure 3.1. Hybrid Baggage Screening Model Architecture

This work involves developing various models to detect threat items, relying on input images. The project is divided into four modules, with the first module being a computer vision algorithm based on ESRGAN. It generates a high-resolution image. The second module is a technique related to image enhancement. The third module is the annotation creation for the dataset GDXray. After the module 1 and module 2, the output images are high-resulted and sharpened equally through histograms images. Annotations are created for all three types of images. The final module includes various state-of-the-art models to test the theory of the proposed work

3.2. Preprocessing Module 1

The super-resolution module is a Computer Vision (CV) algorithm that enhances low-resolution images into high-resolution ones using a Generative Adversarial Network (ESRGAN). Compared to standard definition (SD) images, high definition (HD) images provide more accurate results and improve object detection clarity. The GAN generates a super-resolution (SR) image from a low-resolution (LR) input produced by the generator. The model's performance is evaluated using PSNR with respect to the dataset.

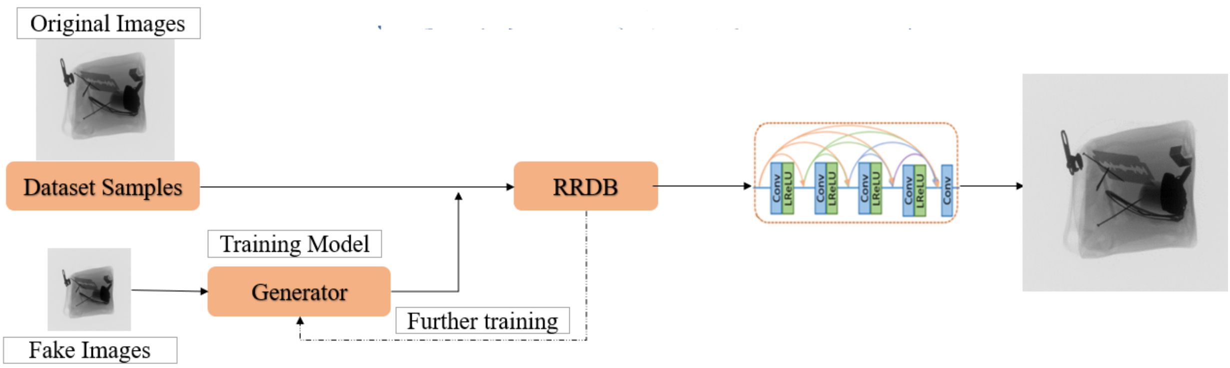


Figure 3.2. Enhanced super resolution using generative adversarial networks

GAN model is an unsupervised algorithm. In this module, the dataset will be fed to the discriminator and fake images are fed into generator. RRDB (Residual in Residual Dense Block) is a special function which is used in further training of generator. It covers all the loss features and maximize the pixels. The reason to use this RRDB function is that its supports Super-Resolution for grey images i.e., X-ray images.

3.3. Preprocessing Module 2

The Image-Enhancement is a Computer Vision (CV) algorithm which is used to get an Adaptive Contrast image. The model which is used in this work is CLAHE. The CLAHE model amplifies the noisy areas. The threat item images will be fed to CLAHE (Contrast Limited Adaptive Histogram Equalization) model. The image will be divided into different segments and each segment has some pixel values. The CLAHE model measure the histogram of each segment and perform Histogram equalization method on the identified pixels. At last, the model maps and merges all the segments and then form a new image**.**

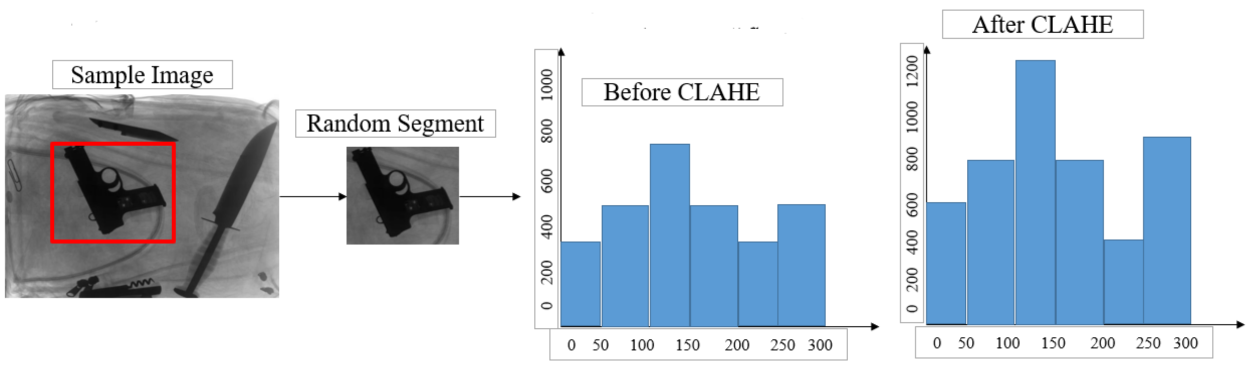


Figure 3.3. Sample histogram representation of a random segment

The steps of CLAHE are represented in the form a flow diagram to understand.

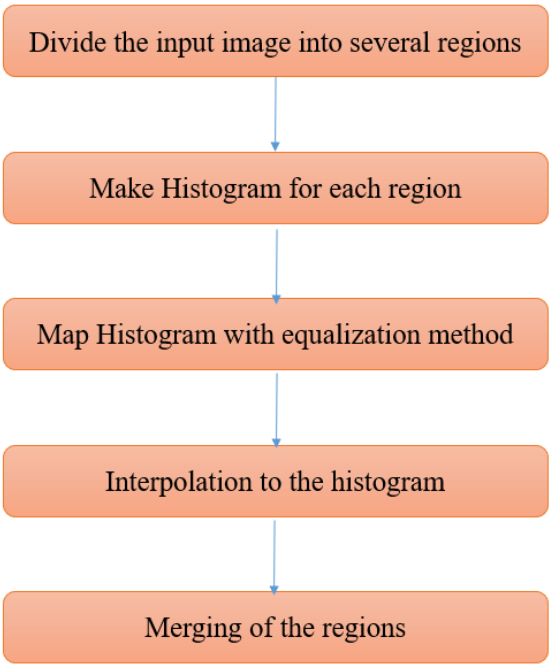


Figure 3.4. Flow diagram of steps of adaptive histogram equalization

3.4. Annotation Creation Module

This project work will be done on the dataset named as GDXray Baggage's. It contains various x-ray images of the baggage. The threat items images should be annotated. The annotations are done for all 1st and 2nd modules and normal input images. To refine the annotations, we cover all the threat item images in all angles and created bounding box labels. The annotations will be saved in xml, json, tfrecords file format. This file will further gets used in the DL object detection models. To annotate the images, we have used VGG annotator. This annotator creates the required bounding box regions for the threat items and save them as a xml file.

3.4. Object Detection Models Module

In this project, there are 6 object detection models.

They are **Faster R-CNN, AI Detectron2, YOLO v5, v6, v7.**

Faster R-CNN: **(tfrecords annotations)** The regions of the images are extracted, and classification of the objects are done. The training of this model takes lot of time.

AI Detectron2: **(JSON)** The backbone of this algorithm is Faster R-CNN. It supports large databases and enhances pixeled images.

YOLOv5: **(xml)** This is the best algorithm for bounding box detection problem. It shows significant results when compared with other models. It has more stability than v6, and v7.

YOLOv6: **(xml)** The backbone of this model is efficient. It takes less taking time. Comparing with v5 it is little less stable.

YOLOv7: **(xml)** The speed of this model is very high. It has good stability and good prediction rate of bounding boxes.

If we consider the threshold of prediction rate of threat items as 0.5 then, AI Detectron2, and YOLOv5 outperforms all the models.

4. RESULTS & DISCUSSIONS

4.1. Major Performance Metrics

4.1.1. Peak signal noise ratio:

- It is a metric which is used to compare the noise reduction of the original and the generated or compressed image.
- The PSNR ranges depends upon the bit depth of the images.

- 30 to 50 dB is 8 bits, 60 and >60 dB is 12 bits, and 60 to 80 dB is 16 bits.
- But if the SR image (8 bits) is way qualitied than input image (8 bits) then the PSNR will be higher.

4.1.2. Average precision over IoU:

- The average precision over the union of ground truth label and predicted bounding boxes is known as the AP over IOU.

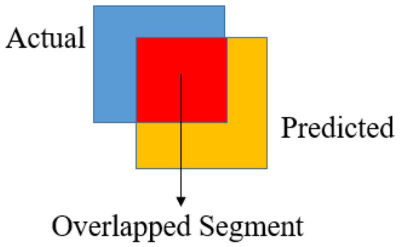


Figure 4.1. Sample actual & predicted bounding box overlapping

4.2. Results with images and explanation

4.2.1. Module 1 Results

Typically, CNN layers reduce the size of the input image. However, to increase the image size, the pixel features must be enhanced. RRDB is used to recover the lost features in the subsequent layers. The input images are upsampled at a rate of 4x, achieving a PSNR value of 91.1 dB between the original and super-resolution (SR) images.

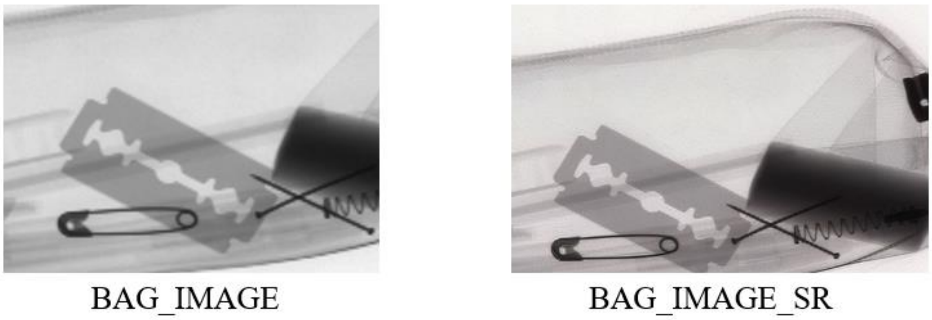


Figure 4.2. Sample image comparison of normal image and ERGAN image

4.2.2. Module 2 Results

Histogram Equalization performs equally on all regions in an image whereas the Adaptive Histogram Equalization performs regarding to the pixel wise. The image is divided into segments and then contrast of the areas will be increased regarding to features present in the image. A boundary around the objects will be made during the process. The gaps such noising, void spacing, and overlapping of the objects can be mitigated.

Figure 4.3. Sample image comparison of normal image and CLAHE image

4.2.3. Module 3 Results

The annotations are made from the bounding box regions of the threat items. The dataset i.e., GDXray is a large database baggage' images. It contains several threat items' images. This project is a multi-categorical detection of object. There is main 4 classes of the threat items. They are blade, gun, knife, shuriken. The bounding boxes are drawn for these four classes. The annotations that are drawn for the DL models are xml, tfrecords, and json.

4.2.4. Module 4 Results

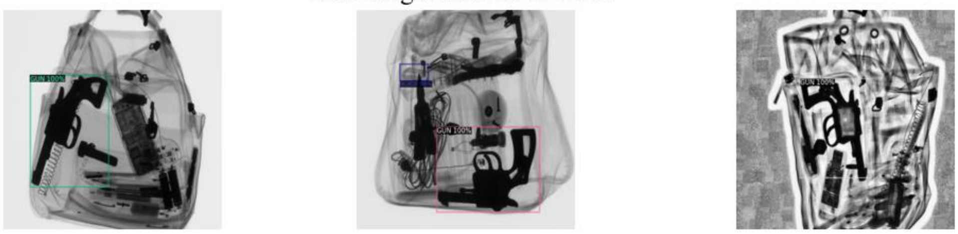
The results of various object detection model are compared using below table.

Table 4.1. Average precision comparisons of various detection models

	Model	Normal (AP)	ESRGAN (AP)	CLAHE (AP)	AVG (AP)
1	Faster R-CNN	42.4%	47.7%	62.4%	50.83%
2	AI Detectron2	87.7%	92.3%	96.5%	92.16%
3	YOLOv5	96.5%	89.3%	92.2%	92.60%
4	YOLOv6	79.2%	87.3%	84.8%	83.76%
5	YOLOv7	90.7%	87.8%	95.2%	91.23%

The best models are AI Detectron2 and YOLOv5. Not only with AP but also confidence level of detecting the threat items with test images.

Test Image of AI Detectron2:



Test Image of YOLOv5:

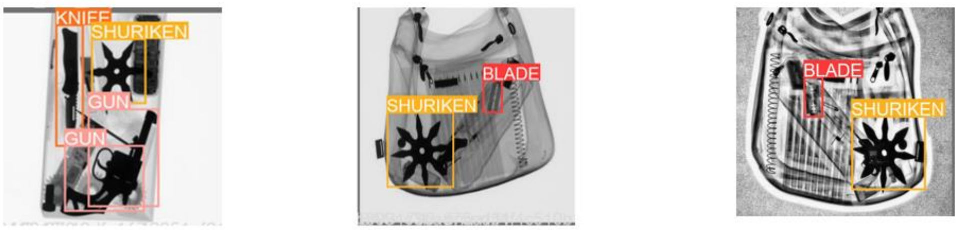


Figure 4.4. Sample test images predictions of AI Detectron2 and YOLOv5

5. CONCLUSION

In this work, object detection models are applied to all three types of datasets. While some models effectively predict the confidence percentage of threat items, their overall mean Average Precision (AP) is relatively low. For instance, Faster R-CNN performs well in confidence prediction but has a lower mean AP for normal images. Among the different image types, CLAHE images are best predicted using Faster R-CNN compared to normal and ESRGAN images. AI Detectron2, with a Mask R-CNN backbone, demonstrates strong performance in both mean AP and confidence prediction. YOLO models are straightforward, single-stage models, with YOLOv5 excelling in training time, mean AP, and confidence percentage. Overall, AI Detectron2 and YOLOv5 are the most effective models for detecting threat items with high confidence.

6. FUTURE WORK

ESRGAN-based image generation is an effective preprocessing task, but it is time-consuming. Despite using Colab Notebooks with a 16 GB GPU and a 4x upsampling rate, the GPU memory frequently reaches full capacity. Moving forward, we aim to generate images using a 32 GB GPU for improved performance.

The CLAHE images depends on the size of the input image. It divides the entire iteration as the length of the image and apply CLAHE on each of every 100 iterations. So that if resize the input image as 512x512 the model will be work fine. But the resizing loss some information. Further, we apply super resolution and then resize the images. Later those are given to CLAHE model

We faced significant pressure and time constraints during annotation creation. To accurately detect threats, it is essential to refine the bounding boxes efficiently, defining them for all images in the dataset. However, manually drawing bounding boxes for all images is a challenging task.

In object detection models, Faster R-CNN underperformed compared to other models. To enhance its detection rate, we plan to increase the number of steps or epochs used during training.

The CLAHE images generated from Module 2 create a distinct border around each item in the X-ray image. Existing state-of-the-art methods utilize Trainable Tensor Structure (TTS) to generate the required ground truths for input images. Moving forward, we aim to explore TTS for automating ground truth labeling.

Data Availability Statement

The data used to support the findings of this study are included in the article.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Funding

Any organization does not fund this research work

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