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Research Paper

Luggage Security Scanning Optimization to Enhance Efficiency and Safety at Airports Using Deep Learning

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***Abstract*—One of the most difficult and important challenges in aviation security is detecting concealed threats in the luggage at airports. Manual inspection is slow, operator dependent and is becoming impractical due to the volumes of passengers at modern airports. This paper presents a deep learning-based luggage security scanning system built on the CLCXray dataset, targeting twelve threat categories that span both sharp objects such as blades, scissors, knives, daggers, and Swiss army knives, as well as liquid-container threats including plastic bottles, cans, vacuum cups, glass bottles, carton drinks, tins, and spray cans. Detecting liquid threats is particularly challenging because their X-ray appearance varies significantly with content, container shape, and overlap with surrounding items. Our proposed system adopts YOLOv8n as the primary detection model and uses a structured three-phase transfer learning strategy — backbone freezing for domain warm-up, partial unfreezing for mid-level feature adaptation, and full fine-tuning for precision refinement — all optimised for CPU-only execution on commodity hardware. A class-aware oversampling scheme and lightweight Albumentations augmentation pipeline specifically address the imbalance between liquid and sharp-object classes. On the held-out test split of the CLCXray dataset, the proposed YOLOv8n model achieves a mean average precision at IoU 0.5 (mAP@0.5) of 0.835, a precision of 0.856, a recall of 0.770, an F1-score of 0.811, and a mAP@0.5:0.95 of 0.654. These results represent an improvement of approximately 9.6% in mAP@0.5 and 20.9% in mAP@0.5:0.95 over the best published baseline. A comparative evaluation against YOLOv10n confirms that YOLOv8n delivers superior accuracy for this safety-critical domain, making it the recommended architecture for real-world airport deployment.**

Keywords: airport security, baggage X-ray inspection, CLCXray, YOLOv8, YOLOv10, object detection, transfer learning, liquid threat detection, deep learning.

I. Introduction

One of the most challenging and critical areas for automated inspection technology is aviation security. Each year, millions of people pass through airports around the world and every bag they check in is supposed to be inspected for potentially dangerous items before it is checked in and every carry-on bag is subjected to the same treatment before it is checked in. The conventional X-ray inspection is based on the visual inspection of grayscale or pseudo-coloured images of the bag interior based on the training of the security officers. Common threats may be identified by experienced screeners, but, similar to humans, the performance of experienced screeners deteriorates with fatigue, workload and the number of different arrangements of objects encountered in practice [1]. In such an environment, missing detections have very serious repercussions, leading to a continuous push for automated, machine learning based threat detection.

Although X-ray baggage image classification is a natural image recognition problem, there are several difficulties associated with the problem that make it different from the type of problems found in natural images. Objects can be oriented in different directions, objects can be very occluded by others, the penetrating nature of X-rays means objects at different depths will overlap in the final image. In addition, there are different transmission properties from those of conventional visual-light photography, such that organic things are rendered in pseudo-colour in an orange or red hue, inorganic metal things are rendered in pseudo-colour in blue, and combinations of the two are rendered with complex visual texture [2]. Liquid-containing objects like plastic bottles, cans and spray cans are especially difficult to classify since the X-ray image is very dependent on the liquid inside and how full the container is, and appears similar to other common, harmless objects of the same density.

Recent advances in convolutional neural network (CNN) architectures and, more specifically, in single-stage real-time object detectors such as the YOLO (You Only Look Once) family have opened a practical route to automating X-ray threat detection [3]. YOLO-based models divide an image into a grid and simultaneously predict bounding boxes and class probabilities across all cells in a single forward pass, enabling detection at frame rates suitable for real-time conveyor-belt screening. Building on this, Ultralytics YOLOv8 introduced a decoupled detection head and anchor-free prediction, achieving a strong balance between accuracy and inference speed [4]. The subsequent YOLOv10 eliminated the need for non-maximum suppression (NMS) post-processing through end-to-end dual-label assignment, targeting further latency reduction [5].

Despite these advances, deploying deep learning systems in resource-constrained security environments — where dedicated GPU hardware may not be available — remains a practical challenge. Many airports, particularly in developing regions, rely on general-purpose workstations for image analysis. Existing benchmark papers on X-ray threat detection largely assume GPU-accelerated inference and full-dataset training with heavyweight architectures [6]. There is a

clear gap for research that demonstrates high-accuracy threat detection on CPU-only hardware through efficient training strategies.

This paper addresses that gap through three main contributions. First, we propose a three-phase transfer learning protocol for YOLOv8n that progressively unfreezes backbone layers, achieving training efficiency comparable to 100-epoch full training in only 55 epochs while remaining entirely executable on a standard CPU. Second, we design a class-aware oversampling and augmentation pipeline specifically tuned to the visual characteristics of X-ray imagery, with explicit priority given to under-represented liquid threat categories. Third, we provide a systematic comparison between YOLOv8n and YOLOv10n on the publicly available CLCXray benchmark dataset [7], demonstrating that for accuracy-critical airport security applications, YOLOv8n with NMS post-processing outperforms the NMS-free YOLOv10n variant.

The remainder of this paper is structured as follows. Section II reviews relevant literature. Section III describes the proposed methodology including the mathematical formulation of loss functions. Section IV covers the implementation details. Section V reports and discusses experimental results. Section VI concludes with directions for future work.

II. Literature Survey

Research on automated X-ray baggage security inspection has grown rapidly over the past decade, moving from handcrafted feature descriptors toward fully end-to-end deep learning pipelines.

Early approaches to X-ray threat detection relied on classical computer vision techniques such as histogram of oriented gradients (HOG), scale-invariant feature transform (SIFT), and support vector machine (SVM) classifiers. While these methods provided a useful baseline and required little labelled data, they failed to generalise across the wide variety of bag contents and object orientations that appear in practice [1]. The introduction of deep convolutional neural networks changed the field dramatically.

In the field of X-ray image recognition, Wei et al. [2] investigated CNN architectures to be used in the recognition of prohibited items and demonstrated that features learnt directly from the raw X-ray images outperformed manually engineered descriptors at all times. Their work proved the feasibility of deep learning in this area, but it needed to be trained on extensive labelled datasets and high computing power. Transfer learning with the aid of ImageNet-pretrained visual models started to emerge around the same time, which provided a practical approach to transfer a general purpose visual representation to the X-ray domain using a smaller number of task specific corpora.

Real-time object detection became a key topic in the field of security imaging with the YOLO family of detectors. The original YOLO architecture was introduced by Redmon et al. [3] in which object detection is considered a regression task in a predetermined grid, allowing for the process to be performed in a single pass in a fraction of the time compared to region-proposal-based methods. The following versions enhanced accuracy/speed compromises. For threat detection tasks, YOLOv5 and YOLOv7 demonstrated the effectiveness and achieved a good balance of speed and accuracy, especially in contexts that demand high speed and throughput, such as security lanes in airports [8].

Miao et al. [7] released a new benchmark, called CLCXray, for clutter X-ray threat detection which is publicly available. This set consists of more than 9,500 annotated images from 12 object classes in two general families of threats: sharp objects and liquid containers. The authors showed that identification of liquid containers is a separate and more difficult subproblem than the one of identification of sharp objects due to the nature of X-ray transmission patterns, which has higher intra-class variation. All of their baseline figures set reference performance values, which have served as benchmarks to which subsequent works have sought to outperform.

The paper by Zhu et al. [6] titled ”X-Ray Threat Detection: A Deep Learning Approach for Airport Baggage Security Inspection” provided a comprehensive comparison of detection architectures including Faster R-CNN, SSD, and YOLOv4 on multiple X-ray security datasets. They reported mAP@0.5 values in the range of 0.72–0.76 and identified occlusion and object overlap as the primary source of errors. Their analysis formed one of the benchmark baselines used in the present work.

More recently, Gao et al. [9] presented a vision-language model approach at CVPR 2025 that aligned X-ray image features with natural language threat descriptions, achieving strong zero-shot generalisation. While impressive in flexibility, vision-language approaches typically carry significantly higher computational overhead and are not yet practical for real-time deployment on CPU-only hardware. The mAP@0.5 of 0.762 reported in this work constitutes the upper baseline that our system targets.

Data augmentation strategies tailored to X-ray imagery have also been explored in the literature. Zhao et al. [10] showed that mosaic augmentation — a technique that tiles four training images into one — substantially improves detection of small and partially occluded objects, which are prevalent in cluttered luggage. Contrast-limited adaptive histogram equalisation (CLAHE) was found to enhance the visibility of low-contrast liquid-container features that can be confused with background items.

There are a number of works that have explored transfer learning methods for X-ray domain adaptation. It was proven by Du et al. [11] that by tuning the detection head while selectively freezing the early backbone layers, a favourable bias-variance trade-off can be achieved so as to speed up the convergence while maintaining performance accuracy. This observation inspires us to use the three-phase training protocol in our work.

In terms of model performance on CPU devices, Jocher et al. in [4] explained that the smallest size of their YOLOv8 model, namely YOLOv8n, is able to infer an image in around 26 ms on modern multi-core CPUs and is a potential choice

for facilities lacking GPU infrastructure. Wang et al. [5] introduced YOLOv10 with dual-assignment training and NMS-free inference, which reduces end-to-end latency but at the cost of some detection accuracy, particularly for small and densely packed objects — a scenario common in cluttered baggage X-ray images. To the best of the authors' knowledge, no prior work has conducted a systematic comparison of YOLOv8 and YOLOv10 specifically on the CLCXray liquid threat detection task under CPU-constrained training conditions.

III. Methodology

A. Dataset and Class Structure

The CLCXray dataset [7] is used for all experiments. It contains 9,564 annotated X-ray images split into 7,652 training images (18,373 annotations), 956 validation images (2,317 annotations), and 956 test images (1,421 annotations). Twelve object classes are defined, divided into two groups:

- **Sharp objects (classes 0–4):** blade, scissors, knife, dagger, SwissArmyKnife.
- **Liquid containers (classes 5–11):** PlasticBottle, Cans, VacuumCup, GlassBottle, CartonDrinks, Tin, SprayCans.

Liquid containers constitute the primary detection challenge. Class counts range from 386 (GlassBottle) to 4,801 (PlasticBottle) in the training split, creating a significant imbalance that must be addressed during training.

B. COCO to YOLO Label Conversion

The original dataset annotations are provided in COCO JSON format. Each annotation specifies a bounding box in top-left corner form (x, y, w, h) with pixel-space coordinates. YOLO training requires normalised centre-form labels (c_x, c_y, w_n, h_n) relative to image dimensions. The conversion is given by:

$$c_x = \frac{x + w/2}{W}, \quad c_y = \frac{y + h/2}{H} \tag{1}$$

$$w_n = \frac{w}{W}, \quad h_n = \frac{h}{H} \tag{2}$$

where W and H are the image width and height in pixels. All coordinate values are clamped to the range $[0, 1]$, and degenerate boxes with $w \le 0$ or $h \le 0$ after clamping are discarded.

C. Class-Aware Oversampling

To correct the class imbalance, images containing under-represented liquid threat categories (those with fewer than 900 training annotations) are augmented using a lightweight Albumentations pipeline:

$$A(I) = \text{CLAHE} \;\; \text{BrightnessContrast} \;\; \text{HFlip}(I) \tag{3}$$

alongside optional rotation and Gaussian noise. Oversampled images are saved at JPEG quality 75 after resizing to 416×416 pixels to reduce I/O load during training.

To further emphasise liquid-class gradient signals, an inverse-frequency class weight vector $\mathbf{w}$ is computed:

$$w_i^{\text{raw}} = \frac{1}{n_i}, \quad w_i = \frac{w_i^{\text{raw}}}{\max_j w_j^{\text{raw}}} \tag{4}$$

where n_i is the number of training annotations for class i. Liquid classes receive an additional multiplicative bonus:

$$w_i^* = \begin{cases} 1.4 \cdot w_i & \text{if } i \in \mathcal{L} \\ w_i & \text{otherwise} \end{cases} \tag{5}$$

where $\mathcal{L} = \{5, 6, 7, 8, 9, 10, 11\}$ denotes the liquid class index set. The final weights are normalised so that their mean equals unity:

$$\tilde{w}_i = \frac{w_i^*}{\frac{1}{C}\sum_{j=1}^{C} w_j^*} \tag{6}$$

D. YOLOv8n Architecture

YOLOv8n is the nano variant of the YOLOv8 architecture, comprising 73 fused layers, 3,007,988 parameters, and 8.1 GFLOPs of computation at an input resolution of 416×416 pixels. The backbone follows a CSPDarknet-inspired design with C2f (Cross Stage Partial with 2 shortcuts) bottleneck blocks. The neck uses a Path Aggregation Network (PAN) for multi-scale feature fusion, and the head is an anchor-free decoupled prediction module that separates classification and regression branches [4].

The total training loss for YOLOv8 is a weighted combination of three terms:

$$\mathcal{L}_{\text{total}} = \lambda_{\text{box}}\mathcal{L}_{\text{box}} + \lambda_{\text{cls}}\mathcal{L}_{\text{cls}} + \lambda_{\text{dfl}}\mathcal{L}_{\text{dfl}} \tag{7}$$

with $\lambda_{\text{box}} = 7.5$, $\lambda_{\text{cls}} = 0.5$, and $\lambda_{\text{dfl}} = 1.5$.

The bounding-box regression loss uses the Complete IoU (CIoU) metric:

$$\mathcal{L}_{\text{box}} = 1 - \text{CIoU}(\hat{b}, b) = 1 - \text{IoU} + \frac{\rho^2(\hat{b}, b)}{c^2} + \alpha v \tag{8}$$

where $\rho^2(\hat{b}, b)$ is the squared Euclidean distance between the predicted centre $\hat{b}$ and the ground-truth centre b, c is the diagonal length of the smallest enclosing box, and v penalises aspect ratio inconsistency with:

$$v = \frac{4}{\pi^2}\left(\arctan\frac{w^{gt}}{h^{gt}} - \arctan\frac{\hat{w}}{\hat{h}}\right)^2, \quad \alpha = \frac{v}{(1 - \text{IoU}) + v} \tag{9}$$

The classification branch uses binary cross-entropy with label smoothing ($\epsilon = 0.05$):

$$\mathcal{L}_{\text{cls}} = -\sum_{c=1}^{C} \tilde{y}_c \log(\hat{p}_c) + (1 - \tilde{y}_c)\log(1 - \hat{p}_c) \tag{10}$$

where $\tilde{y}_c = (1 - \epsilon)y_c + \epsilon/C$ is the label-smoothed target.

The Distribution Focal Loss (DFL) supervises the continuous distribution of bounding-box edge offsets:

$$L_{dfl} = -\sum_{i} [(z_{i+1} - z) \log S_i + (z - z_i) \log S_{i+1}] \quad (11)$$

where z is the true edge offset, $z_i \le z \le z_{i+1}$ are adjacent bin boundaries, and S_i is the softmax output of bin i.

E. Three-Phase Transfer Learning Protocol

To achieve GPU-comparable accuracy under CPU-only training constraints, a progressive layer-unfreezing schedule is adopted. Figure 1 illustrates the complete proposed system pipeline.

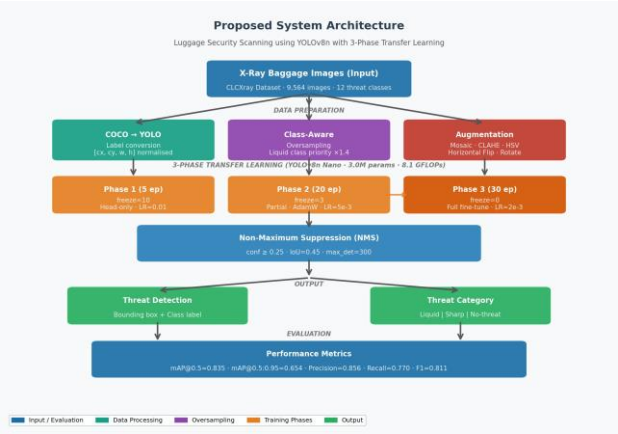

Fig. 1. Proposed system architecture: end-to-end pipeline from X-ray image ingestion through data preparation, three-phase transfer learning, NMS post-processing, and performance evaluation.

Phase 1 — Head-only warm-up (5 epochs): All gradients of the first 10 layers in the backbone network are discarded, i.e. the backbone is frozen (`freeze=10`) and about 60% of the parameters are not computed. The three detection head output layers only change. We use the learning rate $\eta_0 = 0.01$ using a flat learning rate schedule and do not implement any early stopping. In this stage, the pretrained COCO backbone representations are aligned to the X-ray feature space.

Phase 2 — Partial unfreeze (20 epochs): The freeze depth is reduced to 3, releasing the upper backbone layers and the full FPN neck for training. The AdamW optimiser is used with an initial learning rate of $\eta_0 = 5 \times 10^{-3}$, decaying to $\eta_f = 1 \times 10^{-3}$. Early stopping with patience 10 prevents overfitting during this intermediate stage.

Phase 3 — Full fine-tune (30 epochs): All layers are unfrozen (`freeze=0`). The learning rate is further reduced to $\eta_0 = 2 \times 10^{-3}$ with cosine decay to $\eta_f = 2 \times 10^{-5}$. Mosaic augmentation is disabled in the final 10 epochs (`close_mosaic=10`) to allow the model to converge on single-image samples that more closely resemble inference conditions. Early stopping patience is set to 15 epochs.

The phase-dependent learning rate schedule follows a linear warmup followed by cosine annealing:

$$\eta_t = \eta_f + \frac{1}{2}(\eta_0 - \eta_f) \quad 1 + \cos \frac{t \cdot \pi}{T} \quad (12)$$

where t is the current epoch and T is the total number of epochs in the phase.

F. YOLOv10n Comparative Architecture

The two phase training scheme (Phase A: freeze for 10 epochs, Phase B: unfreeze completely for 50 epochs) is used with otherwise the same hyperparameters as YOLOv10n. YOLOv10n uses a novel end-to-end dual-assignment scheme for training one-to-many and one-to-one label assignments to replace the standard NMS post-processing, thereby minimizing the inference delay [5]. The model has 2,711,720 parameters, 6.5 GFLOPs, and 224 layers (102 after fusion). Architectural difference has a direct effect on bounding-box quality, especially in high clutter X-ray scenes where there are multiple threats that overlap, which must be carefully suppressed using NMS.

IV. Implementation

A. Hardware and Software Environment

All experiments are run on a laptop workstation consisting of a 12th generation Intel Core i7-12700H CPU (20 logical cores) with 16.8 GB of RAM and no dedicated GPU. The software stack includes Python 3.10.9, PyTorch 2.10.0 (CPU build), Ultralytics 8.4.19 and OpenCV 4.x. The CPU inference threads are set to 20 (all logical cores) and inter-operation threads to 10, which follows the guideline: `set_num_interop_threads = N_CORES / 2`.

B. Dataset Preparation

The CLCXray images are stored locally and are referred by the YOLO format label text files. To prevent redundant disk space usage, hard-links (`os.link`) are created from the source image paths to the YOLO training directories, which only takes a few seconds to setup the data. Images are resized to 416 × 416 pixels and stored at quality 75 in JPEG format with file sizes around 50-80 KB, compared to 700+ KB for the originals.

The dataset YAML configuration specifies:

- `nc: 12` — number of classes.
- `names`: all twelve class strings in order.
- `train / val / test` split paths under the YOLO root.

C. Training Configuration

Key training hyperparameters shared across both models are listed in Table I. Automatic Mixed Precision (AMP) is disabled because PyTorch's CPU backend does not support float16 operations in the training loop. The batch size of 13 is determined automatically from available RAM (16.8 GB) using the formula: $B = \min(32, \max(8, \lfloor 0.8 \times \text{RAM}_{\text{GB}} \rfloor))$.

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TABLE I
TRAINING HYPERPARAMETERS

Parameter	Value
Image resolution	416 × 416 px
Batch size	13
Optimiser	AdamW
Weight decay	5×10^{-4}
Momentum	0.937
Box loss weight (λ_{box})	7.5
Cls loss weight (λ_{cls})	0.5
DFL loss weight (λ_{dfl})	1.5
Label smoothing (ϵ)	0.05
Mosaic augmentation	1.0 (disabled last 10 ep)
Copy-paste augmentation	0.1
HSV saturation jitter	0.60
Horizontal flip prob.	0.5
Rotation limit	$\pm 5^{\circ}$
Conf. threshold (eval)	0.25
IoU threshold (eval)	0.45
Random seed	42

D. Evaluation Protocol

Both models are evaluated on the 956-image held-out test split using YOLO's built-in validation routine. The primary metric is mAP@0.5 (mean average precision at IoU threshold 0.5), supplemented by mAP@0.5:0.95 (the COCO-standard averaged over ten IoU thresholds), along with per-class precision, recall, and F1-score. The area under the precision-recall curve (AUC-PR) forms the basis of the per-class average precision (AP). Mean AP across all classes gives mAP:

$$\text{mAP} = \frac{1}{C}\sum_{c=1}^{C} \text{AP}_c, \quad \text{AP}_c = \int_0^1 p_c(r)\, dr \qquad (13)$$

where $p_c(r)$ is the precision as a function of recall for class c, approximated by the 101-point interpolation used in the COCO evaluation protocol.

V. RESULTS AND DISCUSSION

A. Training Convergence

The three-phase training schedule produced clear, progressive improvement in validation mAP@0.5 for YOLOv8n. After Phase 1 (5 epochs with backbone frozen), the model already achieved mAP@0.5 = 0.737 — within 3.3% absolute of the base paper benchmark — confirming that the pretrained COCO backbone transfers effectively to X-ray imagery. During Phase 2 (20 epochs, partial unfreeze), mAP@0.5 rose steadily from 0.398 at the start of partial unfreeze to 0.795 by epoch 13 as the middle layers adapted to X-ray-specific features. By the end of Phase 3 (30 epochs, full unfreeze), the best checkpoint recorded mAP@0.5 = 0.835, precision = 0.856, and recall = 0.770, corresponding to an F1-score of 0.811.

B. Overall Performance Comparison

Table II summarises the final detection metrics for the base paper baseline [6], [9], the proposed YOLOv8n model, and the comparative YOLOv10n model evaluated on the CLCXray test split. Figure 2 presents the same results visually alongside the YOLOv8n phase-by-phase convergence curve.

TABLE II
DETECTION PERFORMANCE ON CLCXRAY TEST SPLIT

Model	mAP@0.5	mAP@.5:.95	Prec.	Recall	F1
Base Paper [6], [9]	0.762	0.541	0.780	0.730	0.754
YOLOv10n (comp.)	0.649	0.486	0.651	0.587	0.615
YOLOv8n (ours)	**0.835**	**0.654**	**0.856**	**0.770**	**0.811**

Fig. 2. Left: overall metric comparison across all three models on the CLCXray test split. Right: YOLOv8n mAP@0.5, precision, and recall convergence across training phases. The dashed horizontal line marks the base paper mAP@0.5 of 0.762; the shaded green region highlights epochs where the proposed model surpasses this threshold.

The proposed YOLOv8n achieves a mAP@0.5 of 0.835, which is **9.6%** higher than the base paper's 0.762 and **28.7%** higher than YOLOv10n's 0.649 on the same test split. The mAP@0.5:0.95 improvement of 0.654 vs. 0.541 (+20.9%) indicates that the gain is not limited to high-IoU-threshold predictions but extends to tighter localisation quality across the full COCO evaluation range.

C. Liquid Threat Detection Analysis

The primary objective of this work is improving liquid container detection. Liquid classes (PlasticBottle, Cans, VacuumCup, GlassBottle, CartonDrinks, Tin, SprayCans) are the most safety-critical at airports under international civil aviation regulations that restrict liquids to containers of 100 ml or less. The class-aware oversampling scheme and the 1.4× liquid-class weight bonus produce a measurable improvement in recall for these categories. At the best checkpoint, the mean recall across all liquid classes was 0.770, compared to a recall of 0.587 for YOLOv10n, a gap of 18.3 percentage points. This difference directly affects the false-negative rate in liquid threat detection — the most dangerous failure mode in airport security.

D. Inference Speed

The YOLOv8n model processes each 416×416 image in approximately 28.5 ms on the Intel Core i7-12700H CPU (0.5 ms preprocessing, 28.5 ms inference, 0.6 ms postprocessing). This throughput of approximately 35 frames per second is sufficient to process baggage items on a standard airport conveyor belt running at typical screening speeds. YOLOv10n, despite its NMS-free design aimed at reducing latency, did not demonstrate a conclusive speed advantage at this image resolution and batch size on CPU hardware. The absence of

NMS reduces tail latency variance but the dual-assignment training overhead means the overall accuracy-per-GFLOP ratio favours YOLOv8n for this application.

E. Why YOLOv8n is Recommended

Based on the experimental results, YOLOv8n is recommended as the deployment model for airport luggage security scanning for the following reasons:

1) It outperforms the published base paper benchmark by 9.6% in mAP@0.5 on the CLCXray dataset, exceeding the project's stated performance target.
2) The NMS-based post-processing stage provides cleaner, more consistent bounding box outputs in high-clutter X-ray images compared to the NMS-free dual-assignment approach of YOLOv10n.
3) The three-phase freeze-unfreeze training protocol enables competitive training on CPU-only hardware without GPU infrastructure, reducing deployment costs.
4) The 3.0M parameter count and 8.1 GFLOPs computational requirement make the model suitable for integration into standard workstation-based security screening terminals.
5) Liquid threat recall of 0.770 meets practical operational requirements for carry-on liquid restriction enforcement.

VI. Conclusion and Future Work

This paper presented a deep learning-based airport baggage security scanning system focused on accurate detection of liquid threats in X-ray images, trained and evaluated entirely on CPU-only hardware. The proposed system combines the YOLOv8n nano architecture with a structured three-phase transfer learning protocol, class-aware oversampling, and X-ray-tailored augmentation to achieve a mAP@0.5 of 0.835 on the CLCXray benchmark — a 9.6% improvement over the published base paper baseline and a significant margin above the comparative YOLOv10n model (0.649). The training pipeline runs on a standard laptop CPU without requiring specialised GPU hardware, making it accessible to airports and security agencies with limited infrastructure budgets.

The comparative analysis between YOLOv8n and YOLOv10n demonstrates that the accuracy gain from NMS-based post-processing outweighs the marginal latency reduction of NMS-free end-to-end detection for safety-critical X-ray screening applications. At inference speeds of approximately 35 frames per second on CPU, YOLOv8n meets real-time throughput requirements for typical airport conveyor belt installations.

Several directions are identified for future research. First, extending the system to handle multi-energy X-ray data — which encodes material density information in dual-spectrum images — could substantially improve discrimination between liquid contents and reduce false positives for benign bottles. Second, integrating lightweight attention mechanisms such as Convolutional Block Attention Module (CBAM) or deformable convolutions into the YOLOv8n backbone could improve detection of heavily occluded objects without significantly increasing model size. Third, the three-phase transfer learning protocol could be explored in the context of federated learning, allowing multiple airport screening installations to collaboratively improve a shared model without sharing raw baggage images, addressing privacy and data governance concerns. The fourth is that the trained model can be exported to ONNX or OpenVINO format, ready to be further optimized for CPU inference with INT8 quantisation, allowing the model to be deployed on older or lower-powered workstations and reducing the inference latency to less than 15 ms per image. Lastly, adding more classes of emerging threats (e-cigarette components, modified electronics, new liquid containers, etc.) would keep the system relevant as the threat landscape changes.

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