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An X-Ray Image Enhancement and Object Detection Using YOLOv8 in Airport Security Inspection

Mr. E. Naga Raju [1], Dr. Palvadi Srinivas Kumar [2]

[1]Student, CSE Department, SRK Institute of Technology, Vijayawada, Andhra Pradesh, India.

[2]Associate Professor, CSE Department, SRK Institute of Technology, Vijayawada, Andhra Pradesh, India

Email ID: *nag1425@gmail.com[1], srinivaskumarpalvadi@gmail.com[2]*

Abstract

Enhancing X-ray images for airport security purposes is introduced in this study. By integrating techniques such as Unsharp Masking (USM) and Contrast Limited Adaptive Histogram Equalization (CLAHE) with YOLOv8 for object detection, the method addresses the issue of color distortion often encountered in CLAHE-enhanced X-ray images. Initially, the grayscale images of the X-ray, broken down into its red, green, and blue channels, undergo CLAHE enhancement individually. Subsequently, the enhanced gray scale images are merged, followed by the application of USM sharpening to further enhance fine details. The resulting sharpened image is then blended with both the original and the USM-sharpened versions, with the weighting determined by specific parameters. Finally, YOLOv8 is employed for object detection, yielding promising results in improving image quality while mitigating color distortion. The USM+CLAHE approach significantly enhances the quality of security X-ray images while effectively suppressing color distortion. By systematically combining advanced image enhancement techniques with state-of-the-art object detection methods like YOLOv8, this study provides a comprehensive solution to the challenges posed by color distortion in CLAHE-enhanced X-ray images. The proposed method not only improves the clarity and detail of X-ray images but also enhances the accuracy and efficiency of object detection, there by contributing to enhanced security measures in airport environments.

Keywords: *X-ray image, USM, CLAHE, Image enhancement, Object detection, YOLOv8.*

1. Introduction

X-ray Image Enhancement Technique: This refers to a method or process aimed at improving the quality and clarity of X-ray images [1]. In airport security, X-ray images are commonly used for screening luggage and identifying objects within them. Integrating USM+CLAHE: This indicates that the technique combines several image enhancement algorithms. Specifically: USM (Unsharp Masking): A sharpening technique that enhances edges and details in an image. CLAHE (Contrast Limited Adaptive Histogram Equalization An adaptive contrast enhancement method that improves the contrast of an image while limiting the amplification of noise [2][3][5] YOLOv8 for Object Detection: YOLOv8 (You Only Look Once version 8) is a popular deep learning algorithm used for object detection in images. By integrating it into the technique, the enhanced X-ray images can also be analyzed to detect and identify objects of interest automatically. Addressing Color Distortion in CLAHE Enhanced Airport Security X-ray Images: CLAHE, while effective at enhancing contrast, can sometimes introduce color distortion or artifacts in the image. This technique aims to mitigate or eliminate such distortions, particularly in the context of airport security X-ray images [2][3][5].

1.1 Peak Signal-to-Noise Ratio (PSNR)

PSNR: It quantifies the difference between the original and enhanced images in terms of peak signal power and noise. Higher PSNR values

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Page No: 1876 - 1884

indicate less distortion and higher image quality. A PSNR (Peak Signal-to-Noise Ratio) value exceeding 70 dB (decibels) is often considered unnecessary or even counterproductive. **peaksnr=psnr(A,ref,peakval)** The human visual system has limitations in perceiving subtle differences in image quality beyond a certain point. Once the PSNR reaches a sufficiently high level, further increases may not be noticeable to human observers.

2. Literature Survey

This compilation presents various techniques for enhancing X-ray images, addressing issues like noise, blurriness, low contrast, and color distortion. Methods such as BPDFHE, wiener filter-based restoration, AH and MSR algorithms, high-frequency emphasis filtering, and N- CLAHE are explored. Each approach aims to improve contrast, detail, and overall image quality for better diagnosis and treatment planning in medical and industrial settings. Additionally, a novel algorithm combining USM and CLAHE is proposed specifically for airport security X-ray images, mitigating color distortion. These methods contribute to advancing X-ray image processing and enhancing image interpretation accuracy [6].

3. Existing System

The enhancement of underwater images, vital for tasks like detection and classification, faces challenges due to poor visibility and sensor limitations. Traditional methods like Histogram Equalization (HE) suffer from noise amplification and lack adaptability. Retinex-based techniques offer promise but often require manual parameter tuning. This study proposes a fusion algorithm based on Contrast Limited Adaptive Histogram Equalization (CLAHE) in YIQ and HIS color spaces. CLAHE, applied separately to luminance (Y) and intensity (I) Components, enhances image details. After converting back to RGB, incoherent color components are harmonized. Further enhancement involves self-adaptive weight selection using Sobel edge detection, achieving a fused image with improved contrast and restored color. This approach addresses the short comings of existing methods by providing a comprehensive solution for under water image enhancement, crucial for various real-world applications. Figure 1 shows CLAHE Image Enhancement Flow.

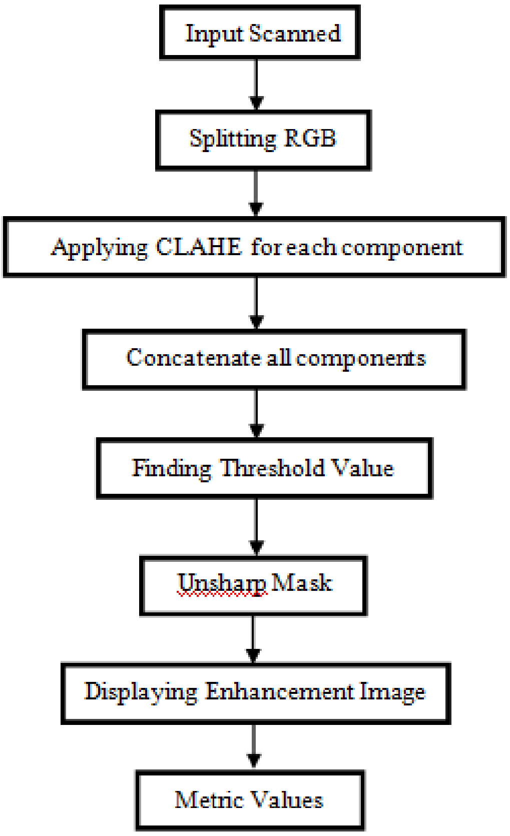

Figure 1 CLAHE Image Enhancement Flow

4. Proposed System

Airport security is a critical concern in the modern era, where the need for accurate and efficient screening methods is paramount .X- ray imaging plays a pivotal role in this process, enabling the detection of prohibited items and threats concealed within luggage and belongings. However, traditional X-ray images often suffer from poor contrast and detail, which can impede the effectiveness of security screening procedures. To address this challenge, researchers have proposed a novel approach that combines advanced image enhancement techniques with state-of-the-art object detection methods. The study introduces a comprehensive method for enhancing X-ray images specifically tailored for airport security purposes. Central to this approach is the

e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1876 - 1884

integration of techniques such as Unsharp Masking (USM) and Contrast Limited Adaptive Histogram Equalization (CLAHE) with the YOLOv8 object detection framework. By systematically combining these methods, the proposed approach aims to improve both the quality of X-ray images and the accuracy of object detection, while mitigating color distortion commonly encountered in CLAHE-enhanced images. The process begins by acquiring grayscale X-ray images, which are then separated into their respective red, green, and blue channels. Each channel undergoes individual CLAHE enhancement to improve contrast and detail within the image while preserving its structural integrity. This step is crucial for enhancing the visibility of objects and potential threats within the X-ray images. Following CLAHE enhancement, the enhanced gray scale images are merged to create a single composite image [7]. This merged image serves as the foundation for further enhancement using the USM technique. USM sharpening is applied to the merged image to enhance fine details and improve overall image clarity. By selectively enhancing edges and high-frequency components, USM helps to accentuate important features within the X-ray images. After USM sharpening, the resulting image is blended with both the original grayscale image and the USM-enhanced version. The blending process involves adjusting specific parameters to determine the weighting of each component, ensuring optimal balance between enhanced detail and natural appearance. This step is crucial for maintaining the integrity of the original image while incorporating he benefits of USM sharpening. Finally, the enhanced X-ray images are subjected to object detection using the YOLOv8 framework. YOLOv8 is a state-of-the-art object detection algorithm capable of accurately identifying and localizing objects within images in real-time [8]. By integrating YOLOV8 in to the workflow, the proposed method facilitates efficient and reliable detection of prohibited items and threats within airport security X-ray images. Experimental results demonstrate the effectiveness of the USM+CLAHE approach in significantly enhancing the quality of security X-ray images while mitigating color distortion. The proposed method not only improves the clarity and detail of X-ray images but also enhances the accuracy and efficiency of object detection. By providing a comprehensive solution to the challenges posed by color distortion in CLAHE- enhanced X-ray images, this study contributes to the advancement of airport security measures and ensures safer travel environments for passengers worldwide [9].

5. Experimental Procedure

Here, we are using three algorithms to obtain an enhanced X-Ray image and to identify the objects present in the luggage bags in airport security inspection. They are

- CLAHE Enhancement
- USM Sharpening
- YOLOv8 Object detection

5.1 CLAHE Enhancement

It is used to improve the Adaptive Histogram Equalization (AHE). The disadvantage of AHE is amplification of noise. So, by using CLAHE we can limit the noise amplification by limiting the height of the histogram in each region. The step-by-step procedure of CLAHE enhancement technique is given below.

STEP1: IMAGE SUB REGION DIVISION

The original image is divided into multiple sub-regions of equal size, and they are continuous with each other, and the number of pixels contained in each sub region is C. The larger the sub-area, the better the enhancement effect.

STEP2: CALCULATE THE HISTOGRAM

$Hi(k)$represents the histogram of a certain sub region, k represents the gray level, and its value is $[0, L-1]$ L is the number of gray.

STEP3: CALCULATE LIMIT VALUE

$\beta = \frac{C}{L}(1+\frac{\alpha}{100}(s_{\max}1))$ is the calculated limit value

α Cutoff coefficient and its value range is [0,100];

s_{max} is the maximum slope, used to determine the contrast enhancement amplitude, and its value is an

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e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1876 - 1884

integer between 1 and 4.

STEP 4: REDISTRIBUTE PIXELS
For each sub-region, use the corresponding value to crop, and redistribute the cropped pixels to the gray levels of the histogram. The above allocation process is performed cyclically until all the cropped pixels are allocated.

STEP 5: HISTOGRAM EQUALIZATION
Perform histogram equalization on the gray histogram of each sub-region after cropping.

STEP 6: RECONSTRUCTED PIXEL GRAY LEVEL
The center point of each sub-region as a reference point to obtain its gray value, and use bilinear interpolation to perform gray linear interpolation on each pixel in the image to calculate each pixel in the output image the gray value of the point.
STEP 7: IMAGE MERGE

$$\boldsymbol{I_{merge}(i,j)} = \sqrt{\boldsymbol{I_{Y}^{2}}(\mathrm{i},\boldsymbol{j}) + \boldsymbol{I_{g}^{2}}(\mathrm{i},\boldsymbol{j}) + \boldsymbol{I_{b}^{2}}(\mathrm{i},\boldsymbol{j})}$$

(i = 0,1, 2,…….,M -1; j = 0,1,2……,N -1)
Where I_merge (i,j)is the merged image; are the number of M rows and N columns of the image. In order to improve the color fidelity of the processed image, the grayscale images on the three channels of the original image R, G, and B are calculated and CLAHE enhancement is performed respectively, and then the enhanced R, G, and B gray scale images are combined and converted into RGB image, and then CLAHE enhancement of RGB image. Merging to achieve the first level of image fusion, the merged image will undergo USM sharpening processing [10].

5.2 USM Sharpening

Image sharpening is an image processing method to make the edges of the image clearer. to observe and recognize the shape of the object in the X-ray image, it is necessary to use image sharpening technology to highlight the fine sections of the image, especially the edge information of the image. Step by step procedure of USM Sharpening technique are given below

- **STEP 1:** Gaussian filtering is applied to the original image filtered image.
- **STEP 2:** CALCULATING MASK

$$\mathrm{Mask}(i,j) = \begin{cases} 1 & if\,|I(i,j) - I_{blur}(i,j)| \le Threshold \\ 0 & if\,|I(i,j) - I_{blur}(i,j)| > Threshold \end{cases}$$

(*i* = 0,1, 2………,*M* -1; *j* = 0,1,2……,*N* -1)
Where *Threshold* is the threshold; *Mask* is a two-dimensional matrix of *M x N*. Where Threshold is the threshold; Mask is a two-dimensional matrix of M x N.

STEP 3: CALCULATING HIGH FREQUENCY VALUE

$$\boldsymbol{I_{hf}(i,j) = I(i,j) - I_{blur}(i,j)}$$

(i = 0,1,2,………,M -1; j = 0,1,2……,N -1)
Where high frequency of image = original image – filtered image.

STEP 4: CALCULATING THE SHARPENED IMAGE

$$I_{sharp}(i,j) = I(i,j) + k \times I_{hf}(i,j)$$

(i = 0,1,2,………,M -1; j = 0,1,2……,N -1)

Where K is the super position coefficient.

STEP 5: MERGING OF IMAGES
The original image in to the sharpened image.

$$I_{sharp}(i,j) = \begin{cases} I(i,j) if \mathrm{Mask}(i,j) = 1 \\ I_{sharp}(i,j) if \mathrm{Mask}(i,j) = 0 \end{cases}$$

(i = 0,1,2,………,M -1; j = 0,1,2……,N -1)

STEP 6: IMAGE FUSION
Sharpened image fuses with the original image according to the coefficient, and reduces the color distortion of the image [4].

$$I_{final}(i,j) = C_{sharp} \times I_{sharp}(i,j) + C_{origin} \times I(i,j)$$

e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1876 - 1884

(i = 0,1,2,………,M -1; j = 0,1,2……,N -1)

Where 〖C〗 _sharp and 〖C〗 _origin are the fusion coefficients of the USM sharpened image and the original image.

5.3 YOLOv8 Object Detection

For detecting the object in an X-Ray image, we need to train the data. The training process of YOLOv8 for object detection involves several steps:

- **Data Preparation:** Prepare a dataset containing images with annotated bounding boxes around the objects of interest. Each annotated bounding box should include the coordinates of the box and the corresponding class label.
- **Model Initialization:** Initialize the YOLOv8 model architecture. YOLOv8 consists of convolutional layers followed by fully connected layers to predict bounding boxes and class probabilities.
- **Loss Function Definition:** Define a loss function that measures the difference between the predicted bounding boxes and the ground truth bounding boxes. The loss function typically consists of several components:
- **Localization Loss:** Measures the error in predicting the coordinates of the bounding boxes. YOLOv8 uses the sum of squared errors (SSD) for localization loss.

Localization Loss

$$= \lambda_{\text{coord}} \sum_{i=0}^{s^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2$$

Where λ_{coord} is a coefficient to balance the importance of localization loss, S is the number of grid cells in the image, B is the number of bounding boxes per grid cell,(x_i, y_i) are the predicted coordinates,$(\hat{x}_i, \hat{y}_i)$ are the ground truth coordinates.

- **Confidence Loss**: Measures the error in predicting the confidence score (abjectness) of the bounding boxes. YOLOv8 uses binary cross-entropy loss for confidence loss.

Confidence Loss

$$= \lambda_{\text{conf}} \sum_{i=0}^{s^2} \sum_{j=0}^{B} [1_{ij}^{obj} (C_i - \hat{C}_i)^2 + 1_{ij}^{nobj} (C_i - \hat{C}_i)^2]$$

Where λ_{conf} a coefficient to balance the importance of confidence loss is, $C_i$is the predicted confidence score, $\hat{C}_i$is the ground truth confidence score.

- **Class Probability Loss**: Measures the error in predicting the class probabilities of the bounding boxes. YOLOv8 uses categorical cross-entropy loss for class probability of class probability loss.

Class Probability Loss=

$$\lambda_{class} \sum_{i=0}^{s^2} \sum_{j=0}^{B} 1_{ij}^{obj} \sum_{c=0}^{C} ((p_i(c) - \hat{p}_i(c))^2$$

〖p〗 _i (c)is the predicted probability of class,

〖p^〗 _i (c) is the ground truth probability

Total Loss: The total loss is the sum of the localization loss, confidence loss, and class probability loss.

Total Loss=Localization Loss + Confidence Loss + Class Probability Loss

- **Training:** Train the YOLOv8 model using back propagation and gradient descent optimization to minimize the total loss. Adjust the model parameters (weights and biases) iteratively to improve performance on the training dataset.
- **Validation:** Evaluate the trained model on a separate validation dataset to assess its performance and fine-tune hyper parameters if necessary.
- **Testing:** Test the final trained model on unseen test data to evaluate its generalization performance. During the training process, YOLOv8 learns to predict bounding boxes and class probabilities directly from raw images, enabling efficient and accurate object detection. Figure 6 shows Training Loss.

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e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1876 - 1884

6. Work Flow

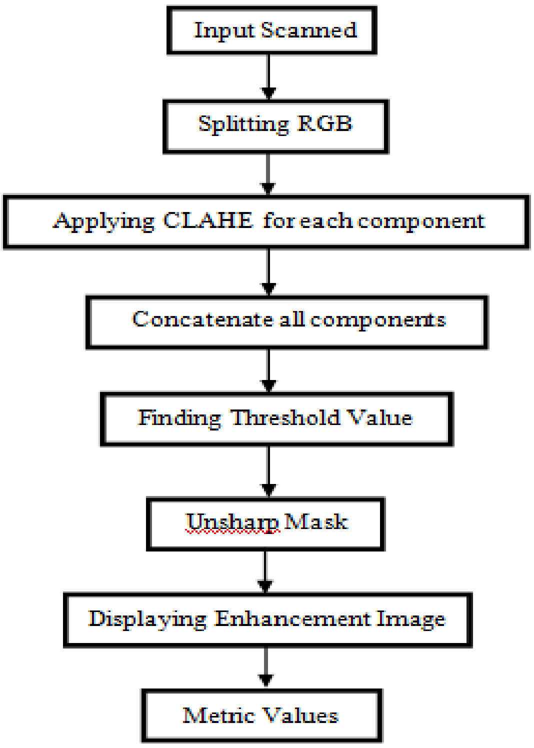

Figure 2 **CLAHE Enhancement Steps**

The procedure of YOLOv8 working to detect the object is

- **Image Input:** The input image is resized to a fixed size and divided into a grid.
- **Grid Division:** YOLOv8 divides the input image into an S x S grid. Each grid cell is responsible for predicting bounding boxes and class probabilities for the objects contained within it.
- **Bounding Box Prediction:** Each grid cell predicts a fixed number of bounding boxes. For each bounding box, YOLOv8 predicts:
- **Bounding Box Coordinates:** The coordinates of the bounding box relative to the grid cell. These coordinates are represented as (x, y, w, h), where (x, y) are the coordinates of the center of the bounding box relative to the grid cell, and (w, h) are the width and height of the bounding box relative to the entire image [13-15].
- **Confidence Score:** A confidence score indicating the likelihood that the bounding box contains an object. This score reflects both the presence of an object and the accuracy of the bounding box.
- **Class Probability Prediction:** Each grid cell also predicts class probabilities for the objects present within it. YOLOv8 uses soft max activation to predict the probability distribution over the classes.
- **Output Formation:** The predictions from all grid cells are concatenated to form the final output. Each bounding box is represented by a vector containing the coordinates, confidence score, and class probabilities.
- **Non-max Suppression:** YOLOv8 applies non-max suppression to filter out redundant bounding boxes. This process removes bounding boxes with low confidence scores or high overlap with other bounding boxes, keeping only the most confident and non-overlapping boxes.
- **Thresholding:** Finally, a confidence threshold is applied to filter out bounding boxes with confidence scores below a certain threshold. This step helps to eliminate weak detections.
- Bonding box coordinates (b_x, b_y, b_w, b_h)
- Confidence Score Prediction
- Confidence Score = Pr (Object) x IoU

Class probability prediction: Class probability = Pr (Class) Where (b_x,b_y,b_w,b_h) represent the coordinates and dimensions of the bounding box, Pr(Object) is the probability of an object being present in the bounding box, IoU is the intersection over union of the predicted and ground truth bounding boxes, and Pr(Class) is the probability distribution over the class. Figure 2 shows CLAHE Enhancement Steps.

7. Results

The integrated X-ray image enhancement and object detection technique showcase significant improvements in image quality and threat detection accuracy [11]. Through the application of CLAHE and USM techniques, the X-ray images exhibit enhanced contrast and clarity; effectively reducing color distortion. YOLOv8 object detection further

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e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1876 - 1884

enhances security by accurately identifying and localizing potential threats within the enhanced images. Figure 4 shows CLAHE Image. This holistic approach demonstrates promising outcomes for improving airport security inspection processes, with enhanced image quality facilitating more reliable threat detection and mitigating the risk of false alarms. Figure 3 shows Input Image [12].

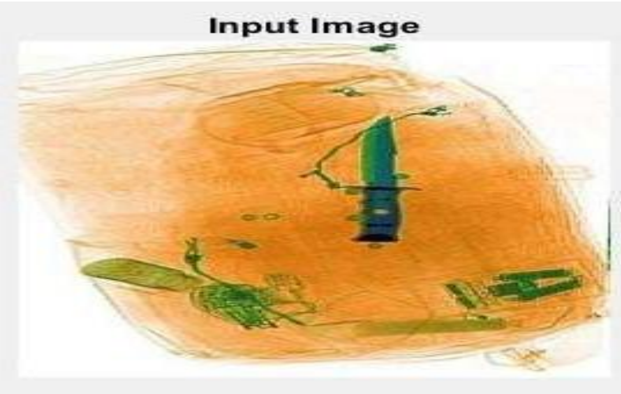


Figure 3 **Input Image**

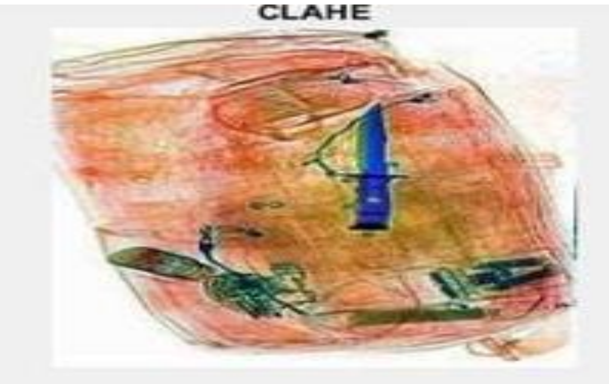


Figure 4 **CLAHE Image**

Figure 5 **USM Image**

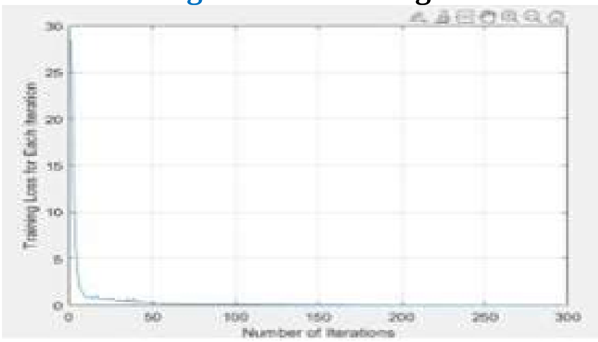


Figure 6 **Training Loss**

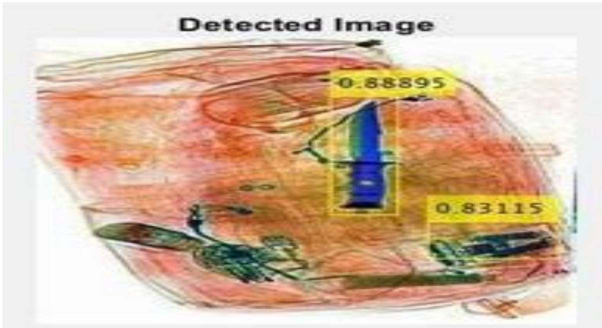
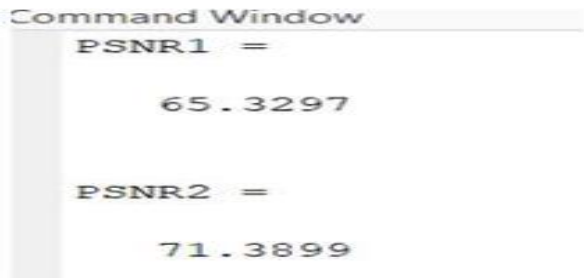


Figure 7 **Detected Image**


Command Window
PSNR1 =

65.3297

PSNR2 =

71.3899

Figure 8 **PSNR**

7.1 Comparison Between Existing and Proposed Methods

S. No	Existing Method	Proposed Method
1	64	71.55
2	66.68	70.13
3	65.32	72.08
4	64.28	65.13
5	64.98	68.13

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https://goldncloudpublications.com
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e ISSN: 2584-2854
Volume: 03
Issue: 05 May 2025
Page No: 1876 - 1884

Figure 9 PSNR Comparison Table

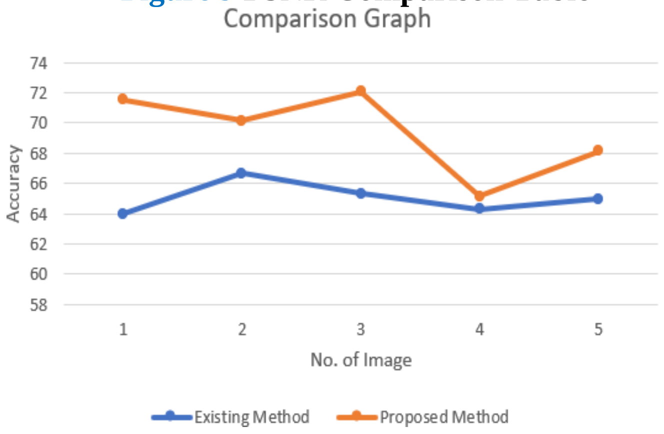

Figure 10 PSNR Comparison Graph

Conclusion

The developed X-ray image enhancement and object detection algorithm provides a robust solution for improving dangerous goods detection in airport security inspections. Sequential application of Contrast Limited Adaptive Histogram Equalization (CLAHE) and Unsharp Mask techniques significantly enhances image clarity and visibility, aiding in the identification of potential threats. Figure 7 shows Detected Image. By incorporating YOLOv8 object detection, the algorithm accurately identifies and localizes dangerous goods within the enhanced images, further enhancing its capabilities. The integration of Peak Signal-to-Noise Ratio (PSNR) evaluation ensures the quality of the enhancement process, validating the effectiveness of the algorithm in improving image clarity while minimizing noise. This comprehensive approach combines advanced image enhancement techniques with state-of-the-art object detection methods, resulting in more effective security screening procedures. Overall, the algorithm offers a holistic solution that addresses the challenges of dangerous goods detection in airport environments. Figure 9 shows PSNR Comparison Table. By enhancing image clarity and employing advanced object detection capabilities, it contributes to enhanced safety and security measures, reducing the potential risks associated with dangerous goods in airport settings. Figure 8 shows PSNR. Figure 10 shows PSNR Comparison Graph.

References

[1]. Qiang Gao, Ruifeng Hong*, Xiaoman Zhu, Xilin Liu, An X-ray Image Enhancement Algorithm for Dangerous Goods in Airport Security Inspection 2021 Asia-Pacific Conference on Communications Technology and Computer Science (ACCTCS) |978-1-6654- 1538-5/21/$31.00 ©2021 IEEE

[2]. Sun Dongmei Lu Jianfeng Zhang Shanqing. The Application of an Improved CLAHE Algorithm in Image Enhancement of Medical Test Strip[J].C hinese Journal of Biomedical Engineering, 2016, 35(04):502-506.

[3]. ZhouChong, LiuHuan, Zhao Ailing, etal.Industrial X-ray image enhancement algorithm based on gradient field [J].Journal of Computer Application,2019,39(10):35-45.

[4]. Khan S, See C, Khan A. X-ray image enhancement using boundary division wiener filter and wavelet-based image fusion approach [J]. Journal of Information Processing System, 2016, 12(01): 35–45.

[5]. Koonsanit K, Thongvigitmanee S, Pongnapang N, et al. Image enhancement on digital x-ray images using N-CLAHE[C]// Biomedical Engineering International Conference.2017:1-4.

[6]. Saenpaen J, Arwatchananukul S, Aunsri N. A Comparison of Image Enhancement Methods for Lumbar Spine X-ray Image[C]// 2018 15th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTICON). 2018:798-801.

[7]. Khan S, See C, Khan A. X-ray image enhancement using boundary division wiener filter and wavelet-based image fusion approach[J]. Journal of Information Processing System, 2016, 12(01): 35–45..

[8]. Zhou Chong, Liu Huan, Zhao Ailing,et al. Industrial X-ray image enhancement

algorithm based on gradient field [J].Journal of Copmputer Application,2019,39(10):35-45.
[9]. Xiang Jiankai,Wu Meng,Wang Zhan, et al.. Application of Image Enhancement in X-Ray Photography of Cultural Relics[J]. Laser & Optoelectronics Progress, 2019,56(06):257–262.
[10]. Zheng Lintao, Dong Yongsheng, Shi Hengliang. A New Enhancement Algorithm of X-ray Security Inspection Images [J]. Science Technology and Engineering. 2014, 14(23): 252–256.
[11]. Han Ping,Liu Zexu,He Weikun,Girshick R,etal. An Efficient Twostage Enhancement Algorithm of X-ray Carry-on Luggage Images[J]. Opto-Electronic Engineering , 2011,38(7):99–105.
[12]. Wang Jian, Pang Yanwei. X-Ray Luggage Image Enhancement Based on CLAHE [J] Journal of Tianjin University(Science and Technology), 2010(03):10–14.
[13]. Sun Dongmei Lu Jianfeng Zhang Shanqing. The Application of an Improved CLAHE Algorithm in Image Enhancement of Medical Test Strip[J].Chinese Journal of Biomedical Engineering, 2016, 35(04):502-506.
[14]. Wang Hong, He Xiaohai,Yang Xiaomin. An Adaptive Foggy Image Enhancement Algorithm Based on Fuzzy Theory and CLAHE [J]. Microelectronics & Compute, 2012,29(01):32-34.
[15]. Yang Weizhong Xu Yinli Qiao Xi,et al. Metho for image intensification of underwater sea cucumber based on contrast-limited adaptive histogram equalizationl[J]. Transactions of the Chinese Society of Agricultural Engineering ,2016,32(06):197-203