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Detection of Illegal Goods using X-ray Image Enhancement Algorithm

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Abstract: An X-ray image enhancement technique integrating USM+CLAHE+HAZEREMOVAL and YOLOV2 for object detection is presented to address the problem of colour distortion in CLAHE enhanced airport security X-ray images. Calculating the grayscale images on the R, G, and B channels of the X-ray image and applying CLAHE enhancement to each, then merging the enhanced R, G, and B grayscale images will take place. After that, USM sharpening operation is applied to the CLAHE-enhanced X-ray image, and then it is merged with the original and USM-sharpened images according to the weight. Later haze removal technique is added to obtained results. For detection, YOLOV2 is used. The results of the experiments reveal that the USM+CLAHE+ HAZEREMOVAL algorithm can successfully improve the security X-ray image while also suppressing colour distortion in the enhanced image.

I. INTRODUCTION

Security inspection of illegal goods is a challenging task. There are a large number of dangerous goods passing through airports and many other places daily, and it is very hard to inspect each item manually. The security of airports is very important because there are many people who travel in them every day. The main purpose of airport security is to prevent any dangerous item that could harm passengers or staff. The purpose of this project is to develop a novel algorithm for detecting dangerous goods from an X-ray image. The algorithm will aid airport security officers in their inspection of luggage and other packages for threats such as explosives or weapons. This research is motivated by the need for improved security at airports due to the increase in terrorist attacks over the past decade. Airport security is a vital component of the aviation industry, as it is responsible for protecting passengers and their luggage from potentially dangerous goods. One of the most critical aspects of airport security is the use of X-ray machines to scan luggage, which allows security personnel to view the contents of luggage and detect any hazardous items.

However, the quality of X-ray images can be poor, making it challenging for security personnel to identify dangerous goods. This is particularly true for items that are dense, such as metals or electronic devices, which can obscure other items in the luggage. To address this issue, researchers have developed an X-ray image enhancement algorithm that can improve the quality of X-ray images and make it easier for security personnel to identify dangerous goods. The algorithm uses a combination of image processing techniques, such as contrast enhancement, noise reduction, and edge detection, to improve the clarity and visibility of the images.

There are currently few publications on X-ray image enhancement in security, and most domestic and international research on X-ray image enhancement is focused on the medical area and industrial inspection field [1]-[5].and there are few literatures on X-ray image enhancement in security inspection [6]–[8].The most popular picture enhancement technique is histogram equalisation (HE), which has the advantages of a straightforward theory, straightforward application, and high real-time performance.

The Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm, which is based on the local adaptive histogram enhancement algorithm (Adaptive Histogram Equalization, AHE), effectively suppresses the excessive enhancement of local contrast and the amplification of noise, making it particularly suitable for low-contrast images. Researchers have given the CLAHE algorithm a lot of thought since it combines the benefits of two technologies— adaptive histogram equalisation and restricted contrast. To improve picture details, Sun Dongmei et al. [9] devised an adaptive parameter T that automatically modifies the pixel redistribution range of each image sub-block.

Wang Hong et al. [10] proposed the brightness component of the foggy image using the constrained local histogram algorithm, which improved the brightness and contrast of the foggy image. They used the fuzzy enhancement algorithm to achieve the adaptive contrast enhancement of the global foggy image. In order to enhance the underwater sea cucumber image, Yang Weizhong [11] employed the CLAHE method, which successfully preserved the image's fine features while enhancing the image quality. In order to successfully improve the contrast and edge detail information of the original infrared picture, Liu Yuting et al. [12] coupled the CLAHE method with bilateral filtering algorithm

II. EXISTING SYSTEM

In the digital image application field, images with high contrast and bright colors are the crucial prerequisite for good understanding of the real scenes, such as detection and classification for underwater dam cracks, and multitarget detection under complex environment. The images having a higher contrast level usually display a larger degreeof color scale difference as compared to the lower contrast level ones. Light plays a crucial role in generating images of satisfactory quality in photography. Strong light causes an image to have a washed-out appearance; on the contrary, weak light leads toan image that is too dark to be visible.

In these two cases, the contrasts of the images are low and their detailed textures are difficult to discern. The underwater images may lose contrast suffering from degradation due to poor visibility conditions and effects such as light absorption, light reflection, bending of light and scattering of light, which result in dimness and distortion. Furthermore, the poor sensitivity of charge-coupled device /complementary-metal- oxide-semiconductor (CCD/CMOS) sensors leads to images with excessive narrow dynamic ranges and renders their details unclear.

The purpose of image enhancement is a process that allows image features to show up more visibly details and highlight the useful information by making best use of the color presented on the display devices. Image enhancement is used to improve the quality ofan image for visual perception of human being. Therefore, it is particularly important to design effective enhancement algorithms to improve contrast and restore color for the degenerated underwater image.

A. Retinex Theory

Recently, Retinex, Homomorphic and Wavelet Multi-Scale techniques have been popular for enhancing images. These methods perform much better than those traditional ones. The Retinex theory is firstly introduced to image enhancement by Edwin et al.

There are some different algorithms based on Retinex theory such as single-scale Retinex (SSR), multi-scale Retinex (MSR), multi-scale Retinex with color restoration (MSRCR), and fast multi-scale Retinex (FMSR) etc. Among them, the MSRCR method proposes to estimate the illumination of the input image using gaussian surround filtering of different scales and conducts enhancement by applying color restoration followed by linear stretching to the logarithm of reflectance.

Though the MSRCR method has demonstrated a strong ability in providing dynamic range compression, color restoration and preserving most of details, a large number of parameters are involved and setempirically, which limit the generalization ability and often result in pseudo halos and unnatural color.

The classical contrast enhancement is Histogram Equalization (HE) which has good performance in ordinary images, such as human portraits or natural images. This method increases the contrast of an image globally by spreading out the most frequent intensity values. However, it suffers from noise amplification in relatively homogeneous regions. HE has been generalized to a local histogram equalization which is known as adaptive histogram equalization (AHE). AHE is based on HE that the adaptive method formulates each histogram of sub-image to redistribute the brightness values of the images. AHE is therefore suitable for improving the local contrast of an image and bringing out more details. Some AHE algorithms have get important progress in suppressing noise and enhancing contrast.

The hybrid cumulative histogram equalization (HCHE) can improve the enhancement effect on hot objects rather than background. The gap adjustment histogram equalization can solve the over-enhancement problem and alleviate the feature loss problem in the dark regions of the image. However, the problem remains the same with the global histogram equalization because of amplifying noise in relatively homogeneous regions.

In order to overcome this problem, contrast limited adaptive histogram equalization (CLAHE) was proposed. CLAHE is a well-known block-based processing, and it can overcome the over amplification of noise problem in the homogeneous region of image with standard histogram equalization. CLAHE algorithm differs from standard HE in the respect that CLAHE operates on small regions in the image, called tiles, and computes several histograms, each corresponding to a distinct section of the image and use themto redistribute the lightness values of the image.

In order to improve contrast and restore color for underwater image captured by camera sensors without suffering from insufficient details and color cast, a fusion algorithm for image enhancement in different color spaces based on contrast limited adaptive histogram equalization (CLAHE) is proposed in this article.

The original color image is first converted from RGB colorspace to two different special color spaces: YIQ and HSI. The color space conversion from RGB to YIQ is a linear transformation, while the RGB to HSI conversion is nonlinear. Then, the algorithm separately operates CLAHE in YIQ and HSI color spaces to obtain two different enhancement images.

The luminance component (Y) in the YIQ color space and the intensity component (I) in the HSI color space are enhanced with CLAHE algorithm.

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The CLAHE has two key parameters: Block Size and Clip Limit, which mainly control the quality of CLAHE enhancement image. After that, the YIQ and HSI enhancement images are respectively converted backward to RGB color.

When the three components of red, green, and blue are not coherent in the YIQ-RGB or HSI-RGB images, the three components will have to be harmonized with the CLAHE algorithm in RGB space. Finally, with 4 direction Sobel edge detector in the bounded general logarithm ratio operation, a self-adaptive weight selection nonlinear image enhancement is carried out to fuse YIQ-RGB and HSI-RGB images together to achieve the final fused image. The enhancement fusion algorithm has two key factors: average of Sobel edge detector and fusion coefficient, and these two factors determine the effectsof enhancement fusion algorithm.

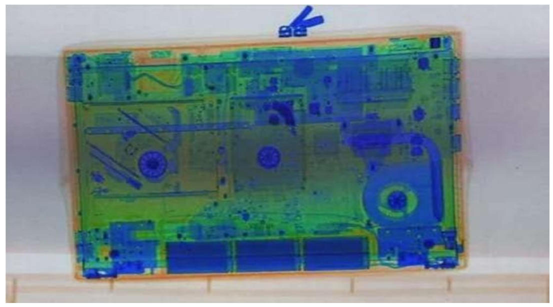

Fig.1 : CLAHE OUTPUT

B. Drawbacks

1) It may increase the contrast of background noise, while decreasing the usablesignal/image data
2) Suffer from color distortion
3) This method is the tendency to over-amplify noise in relatively homogeneousregions of an image.

This section will elaborate on the security inspection Xray image enhancement algorithm process:

a) CLAHE enhancement. First, calculate the grayscale images on the R, enhancement respectively, and then merge the enhanced R, G, and B grayscale images.
b) USM sharpening. This algorithm uses an improved USM (Unsharp Mask) algorithm to sharpen the CLAHE-enhanced image to highlight details such as image edges and shapes. The USM algorithm combines the sharpened image with the original image according to the superposition coefficient for the second level image fusion.
c) Image fusion. The original image and the USM sharpened image are weighted and summed to reduce image color distortion.

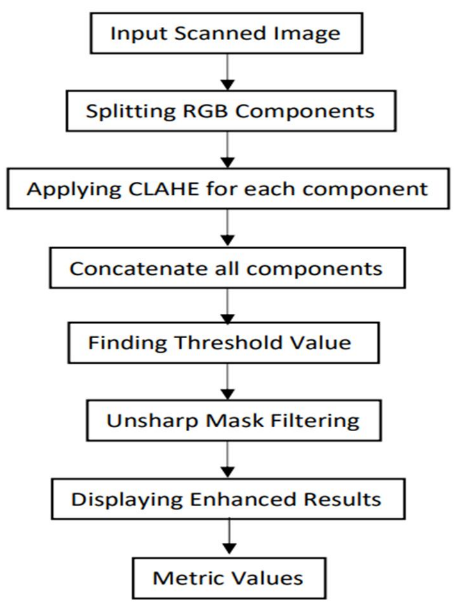

Fig.2: Block Diagram of Proposed Method

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C. CLAHE Enhancement

1) Introduction to CLAHE

The statistical link between each grey level in the image and its frequency is represented by the image histogram, sometimes referred to as the grey level histogram. The histogram's definition is displayed in "(1)".

$$\boldsymbol{P(r_{k})} = \frac{\boldsymbol{n_k}}{\boldsymbol{N}} \quad (k=0,1,2,\ldots\ldots,L-1) \quad (1)$$

Using grayscale transformation, histogram equalisation (HE) is a technique for automatically altering picture contrast quality. The main concept is to expand the original image's grayscale histogram from a relatively narrow grayscale interval to encompass the complete grayscale spectrumuniformity of distribution The conventional HE approach is distinct from adaptive histogram equalisation (AHE). By first computing the local histogram of the picture and then redistributing the brightness, the AHE method modifies the image's local contrast, thus enhancing it and revealing more image details. However, AHE has the issue of overly magnifying the visual noise.

Contrast-limited The approach of adaptive histogram equalisation is improved by the CLAHE algorithm. Noise amplification in AHE may be controlled by restricting the height of the histogram in each section. The following are the main steps of the CLAHE algorithm:

Step1: Division of image subregions: Each subregion of the original image is the same size, has a constant amount of pixels (C), does not overlap any other subregions, and is divided into many equal-sized subregions. The enhancing impact, which can often be modified in accordance with real demands, is better the greater the sub-area.

Step 2: Calculate the histogram. The histogram of a particular subregion is represented by using, where denotes the grey level, its value is, and is the total number of grey levels.

Step 3: Determine the limit value Determine the cutoff limit indicated by "(2)"

$$\beta = \frac{c}{L}\left(1 + \frac{\alpha}{100}(S\,max - 1)\right) \quad (2)$$

The determined limit value, the cutoff coefficient, whose range of values is [0,100], and the maximum slope, which is used to calculate the contrast enhancement amplitude, are among them. The maximum slope's value is an integer between 1 and 4.

Step 4: Redistribute pixels. Use the matching value for each sub-region to crop, then redistribute the cropped pixels to the histogram's grey levels. The aforementioned allocation procedure is carried out repeatedly until all of the cropped pixels have been assigned.

Step 5: Histogram equalisation: Following cropping, equalise the grey histogram for each sub-region.

Step 6: Reconstructed pixel grey value: To compute the grey value of each pixel in the output picture, use bilinear interpolation to conduct grey linear interpolation on each pixel in the input image. This is done by using the centre point of each sub-region as a reference point.

Fig 3. CLAHE

2) Image Merge

The enhanced R, G, and B grayscale images are combined and converted into RGB and HSV images, and then CLAHE enhancement of the RGB image and the HSV image, respectively, is performed to further improve the colour fidelity of the processed image. The enhanced image is then marked with the appropriate CLAHE enhancement of RGB image and HSV image designations marked as Ir,Ig,Ib adopts the Euclidean norm at last, as shown in "(3)" Ir,Ig,Ib the combined picture will go through USM sharpening processing after merging to produce the first degree of image fusion.

$$I_{merge(i,j)} = \sqrt{I_r^2(i,j) + I_g^2(i,j) + I_b^2(i,j)}$$

$$(i=0,1,2,\ldots,M-1;\ j=0,1,2,\ldots,N-1) \quad (3)$$

The merged picture is one of them, and the number of rows and columns is the same below.

3) USM sharpening

It is vital to employ image sharpening technology to emphasise the fine areas of the picture, notably the edge information of the image, in order to make it easier for the security people to view and recognise the shape of the item in the X-ray image. Image sharpening is a technique used in image processing to make the edges of the image more distinct.

The basic idea is to first extract the original picture's high frequency components, then superimpose those components with the original image in accordance with predetermined criteria to obtain the sharpened image. Although the sharpened picture produced by the conventional unsharp mask (USM) procedure is less prone to noise and false edges, it may still

be used to eliminate some minor interference elements from images. As a result, the USM method and threshold are used in this paper.

The following are the key actions.

Step 1: First, the original image is filtered using a Gaussian process.

Step 2: Calculating the mask as indicated in "(4)." The threshold and a two-dimensional matrix are two of them.

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

$$(I = 0,1,2,\ldots,M-1;\ j=0,1,2,\ldots,N-1) \quad (4)$$

Step 3: Calculating the High Frequency Component Image(Ihf) as indicated in "(5)."

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

$$(I = 0,1,2,\ldots,M-1;j=0,1,2,\ldots,N-1) \quad (5)$$

Step 4: Calculating the sharpened picture (I sharp) as seen in "(6)".

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

$$(i = 0,1,2,\ldots,M-1;\ j=0,1,2,\ldots,N-1) \quad (6)$$

The superposition coefficient's location is k.

Step 5: The original picture is combined with the sharpened image (I sharp), as shown in "(7)"

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

$$(i\ 0,1,2,\ldots,M-1;\ j = 0,1,2,\ldots,N-1) \quad (7)$$

4) Image fusion

The edge, form, and other aspects of the security X-ray picture have been improved after CLAHE enhancement and USM sharpening, but the processed image has a significant colour difference from the original image, making it difficult for the security staff to identify the items in the image. In order to decrease colour distortion in the picture produced by the algorithm in this article compared to the original image, as shown in "(8),"

This work fuses the sharpened image with the original image according to the coefficient.

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

$$(i= 0,1,2,\ldots,M-1;\ j = 0,1,2,\ldots,N-1) \quad (8)$$

The fusion coefficients of the original picture and the USM sharpened image, respectively, are among them.

Fig 4. CLAHE+USM

III. PROPOSED SYSTEM

YOLOv2, or YOLO9000, is a single-stage real-time object detection model. It improves upon YOLOv1 in several ways, including the use of Darknet-19 as a backbone, batch normalization, use of a high-resolution classifier, and the use of anchor boxes to predict bounding boxes, and more.

A. Introduction to YOLOv-2

In 2017, Joseph Redmon (a Graduate Student at the University of Washington) and Ali Farhadi (a PRIOR team lead at the Allen Institute for AI) published the published the YOLO9000: Better, Faster, Better paper at the CVPR conference. The authors proposed two *state-of-the-art* YOLO variants in this paper: YOLOv2 and YOLO9000; both were identical but differed in training strategy.
YOLOv2 was trained on standard detection datasets like **PASCAL** and **MS COO**. At the same time, the YOLO9000 was designed to predict more than 9000 different object categories by jointly training it on the MS COCO and IMAGE datasets.

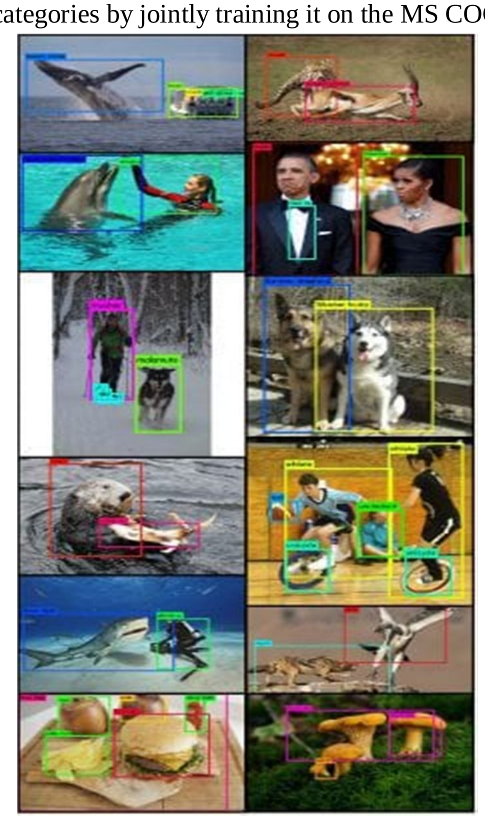

Fig 4: YOLO9000 model can detect a wide variety of object classes in real-time

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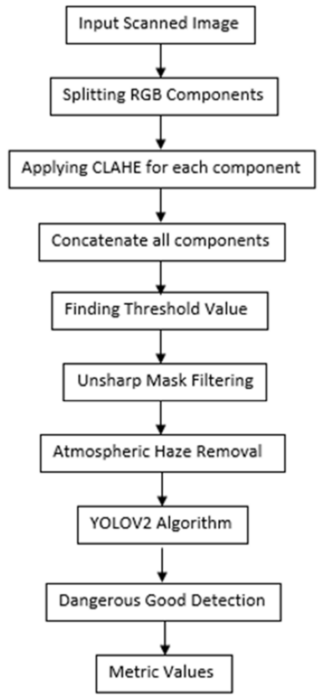
Figure shows the output of the YOLO9000 model that can detect more than 9000 object classes in real-time. The output below shows that the model has learned to detect objects not in the MS COCO dataset.

YOLOv2 is the second version in the YOLO family, significantly improving accuracy and making it even faster

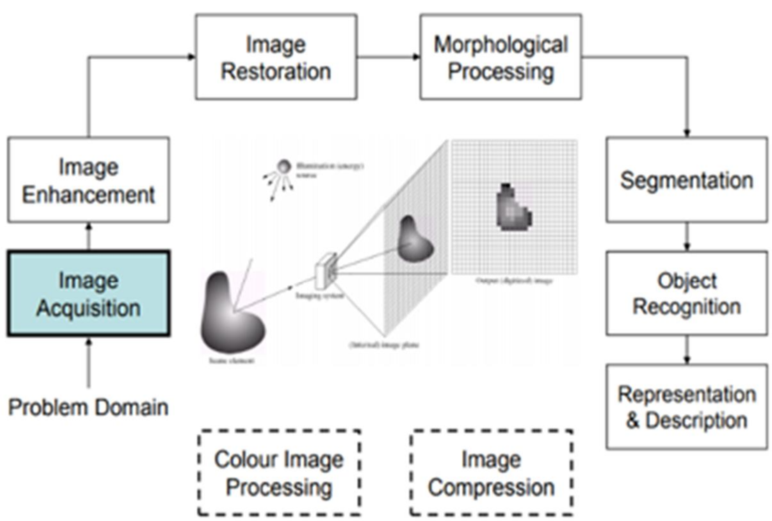
The improved YOLOv2 model used various novel techniques to outperform state-of-the-art methods like Faster-RCNN and SSD in both speed and accuracy. One such technique was multi-scale training that allowed the network to predict at varying input sizes, thus allowing a trade-off between speed and accuracy.

At 416×416 input resolution, YOLOv2 achieved 76.8 mAP on VOC 2007 dataset and 67 FPS on Titan X GPU. On the same dataset with 544×544 input, YOLOv2 attained 78.6 mAP and 40 FPS



Block Diagram of Proposed Method

B. Phases Of Image Processing



In YOLOv2 the details of each block in the visualization can be seen by hovering over the block. Each Convolution block has the BatchNorm normalization and then Leaky Relu activation except for the last Convolution block. YOLO divides the input image into an **S×S** grid. Each grid cell predicts only **one** object. For example, the yellow grid cell below tries to predict the "person" object whose center (the blue dot) falls inside the grid cell. Each grid cell predicts a fixed number of boundary boxes. In this example, the yellow grid cell makes two boundary box predictions (blue boxes) to locate where the person is. However, the one-object rule limits how close detected objects can be.

For each grid cell,

- It predicts **B** boundary boxes and each box has one **box confidence score**,
- It detects **one** object only regardless of the number of boxes B,
- It predicts **C conditional class probabilities** (one per class for the likeliness of the object class).

The boundary boxes contain box confidence score. The confidence score reflects how likely the box contains an object (**objectless**) and how accurate is the boundary box. We normalize the bounding box width *w* and height *h* by the image width and height. *x* and *y* are offsets to the corresponding cell. Hence, *x, y, w* and *h* are all between 0 and 1. Each cell has 20 conditional class probabilities. The **conditional class probability** is the probability that the detected object belongs to a particular class (one probability per category for each cell). The class confidence score for each prediction box is computed as:

Class confidence score = box confidence score * conditional class probability

$$\begin{aligned} \text{box confidence score} &\equiv P_r(object) \cdot IoU \\ \text{conditional class probability} &\equiv P_r(class_i|object) \\ \text{class confidence score} &\equiv P_r(class_i) \cdot IoU \\ &= \text{box confidence score} \times \text{conditional class probability} \end{aligned}$$

where

$P_r(object)$ is the probability the box contains an object.
IoU is the IoU (intersection over union) between the predicted box and the ground truth.
$P_r(class_i|object)$ is the probability the object belongs to $class_i$ given an object is presence.
$P_r(class_i)$ is the probability the object belongs to $class_i$

It measures the confidence on both the classification and the localization (where an object is located). We may mix up those scoring and probability terms easily. Here are the mathematical definitions for your future reference.

YOLO predicts multiple bounding boxes per grid cell. To compute the loss for the true positive, we only want one of them to be **responsible** for the object. For this purpose, we select the one with the highest IoU (intersection over union) with the ground truth. This strategy leads to specialization among the bounding box predictions. Each prediction gets better at predicting certain sizes and aspect ratios.

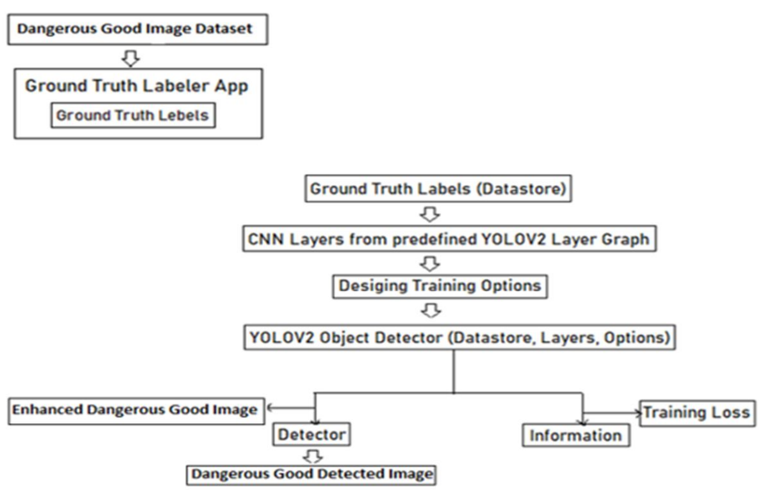


Fig: Block Diagram of YOLOV2 Architecture

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They also proposed the YOLO9000 model trained on the COCO detection dataset with the ImageNet classification dataset. The domain for such training is referred to as weakly supervised learning. This approach helped them achieve 16 mAP on 156 classes that did not have detection ground truth.

Fig.5 CLAHE+USM+YOLOv2(Final Result)

C. Threshold Value

In MATLAB, the threshold value represents a crucial parameter used in various image processing and analysis tasks, particularly in segmentation. Essentially, it defines a dividing line or limit between two regions or classes within an image. When applied to image processing, this value serves as a criterion to differentiate between foreground and background elements or to isolate specific features within an image. For instance, in grayscale images, a threshold value can be set to classify pixels as either black or white, creating a binary image. Choosing an appropriate threshold is vital; it impacts the accuracy of segmentation and subsequent analysis.

IV. SIMULATION RESULTS

MATLAB provides numerous methods to determine an optimal threshold, such as Otsu's method or adaptive thresholding techniques, allowing users to automate this process based on statistical properties of the image. Adjusting the threshold value can significantly influence the outcome of image processing operations, making it a fundamental aspect of MATLAB-based image analysis workflows.

PSNR

In MATLAB, Peak Signal-to-Noise Ratio (PSNR) is a metric used to evaluate the quality of an image by comparing the original image to a compressed or distorted version. It measures the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.

To calculate PSNR in MATLAB, you can use the formula PSNR = 20 * log10(MAX_I) - 10 * log10(MSE), where MAX_I is the maximum pixel value of the image (typically 255 for an 8-bit grayscale image), and MSE is the Mean Squared Error between the original and distorted images. MATLAB provides functions like `imread` to read images, `imresize` to change image dimensions, and `psnr` to directly calculate PSNR between two images. For instance, to compute PSNR for two images `original` and `distorted`, you'd use `psnr_val = psnr (distorted, original) `. This value helps quantify how much the distortion affects the image fidelity, with higher PSNR values indicating better similarity between the images.

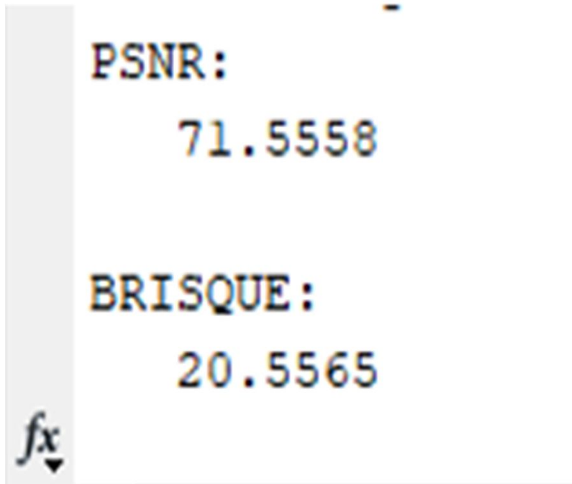

Fig. 6. PSNR & BRISQUE

S.NO	Existing Method		Proposed Method	
	PSNR	BRISQUE	PSNR	BRISQUE
1	64	22.01	71.55	20.55
2	66.68	25.77	70.13	26.93
3	65.32	24.9	72.08	27.13
4	64.28	45.62	65.13	19.16
5	64.98	32.88	68.13	34.08
6	65.84	36.2	69.74	28.2

Fig. .7 PSNR & BRISQE comparison Table

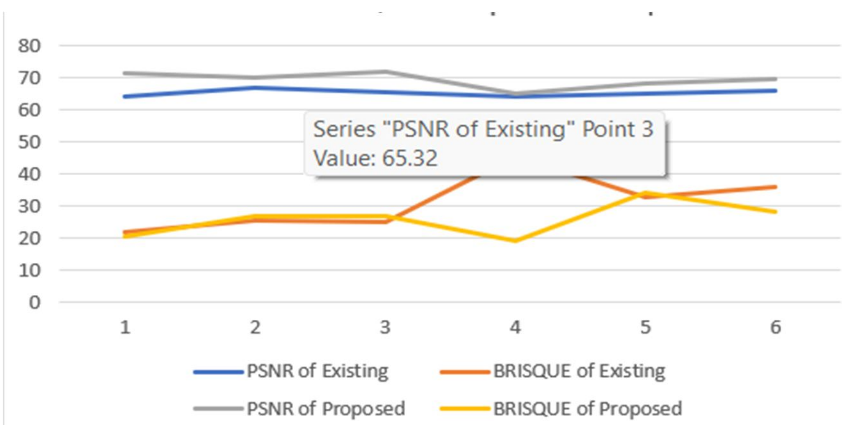

Fig.8 BRISQE comparison Graph

V. CONCLUSION

This work investigates the subject of " In airport security inspection, an X-Ray image enhancement & detection algorithm for dangerous goods " using Matlab as an analytical framework and to solve the problem of colour distortion in CLAHE enhanced airport security X-ray images, an X-ray image enhancement technique incorporating USM+CLAHE+HAZEREMOVAL and YOLOV2 for object recognition is provided. The grayscale pictures on the R, G, and B channels of the X-ray image will be calculated, and CLAHE enhancement will be applied to each, followed by merging the enhanced R, G, and B grayscale images.

The CLAHE-enhanced X-ray image is next subjected to the USM sharpening procedure, which is subsequently blended with the original and USM-sharpened images based on the weight. After that, the collected findings are subjected to a haze removal procedure. YOLOV2 is utilized for detection. The results of the experiments reveal that the USM+CLAHE+ HAZEREMOVAL algorithm can successfully improve the security X-ray image while also suppressing colour distortion in the enhanced image.

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