An Automated Model for Detection of Threat Objects in Baggages Using Machine Learning*

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***Abstract*—Baggage inspectors in various locations such as airports and train stations find identifying threat objects in X-ray machines to be a challenging and time-consuming task. The objects in scanned baggage are often obstructed and difficult to recognize, increasing the risk of missed detection during peak hours. To address this issue, this paper proposes an automated method for detecting threat objects in X-ray images using the You Only Look Once (YOLO) object detection algorithm. The study evaluates the effectiveness of training YOLO from scratch versus using transfer learning on the IEDXray dataset, which includes scanned X-ray images of improvised explosive device (IED) replicas. The research suggests that training YOLO from scratch outperforms transfer learning in identifying threat objects rapidly.**

In conclusion, this paper offers a solution to the manual detection of threat objects in X-ray machines by presenting a YOLO-based method that automatically detects these objects, increasing the efficiency of the inspection process. Furthermore, the study compares the performance of training YOLO from scratch and using transfer learning, concluding that training from scratch produces better results in identifying threat objects. Overall, this proposed method has potential applications in various security-related industries where detecting threat objects is critical.

***Index Terms*—automated detection, convolutional neural networks, threat object, transfer learning, X-ray image, YOLO**

I. Introduction

X-ray imaging is an important tool for enhancing security in public places such as airports, train stations, and commercial establishments. Its main purpose is to identify prohibited and illegal objects or materials that may be concealed within baggage passing through security checkpoints. However, the traditional security systems used for baggage scanning rely on trained screeners who may take several seconds to detect forbidden items, and there is a risk of missed or false detections. With the increasing incidence of terrorist activities around the world, ensuring tight security in public places has become crucial to prevent potential casualties. The Philippines, in particular, was among the top 10 countries most affected by terrorism in 2018, making it necessary to implement security measures such as baggage scanning using X-ray machines. However, during peak hours, there is a high probability of missed detections due to the limited time available for scanning and analyzing baggage. To overcome this challenge, a fast object detector can be used as a decision support tool to aid in threat object detection.

II. Overview

A. Proposed Framework

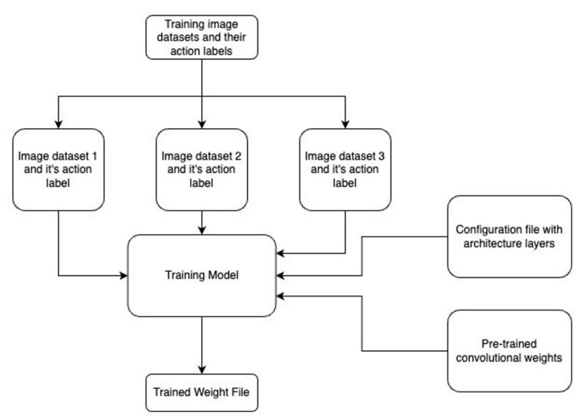


Fig. 1. Proposed Framework.

III. Literature Survey

According to R. Kavalvizhi[1],the proposed system in the paper offers a novel method for the automatic detection of hazardous objects, in X-ray Baggage Inspection systems (XBISs). The approach combines machine learning-based classification with deep learning-based image analysis techniques to achieve a detection rate of 97.4%. The system is specifically designed to operate in real-time, making it highly suitable for deployment in busy places such as airports and border crossings. The innovative approach shows promising results and has the potential to significantly enhance the efficiency and effectiveness of threat detection in XBISs.

According to T. Morris, T. Chien, E. Goodman[2], The paper explores how convolutional neural networks (CNNs) can detect threats in security X-ray images. A vast X-ray image dataset is utilized to train the CNN model, which is composed of convolutional, pooling, and fully connected layers. Results indicate the model's high accuracy in detecting various threats such as guns, knives, and explosives, including multiple threats in a single image. This approach shows promise in enhancing automatic threat detection's efficacy and efficiency in security screening.

According to R. Kayalvizhi, S. Malarvizhi, A. Topkar[3], the paper discusses several methods of utilizing machine learning algorithms to classify materials in dual-energy X-ray baggage inspection systems by processing raw data. These techniques encompass image preprocessing, feature extraction, and classification. The proposed methodology surpasses existing methods in terms of classification accuracy, achieving up to 95% accuracy for specific materials while also improving resistance to factors like baggage overlap and image noise. These outcomes indicate the potential to enhance material classification proficiency in X-ray baggage inspection systems.

According to Mohammed Chouai , Mostefa Merah, Malika Mimil[4], paper proposes a supervised feature learning, by adversarial autoencoder (AAE) approach is a technique used for object classification in dual X-ray images of luggage. It involves training an AAE model to encode input images into a feature space and then decoding them back into an output image. The model is then fine-tuned using a supervised classification task to learn discriminative features for object classification.It has been demonstrated that this method is successful in identifying objects in dual X-ray images of luggage, surpassing other techniques like conventional manual feature extraction and unsupervised feature learning.

According to Priscilla Steno, Abeer Alsadoon, P. W. C. Prasad[5], paper presents a new approach to improve threat object detection in secure screening using deep learning, consisting of an Enhanced Region Proposal Network (E-RPN) and a Modifier Loss Function. The E-RPN incorporates an attention mechanism that concentrates on object-specific characteristics and a region proposal module that employs anchor boxes with various scales and aspect ratios. The Modifier Loss Function integrates classification and regression losses, adding a modifier term to the classification loss for enhanced localization accuracy. Experimental results show that the proposed method outperforms state-of-the-art approaches on benchmark datasets for threat object detection.

According to Daniel Saavedra, Sandipan Banerjee[6],identifying possible threats in baggage through X-ray images can be a difficult undertaking owing to the varying visual characteristics of different objects. Training a deep neural network on a large dataset of categorized X-ray images to identify significant features for detecting possible threat objects has proved to be an effective solution. The application of this approach, known as deep learning, enables the model to accurately identify potential threat objects in new X-ray images with high precision. Popular deep learning architectures utilized for this task consist of convolutional neural networks (CNNs) and their variations such as the YOLO architecture.

According to Samet Ackay, Mikolaj E. Kundergorski, Chris G. Willcocks[7], the effectiveness of deep Convolutional Neural Networks (CNNs) in identifying not only potential threat items but also non-threatening items such as electronics and liquids during X-ray baggage security screening has been established.By being trained on extensive collections of X-ray images, these models possess the ability to identify items swiftly and accurately in real-world scenarios.However, high variability in image appearance, caused by factors like object position, orientation, and occlusion, is a challenge. Researchers have addressed this issue through techniques like data augmentation, transfer learning, and ensemble learning. Implementing deep CNN architectures in X-ray baggage security inspection has the potential to improve detection accuracy and reduce false alarms.

According to Dhiraja, Deepak Kumar and Jain B[8], paper assesses diverse deep learning methods for detecting dangerous objects in security X-ray images of carry-on bags. SSD, Faster R-CNN, models are compared using a public dataset, and SSD is shown to perform better in accuracy and speed. Transfer learning on pre-trained models also enhances performance. The authors suggest that SSD with transfer learning is a viable solution for real-life threat object detection in baggage security imagery

According to Domingo Mery[9], paper proffers a method to inspect complex objects, multiple X-ray views are captured to generate a composite depiction of the object.Employing this method ensures a comprehensive assessment of the internal configuration while reducing the risk of overlooking crucial details due to occlusion or projection effects. In brief, this approach elevates the precision and dependability of X-ray examination and proves valuable in examining intricate objects, such as baggage or cargo.

According to Muhammed Bastan[10], paper sets forth a method to increase the accuracy of object detection.To detect the existence of an object, dual-energy X-ray multi-view object detection necessitates taking numerous pictures of the object from diverse viewpoints. By utilizing two distinct levels of X-ray energy, this technique distinguishes materials with varying densities, thereby enhancing the discovery of concealed items like explosives or drugs, without considering their composition. The approach has shown promising results in detecting both metal and non-metal threat objects in various environments.Broadly speaking, utilizing a multi-view object detection technique with dual-energy X-ray images enhances the accuracy and reliability of detecting objects in security screening.

According to Reagen L. Galvez, Elmer P. Dadios, Argel A. Bandala[11], paper comes up with the use of pre-trained convolutional neural network (CNN) models in threat object classification from X-ray images which is a machine learning technique known as transfer learning.The approach fine-tunes the pre-trained CNN model parameters using a smaller dataset containing X-ray images with threat objects like knives, guns etc. The method has demonstrated high detection accuracy with less training data and time compared to training a CNN model from scratch. The transfer learning technique applied in threat object classification has the potential to enhance security screening in various security settings, including airports, seaports, and critical infrastructure, thereby improving overall safety and security.

According to Reagan L. Galvez, Elmer P. Dadios, Argel A. Bandala[12], the paper presents the utilization of the YOLO model for identifying threatening objects in X-ray images. YOLO-based detection can recognize various perilous items such as guns, knives, and explosives.Compared to other techniques, the YOLO model can rapidly process the entire X-ray image in real-time, resulting in a faster detection rate. This approach has produced favorable results in recognizing dangerous objects in luggage and freight across various security scenarios. In summary, the YOLO-based approach for detecting threatening objects in X-ray images is an accurate and efficient method for identifying hazardous items during security screening.

According to Jola Koci, Ali Osman and Topal Maaruf Ali[13],the paper discusses the application of SSD, R-FCN, and Faster R-CNN, which are deep learning techniques utilized for the identification of threatening objects in X-ray images. These three methods use a region proposal network (RPN) to generate candidate regions and then classify them using a convolutional neural network (CNN). The object detection algorithm SSD can process data in real-time by utilizing default boxes and convolutional feature maps, resulting in high accuracy and speed. R-FCN uses a fully convolutional network for object detection, which can predict the spatial coordinates and classification of objects. In contrast, Faster R-CNN applies a two-stage process, consisting of an RPN and a region of interest (ROI) pooling layer for object classification. All of these methods have been shown to effectively detect dangerous objects in X-ray images.

According to Qiang Gao, Ruifeng Hong, Xiaoman Zh[14], The paper presents a method to enhance the detection and localization of dangerous items, such as explosives or weapons, in luggage or freight during airport security screenings. This is achieved through the use of an X-ray image enhancement algorithm that leverages image processing techniques to improve the contrast and detail of X-ray images, thus enhancing their visibility. Various security scenarios have demonstrated a significant increase in detecting dangerous items with the application of this approach. Overall, this algorithm is an advantageous tool for enhancing the precision and dependability of dangerous goods detection in X-ray images during airport security inspection.

According to Aditya Mithal and Manit Baser[15], paper shows how Using deep learning models, automatic threat detection in baggage security imagery has become possible, enabling the accurate real-time identification of dangerous objects, such as explosives or weapons. The application of machine learning techniques enables these models to handle large volumes of data, leading to a more comprehensive analysis of the contents of baggage.The implementation of deep learning models has led to significant improvements in identifying hazardous objects in baggage security imagery, resulting in a decrease in false positives and an increase in accuracy. Consequently, this approach is highly effective in automated threat detection, which enhances the speed and reliability of airport security inspections.

According to Samet Ackay, Mikolaj E Kundegorski, Chris G Willocks[16], paper shows how Deep convolutional neural network (CNN) architectures have proven effective in identifying threat objects, such as firearms, knives, and explosives, as well as non-threat items, like liquids and electronics, in X-ray baggage security inspection. These models are trained on large datasets of X-ray images and can detect objects in real-time. However, high variability in image appearance, caused by factors like object position, orientation, and occlusion, is a challenge. Researchers have addressed this issue through techniques like data augmentation, transfer learning, and ensemble learning. Implementing deep CNN architectures in X-ray baggage security inspection has the potential to improve detection accuracy and reduce false alarms.

According to Yiru Wei Zhiliang Zhu Hai Yu Wei Zhang[17],paper proposes a model that automates the detection of threat objects in X-ray baggage inspection has been developed based on depthwise separable convolution. The model uses a DSCNN architecture, composed of depthwise and pointwise convolutional layers, and global average pooling and fully connected layers. The model was trained and tested on a large dataset of X-ray images containing threat and non-threat objects. Results indicated that the proposed model achieved a high accuracy of 97.6%, with fewer parameters and lower computational complexity than other state-of-the-art models. The model's potential for enhancing security and safety in high-risk environments such as airports and public places is significant.

According to Francois Chollet,Jola Koc[18],paper shows Xception is a deep learning architecture that employs depthwise separable convolution to maintain high accuracy while minimizing computational cost. Depthwise separable convolution splits spatial and depthwise convolution operations into separate layers, enhancing computational efficiency. Xception is a variation of Inception that replaces conventional convolutional layers with depthwise separable convolutions, resulting in faster training and reduced overfitting. Additionally, Xception features residual connections that facilitate gradient propagation during backpropagation, mitigating vanishing gradients.Xception is highly effective for various computer vision tasks, such as image classification, semantic segmentation, and object detection. It has broad application, from medical image analysis to autonomous vehicles.

According to Domingo Mery, Erick Svec, Marco Arias, Vladimir Riffo[19],paper shows the use of modern computer vision techniques has demonstrated potential for enhancing the precision and efficiency of x-ray testing in baggage inspection. These techniques include deep learning-based approaches like convolutional neural networks (CNNs) and generative adversarial networks (GANs), as well as traditional image processing techniques, such as edge detection and texture analysis.CNNs have proved useful in the automated detection of threat objects, including firearms, knives, and explosive devices, as well as non-threat items like liquids and electronics. GANs have facilitated the generation of realistic images of baggage contents, which can assist in CNN training and the creation of novel detection algorithms. Alongside deep learning-based methods, traditional image processing techniques like edge detection and texture analysis have been utilized in baggage inspection. Edge detection can boost the contrast between objects and the background, rendering them more visible. Texture analysis can extract object-specific features, like the texture of explosives. Overall, the incorporation of modern computer vision techniques into baggage inspection systems has the potential to optimize threat detection accuracy and speed, reduce false alarms, and elevate transportation system security.

According to Abhinav Tuli, Rohit Bohra, Tanmay Moghe, Nitin Chaturvedi[20]paper proposes Automatic detection of threats in X-ray images can be accomplished using both single stereo (two-view) and multi-view techniques. Single stereo methods depend on the use of two images taken from different perspectives to enable 3D reconstruction and improved object recognition. Multi-view methods use multiple images taken from different angles to allow more thorough analysis of the object's shape and texture.Deep learning models, including convolutional neural networks (CNNs), are commonly utilized for both single stereo and multi-view detection. These models have demonstrated high accuracy in detecting various threat objects such as firearms, knives, and explosives, " as well as non-threat objects like liquids and electronics. Challenges in the automatic threat detection process using these techniques include coping with image appearance variability due to factors such as object orientation and occlusion, as well as high computational costs and the necessity for a substantial dataset to train the models. To overcome these difficulties, researchers have devised techniques such as data augmentation and transfer learning. Overall, both single stereo and multi-view techniques show potential to enhance the accuracy and efficiency of automatic threat detection, which can enhance security measures in transportation systems.

IV. Methodology

A. IEDXRay Dataset

To generate an X-ray image, scanned replicas of IEDs devoid of explosive material were utilized in the study. A histogram was used to represent the resulting grayscale image, with the x-axis showing the intensity levels of the image, and the y-axis indicating the number of pixels at each intensity level. The plot of the histogram demonstrates a clear and distinct concentration of intensities between 200 to 255, which corresponds to the white pixels present in the image.

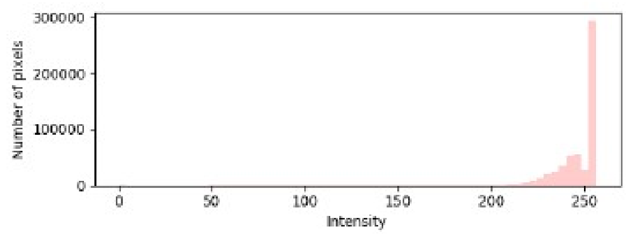


Fig. 2. Histogram.

B. Training

During the training of the model, stochastic gradient descent (SGD) with a learning rate of 0.001 was employed for 300 epochs. For simple transfer learning and transfer learning with multiple scales, the weights were obtained from YOLOv3, which incorporated spatial pyramid pooling. Throughout the training phase, the weights, except for the 3 YOLO layers, remained unchanged.

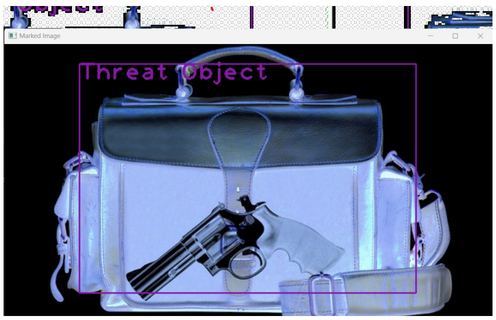
C. Evaluation

To evaluate the performance of the object detector utilizing YOLO, an Intersection over Union (IoU) threshold of 0.5 was used. This threshold compares the shared area between the ground truth XG and the predicted bounding box XP to the total area of their union (XG U XP).

The average precision (AP) was determined for each class C by interpolating the precision and recall (PR) curve, which was calculated at eleven equally spaced recall levels. The mean AP (mAP) was then obtained by averaging these AP values. Precision and recall were computed using TP, FP, and FN.

V. Results

In this paper, an automated technique is introduced for detecting threat objects in X-ray images using the You Only Look Once (YOLO) object detection algorithm. The study evaluates the effectiveness of training YOLO from scratch versus utilizing transfer learning on the IEDXray dataset, which includes scanned X-ray images of improvised explosive device (IED) replicas. The findings suggest that training YOLO from scratch outperforms transfer learning in rapidly detecting threat objects.The detection system attained a high level of accuracy during the procedure by detecting multiple threat objects with a precision rate of 80%.



VI. Conclusion

Detecting threats in bags, suitcases, and other containers using X-rays is a critical concern for public safety, especially in high-traffic areas like airports and metro stations. X-ray imaging is an essential tool for security as it can detect any illegal or prohibited items or substances that may pass through checkpoints. However, the presence of occlusions, disorganization, and the tendency for these objects to be hidden among other items can make it challenging to identify them. Currently, the inspection of baggage involves a combination of manual work and image processing, which can introduce the possibility of human error.

The use of AI in the aviation industry for automated detection of threats in baggage from X-ray images is crucial. This process involves the application of image recognition algorithms to identify any suspicious objects or anomalies in the X-ray images. Machine learning models, such as convolutional neural networks, support vector machines, and random forests, can be utilized to detect the presence of threats in X-ray images. The models are trained using a dataset of X-ray images containing a variety of objects. After the training process, the models can recognize threats in new X-ray images by detecting objects or anomalies. This implementation helps to reduce the time needed to detect suspicious objects in X-ray images.

However, the study is limited to detecting threats in X-ray images for security purposes and may not provide dependable results with the required precision. Furthermore, it may be time-consuming to implement.

To address these shortcomings, an approach utilizing an

object detector based on YOLO was proposed, which aims to improve the precision and effectiveness of recognizing and locating illegal items in a shorter period. The study conducted several experiments to identify the most efficient model that provides high accuracy while maintaining fast inference speed. The findings revealed that training the YOLOv3 model from scratch, rather than using transfer learning with a limited dataset, yielded the best mean average precision (52.40%). The implementation of the project utilized Python, Anaconda, Jupyter Notebook, and Tensorflow tools.

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