



Highly Imbalanced Baggage Threat Classification

Abdelfatah Ahmed*
100059689@ku.ac.ae
Khalifa University
Abu Dhabi, UAE

Divya Velayudhan
100058254@ku.ac.ae
Khalifa University
Abu Dhabi, UAE

Taimur Hassan
taimur.hassan@ku.ac.ae
Khalifa University
Abu Dhabi, UAE

M. Bennamoun
mohammed.bennamoun@uwa.edu.au
University of Western Australia
Perth, Australia

Ernesto Damiani
naoufel.werghi@ku.ac.ae
Khalifa University
Abu Dhabi, UAE

Naoufel Werghi
ernesto.damiani@ku.ac.ae
Khalifa University
Abu Dhabi, UAE

ABSTRACT

Recognizing threats in baggage X-ray scans is one of the most crucial tasks for ensuring safety in high-risk areas, including airports, shopping malls, and cargoes, radiograph. Due to the rise in terrorist activity, particularly in the previous two decades, the identification of baggage threats has received the most attention. Nevertheless, this process is time-consuming and restricted by the security officer's inspection capabilities. To overcome this, several frameworks based on deep learning have been suggested to effectively detect contraband items. However, these approaches primarily suffer from the issue of class imbalance, where prohibited objects are rarely seen in the real world compared to harmless baggage content. This paper proposes a novel classification network optimized with the novel compound balanced affinity loss function to address the class imbalance. This proposed loss function is based on the synergic integration of max-margin learning and the effective sample representation. The suggested method is tested on two datasets, COMPASS-XP and SIXray, where it outperforms the state-of-the-art in terms of F1-score by 2.55% and 2.52%, respectively. Also, the proposed approach has surpassed the existing frameworks by attaining accuracy of 89.16% and 70.31%, respectively. To the best of our knowledge, this is the first contour-driven classification framework injected with a compound loss function for highly imbalanced threat classification.

KEYWORDS

Affinity Loss, Threat Recognition, Class Imbalance, X-ray Scans.

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1 INTRODUCTION

Baggage inspection with X-ray scanners is considered a critical procedure to ensure airport safety and security by reducing the possibility of terrorist action [19, 34]. Therefore, the identification of luggage threats is nowadays a top security priority. However, because of the rising workloads, this procedure is stressful and subject to human mistakes. Furthermore, many studies based on X-ray detection systems have been developed to address these challenges. The first baggage detection and classification [33] systems were based on SURF and SIFT paired with an SVM model. Also, SVM model has been utilized by Franzel et al. [9] with HOG as a feature extractor in order to detect concealed items. Rizzo et al. [29] included Adaptive Implicit Shape Model to detect contraband items of GDXray dataset. Moreover, most recent object detection approaches in computer vision are based on deep learning algorithms that can quickly locate the threat items, and therefore enhance inspection performance. Many researchers have employed anomaly detection [5, 6], transfer learning [25], and contour-driven object detectors [16–18, 20] for threat identification. Hassan et al. [15] developed a novel instance segmentation approach that is injected with incremental learning algorithm and a traditional encoder-decoder architecture to effectively classify the cluttered prohibited objects. This framework can extract overlapped luggage objects from multi-vendor grayscale and colorful X-ray scans. Hu et al. introduced a novel model called SXMnet [23]; this model has the ability in the classification task to deal with the overlapping in X-ray scans. De-occlusion Attention Module (DOAM) was developed by Wei et al. [35]; this model utilizes a plug-and-play configuration that can be coupled with object detectors for contraband item recognition.

Despite the wealth of studies mentioned above, baggage threat detection under extreme class imbalance is still challenging. Many recent approaches suffer from the data imbalance issue, which leads to poor performance [2, 34]. In the context of threat item recognition in X-ray imaging, the class imbalance problem has received insufficient study attention. The only works focused on this issue are [14, 27, 31]. Miao et al. [27] studied the class imbalance issue by proposing the Security Inspection X-ray (SIXray) dataset. This dataset contains a high number of different cluttered X-ray scans with five threat items classes. To deal with that, the authors have developed an approach dubbed CHR for classifying cluttered and imbalanced X-ray images. In addition, Hassan et al. [14] have developed a CST segmentation technique that employs baggage

contours proposal generation. Moreover, in [31], a novel CNN-driven Broad Learning System has been proposed for identifying concealed and highly imbalanced contraband items.

This paper proposes a novel approach for abnormality classification, which involves employing contour maps with injecting the classification backbone with our proposed loss function, dubbed balanced affinity loss. By this, our model is capable of maximizing the margin between highly imbalanced classes in baggage threat detection while utilizing the effective number of samples to obtain robust features from the training X-ray scans. The unique characteristics of the proposed approach are:

- To the best of our knowledge, this is the first work that employs cost-sensitive learning with contour maps representation for highly imbalanced baggage threat classification.
- Max-margin and cost-sensitive learning are blended in our proposed loss function to effectively address the data imbalance.
- The suggested framework is rigorously tested on two public datasets, namely COMPASS-XP and SIXray.

The rest of the paper is structured as: the proposed framework is discussed in Section 2, while Section 3 contains the experimental setup. Section 4 describes the experimentation results. And finally Section 5 concludes the paper.

2 PROPOSED APPROACH

This work suggests a contour-driven classification approach trained using a novel balanced affinity loss function. This proposed framework can classify highly imbalanced and cluttered threatened items from X-ray scans. Moreover, in baggage threat detection, the norm is to have a high percentage of non-threatened items, whilst the contraband items delegate a very rare percentage. Therefore, this is considered a long-tail distribution of prohibited categories. Our proposed compound loss function can handle this distribution by enabling the model to learn discriminative features from novel samples via jointly minimizing the intra-categorical differences and maximizing the inter-categorical distance. The abnormality classification model (shown in Fig. 1) is comprised of three sub-modules. Each module is described next:

The Extraction of Contour Maps: The contour map representation is a popular paradigm that was used successfully in different analysis tasks [11–13, 28, 36–41]. In this work, contour maps are obtained in this framework through structured tensors, a 2×2 symmetric positive-semi definite matrix [17]. This matrix is calculated through the outer products of the image gradients. This reflects changes in a pixel’s neighborhood. For instance, given that the Gaussian smoothing function is represented by ϕ and $\nabla_{\theta_a}(I)$ is the image gradient in the θ_a direction. Also, for a set of η orientations $\theta_1, \dots, \theta_\eta$ [17], the calculation of the outer product is done as follows:

$$\mathcal{T}_{(a=1:\eta, m=a+1:\eta)} = \phi * \nabla_{\theta_a} \nabla_{\theta_m}(I) \quad (1)$$

Based on this, a set of tensors is obtained. Afterward, the coherent contour map representation is constructed by summing up transposition intensity maps representing each tensor (second-moment matrix). An illustration in Fig. 2 shows a sample of the obtained coherent contour maps.

Backbone: The backbone of our proposed framework is employed as a feature extractor. Therefore, we suggested employing a model that is not prone to losing valuable features of the X-ray scans. To that end, we adopted the High-Resolution Network (HRNet). The HRNet is a CovNet model that has the ability to maintain high-resolution maps while employing low-resolution maps via parallel branches [42]. The network starts with a high-resolution convolution stream, then adds high-to-low resolution streams and connects them parallel. Besides, HRNet frequently exchanges information across resolutions, resulting in a richer, more accurate representation [4].

Classification Model: As we mentioned, the contour maps are extracted and then passed to the HRNet to obtain the features. Afterward, the HRNet is appended with an average pooling layer along with two fully connected output layers to acquire model predictions. Hence, the classification model can classify the scan as either threat or non-threat. Besides, our proposed balanced affinity loss is injected within this module, as seen in Fig. 1.

2.1 Class Imbalance

The issue of class imbalance has garnered a lot of attention in the literature on computer vision and machine learning [1, 30, 32]. All currently used methods can be classed as algorithmic [43] or data-driven [7]. In this work, we propose plugging two different loss functions in order to handle the data imbalance. This loss function is based on the paradigm of weighting class samples and max-margin learning. For max-margin learning, we adopt the affinity loss function [3, 21]. Besides, we found that the class-balanced meeting the condition of using weight by the "effective number of samples" [8]. A brief description of the two methods is in the subsequent subsection.

Class-Balanced Loss Function: This loss (\mathcal{CB}) is based on the concept of the effective number of samples [8]. This number is the smallest subset of a given class that contains the most relevant information. Consequently, the duplicated samples are ignored in each class since they do not add any extra information. Given that m refers to the corresponding class; therefore, the effective number of samples of class m and v_m represents the samples in the ground-truth class m is computed by [8]:

$$E_{v_m} = \frac{1 - \beta^{v_m}}{1 - \beta} \quad (2)$$

where the controlling parameter is denoted by $\beta \in [0, 1]$. This parameter is responsible of how fast is the growing of the effective samples. The value of β will be determine further in this work. Moreover, given the utilized loss function as $\mathcal{L}(\cdot)$, the \mathcal{CB} is expressed as follow:

$$\mathcal{CB} = \frac{1}{E_{v_m}} \mathcal{L}(\cdot). \quad (3)$$

Affinity Loss Function: The affinity loss (L_a) has the ability to handle the class and data imbalance by combining the use of max-margin and Gaussian affinity. By that, L_a is characterized by learning both classification and clustering. Using the Gaussian similarity measure, the affinity loss quantifies the similarity in terms of the Bergman divergence [21]. Furthermore, class imbalance is reduced

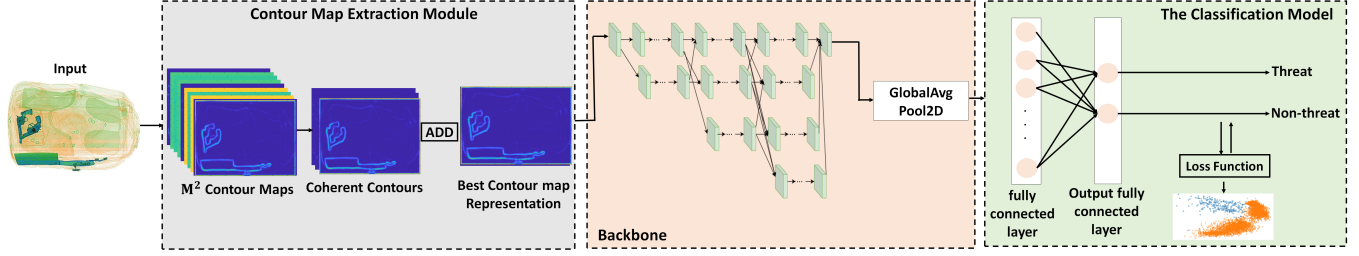


Figure 1: Threat classification block diagram. First, the X-ray scan is passed through the contour map extraction module to obtain the coherent contour representation. Afterward, the representations are passed to the HRNet to extract the features, which will be utilized in the classification model to be classified as either threat or non-threat.

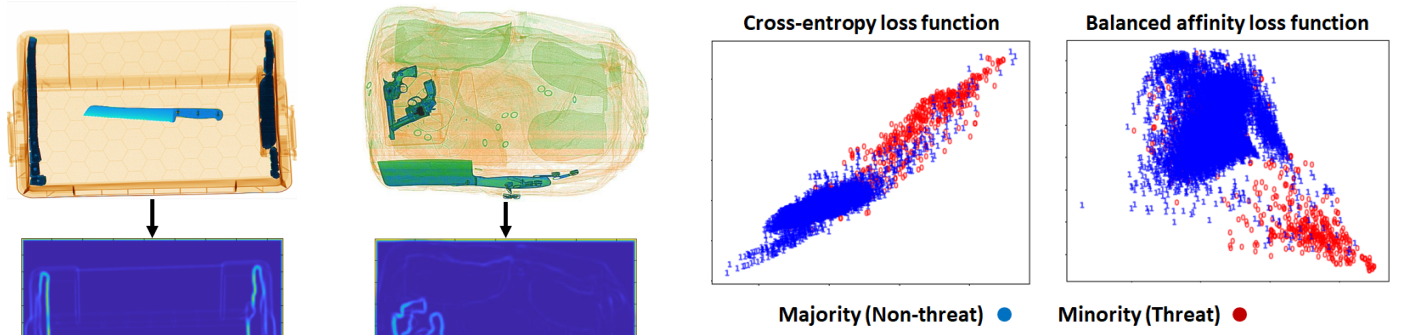


Figure 2: An exemplar X-ray scan from the SIXray and COMPASS-XP dataset and the coherent contour map representation derived from it.

through intra-class centroid delocalization employing diversity regularization and multi-centered partitioning in the L_a . Let $\{K_i, N_i\}$ the input-output pairs, the class and used sample number is denoted by C and S , respectively. And, the representation of feature space from the input samples is referred by $M_i, i = 1 : S$ and also the weights of classes is denoted by $W_j, j = 1 : C$. The affinity loss function can be computed utilizing the following expression:

$$\mathcal{L}_a = R(w) + \mathcal{L}_{mm}, \quad (4)$$

$$R(w) = E[(\|W_j - W_j\|^2 - \mu)^2], j < L, \quad (5)$$

$$\mathcal{L}_{mm} = \sum_j \max(0, \lambda + d(M_i, W_j) - d(M_i, W_{N_i})), j \neq y_i, \quad (6)$$

where $d(M_i, W_j)$, $d(M_i, W_{y_i})$, and λ is referred to the similarity with its true class, the similarity of the sample with other classes, and the enforced margin, respectively. Taking into consideration that $i \in [1, S]$, and $j \in [1, C]$.

Balanced Affinity Loss Function: As mentioned earlier, we propose combining the max-margin learning (L_a) with the class-balanced loss to yield the following proposed compound loss function:

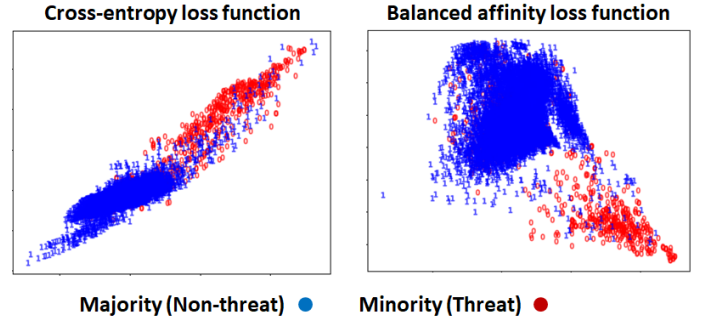


Figure 3: Feature distributions of the proposed balanced affinity loss compared to the Cross-entropy loss function in terms of the SIXray10 [27]. Here, it can be seen that, the suggested loss function’s distribution of clustering quality varies from that of the widely used cross-entropy loss function. The clustering of the proposed balanced affinity is characterized to be more compactness.

$$\mathcal{L}_{BA} = \frac{1}{E_{v_m}} \mathcal{L}_a \quad (7)$$

Compared to the cross-entropy loss function, our proposed balanced affinity loss function can ensure the learning of spaced clusters for the majority and the minority classes, as evident in Fig. 3. Therefore, the proposed loss can leverage the model to differentiate between classes and effectively group them. In contrast, cross-entropy is characterized by poor class separation, leading to a bias towards the majority class.

3 EXPERIMENTATION SETUP

3.1 Datasets

The performance of the proposed framework has been evaluated on two publicly available datasets, namely, SIXray, and COMPASS-XP, each of which is explained in the following sections:

SIXray: Security Inspection X-ray [27] is considered the largest benchmark in the field of threat detection, comprising 1,059,231 challenging baggage X-ray scans. The SIXray dataset holds 8,929 prohibited objects grouped into six classes (guns, scissors, knives, wrenches, pliers, and hammers). Moreover, to study the effect of

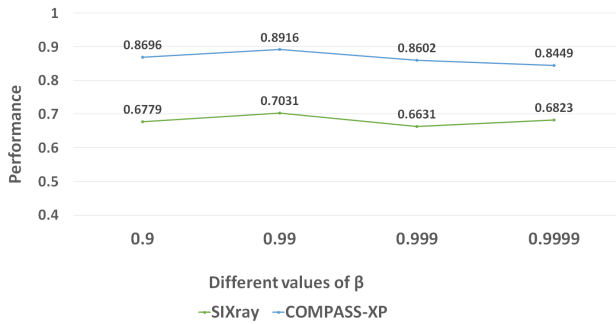


Figure 4: Performance comparison of our proposed compound loss function for abnormality classification with different values of β .

class imbalance, the dataset is organized into three sub-classes, namely, SIXray10, SIXray100, and SIXray1000.

COMPASS-XP: This dataset was introduced in 2019 [10], containing 11,568 scans of both normal and contraband items. The baggage scans have different representations i.e. low-energy and high-energy X-ray, density, color, grayscale and RGB images. Furthermore, this dataset has been designed for the abnormality classification task.

3.2 Implementation Details

The suggested approach has been implemented in Intel(R) Core(TM) i7-10750H processor with a RAM of 24 GB. Besides, the GPU is single NVIDIA GTX 1660Ti. The utilized optimizer for the experiments is Adam, along with 10 as the number of epochs and 32, and 0.1 number of the batch size and dropout, respectively.

3.3 Performance Metrics

To assess the proposed classification framework, we utilized the following classification metrics:

Accuracy: accuracy is defined as the measurement of how correctly a model predicts the classes corresponding to the ground-truth. It is expressed by:

$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \quad (8)$$

where Tn represents the true negative samples, Tp refers to the true positives, Fp is the false positives, and Fn denotes the false negatives.

F1-score:The F1-score is mostly used to solve the problem of unbalanced classes in the acquired dataset. The following equation illustrates how to calculate the F1-score:

$$F1\text{-score} = \frac{2 \times Tp}{2 \times Tp + Fp + Fn} \quad (9)$$

4 RESULTS

In this section, we present the evaluation of the proposed approach and compare it to the state-of-the-art baggage threat classification systems employing two public datasets. Also, we provide ablative experiments in order to choose the optimum framework hyper-parameters.

4.1 Ablation Studies

Selection of the β value: We conducted the first series of experiments to explore the value of β . As mentioned, this hyperparameter’s value ranges from 0 to 1. However, the authors in [8] has fixed the value of β to (0.9, 0.99, 0.999, 0.9999). Consequently, we tested the four beta values in terms of our proposed model. As shown in Fig. 4, $\beta = 0.99$ achieves the highest performance for both SIXray and COMPASS-XP datasets. Hence, we adopted this for the rest of our experiments.

Selection of the optimum loss function: We assessed the performance of our suggested balanced loss function by comparing it with a group of different class imbalanced loss functions. The result of this experiment is depicted in Table 1. For SIXray10, our proposed loss function has yielded an accuracy and F1-score of 91.72% and 89.86%, respectively, beating its best competitor. Moreover, in terms of accuracy, the L_{BA} has outperformed the L_a by 2.31% and 1.72% for SIXray100, and SIXray1000, respectively. Regarding COMPASS-XP, system accuracy and F1-score have reached up to 89.16% and 87.14%, respectively, where it achieved 0.677% and 0.519% better performance compared to the affinity loss.

4.2 Comparative Studies

To assess the performance of the proposed model, we have compared it with other baseline models in terms of accuracy and F1-score. Table 2 reports the results of our compound balanced affinity loss with other state-of-the-art methods based on SIXray and COMPASS-XP datasets. As shown, the proposed approach has improved the classification performance. For instance, the the balanced affinity loss outperforms the second-best state-of-the-art by 1.85% and 2.55% based on COMPASS-XP in terms of accuracy and F1-score. Although the accuracy of the proposed model slightly leads in performance in terms of accuracy for SIXray10, the model has surpassed the ResNet50 injected with balanced affinity loss by 1.18% in terms of F1-score. This metric is crucial for the imbalanced data. Moreover, regarding SIXray100 and SIXray1000, the model has also attained the highest performance leading the state-of-the-art by 0.773% and 0.817% for accuracy, and by 1.69% and 2.52% for F1-score, respectively. Based on these results, our proposed loss function has proven to be effective in boosting performance compared to different existing methods, dealing with highly imbalance issues.

5 CONCLUDING REMARKS

This paper presents a novel classification framework based on HR-Net and injected with a novel balanced affinity loss function to recognize highly imbalanced and cluttered contraband objects within baggage. The concept of the proposed loss function is based on the integration between max-margin learning and effective sample representation, and this leads in improving the performance of recognizing and classifying threatening items. Furthermore, the proposed system has been evaluated on two public datasets in terms of different metrics and compared with the existing methods. In the future, we plan to employ the proposed loss function in different models to perform different tasks, namely, threat detection.

Table 1: Performance comparison of the proposed framework with different loss functions in terms of accuracy and F1-score. Bold indicates the best scores.

Loss Function	Dataset	Accuracy	F1-score
Proposed	SIXray10	0.9172	0.8986
	SIXray100	0.8344	0.8162
	SIXray1000	0.7031	0.6926
	COMPASS-XP	0.8916	0.8714
Affinity Loss [21]	SIXray10	0.9093	0.8823
	SIXray100	0.8156	0.7918
	SIXray1000	0.6912	0.6593
	COMPASS-XP	0.8856	0.8669
Tversky Loss [30]	SIXray10	0.8957	0.8877
	SIXray100	0.8088	0.7859
	SIXray1000	0.6785	0.6671
	COMPASS-XP	0.8764	0.8589
Focal Loss [26]	SIXray10	0.8891	0.8602
	SIXray100	0.8106	0.7942
	SIXray1000	0.6800	0.6690
	COMPASS-XP	0.8776	0.8413
Focal Tversky Loss [1]	SIXray10	0.8561	0.8381
	SIXray100	0.7989	0.7718
	SIXray1000	0.6802	0.6452
	COMPASS-XP	0.8795	0.8593

Table 2: Performance comparison of the proposed framework with state-of-the-art baggage threat classification methods. Best results denoted by bold. Besides, BA stands for Balanced Affinity loss, and CE refers to Cross-Entropy loss.

Framework	Dataset	Accuracy	F1-score
Proposed	SIXray10	0.9172	0.8986
	SIXray100	0.8344	0.8162
	SIXray1000	0.7031	0.6926
	COMPASS-XP	0.8916	0.8714
ResNet50+BA loss [22]	SIXray10	0.9171	0.8881
	SIXray100	0.8280	0.8026
	SIXray1000	0.6974	0.6756
	COMPASS-XP	0.8754	0.8497
DenseNet201+BA loss [24]	SIXray10	0.9016	0.8726
	SIXray100	0.8207	0.7946
	SIXray1000	0.6291	0.6182
	COMPASS-XP	0.8708	0.8431
HRNet+CE loss	SIXray10	0.8891	0.8611
	SIXray100	0.7855	0.7509
	SIXray1000	0.6444	0.6185
	COMPASS-XP	0.8601	0.8417

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