Abstract—Future airports are becoming more complex and congested with the increasing number of travellers. While the airports are more likely to become hotspots for potential conflicts to break out which can cause serious delays to flights and several safety issues. An intelligent algorithm which renders security surveillance more effective in detecting conflicts would bring many benefits to the passengers in terms of their safety, finance, and travelling efficiency. This paper details the development of a machine learning model to classify conflicting behaviour in a crowd. HRNet is used to segment the images and then two approaches are taken to classify the poses of people in the frame via multiple classifiers. Among them, it was found that the support vector machine (SVM) achieved the most performant achieving precision of 94.37%. Where the model falls short is against ambiguous behaviour such as a hug or losing track of a subject in the frame. The resulting model has potential for deployment within an airport if improvements are made to cope with the vast number of potential passengers in view as well as training against further ambiguous behaviours which will arise in an airport setting. In turn, will provide the capability to enhance security surveillance and improve airport safety.

I. INTRODUCTION

Airports are highly secure environments; however, they are one of the busiest locations for human flow in the public transportation sector. Airports need to possess powerful, extensive security solutions whilst also being cost-effective and sensitive. These systems should not only apply to passengers but also to the many airport staff providing services throughout the airport. IATA expects overall higher surveillance capability. Not only is this safer for passengers, but also safer for airline staff too. In effect, this will reduce the impact on airport operations and reduce the chances of terror events escalating quickly with early detection.

The vision-based methods have been widely studied and implemented in many real-world scenarios due to low-cost, easy-implementation characters [3,4]. It can be an efficient solution for the airport monitoring system as current video processing techniques have shown the ability to provide accurate, stable, and real-time performance in the airport environment [5,6]. Therefore, this paper details the development of a Machine Learning (ML) and Machine Vision (MV) model to detect conflicts within crowds for use in airports. Two different approaches are demonstrated for detecting conflict, and the results of the final model are evaluated. The proposed system is designed based upon open-source human pose datasets as well as a bespoke dataset to cover the many different conflict scenarios that could occur in an airport crowd. This study is organized into four main parts. First, existing methods are detailed in the literature review. The methodology will be explained following the system architecture pipeline. This is initialised with the segmentation phase to get people’s pose estimation, following that, the classification phase for action predictions. Third, the experiment results are presented and evaluated by comparing two prediction heads based on Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP). Finally, the future works and conclusions of this study are discussed.

The contribution of the research is more than a standard conflict detection since it aims to implement a conflict detection system adapted for airport scenarios. It specialises in small crowds parsed in different locations. Thus, the camera needs to be able to detect all the people, placing the camera at a good height for easy board viewing. Existing conflict detection algorithms are implemented using standard pose estimators such as OpenPose or AlphaPose. However, in this research, a High-Resolution Network (HRNet) model is chosen as the pose estimator, with a ResNet backbone network for image feature extraction, to further performance.

II. RELATED WORK

Currently, surveillance is done with a human operator monitoring the many feeds of security cameras scattered

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1 This research is supported by Cranfield University and MSc AAI Project. (The corresponding author is Claire Delgove). K.Kheta, C.Delgove, R.Liu, A.Aderogba, M.Pokam, M.Mehmet Unal, Y.Xing, and W.Guo are with the Centre for Autonomous and Cyber-Physical System, Cranfield University, Bedfordshire, MK45 0AL, UK (email: [karan.kheta.633, claire.delgove.263, ruolin.liu.569, adeola.aderegba.155, m.s.pokam.187, m.unal.355, yang.x, weisi.guo]@cranfield.ac.uk)

Codes are available at www.github.com/ClaireDel/Conflict-Detection—GDP2
across the airport however there has been much research in intelligent surveillance and there are many tools available for behaviour recognition. Mabrouk reviews the different methods for detecting abnormal behaviour, done through behaviour representation and modelling [7]. Mabrouk also highlights the many challenges with abnormal behaviour detection and offers suggestions to overcome them [7]. One of the challenges is describing the behaviour of a subject if the scene constantly changes. It also highlights that behaviour detection algorithms assume that the subject is in front of the camera however in a real setting the subject could be anywhere in the view of the camera. To overcome this problem, it is suggested multiple cameras could be used. Thus, cloud computing will be required to cope with the huge amount of data for processing. Li et al. conducts a survey on state-of-the-art techniques for analysing crowded scenes [8]. This paper looks at crowds rather than individuals. Denman talks about the many different intelligent surveillance techniques for pedestrian throughput, crowd size and dwell times that can be used to benefit airport operations and networks [9]. These papers have all discussed in some way detecting anomalous behaviour however Pan et al. outline a method to detect a fight using pedestrian key node positions to estimate a pose, it then also shows how the motion is calculated from the optical flow and if the subject exists next to the target to detect a fight [10].

For detecting suspicious human activity, different approaches can be taken. The most standard one is divided into three steps: detecting a human, segmenting body limbs to estimate a pose, and finally detecting an action according to the body key points previously estimated. For human detection in particular, a HOG (Histogram of Oriented Gradients) feature pyramid [11] can be used to detect the upper bodies (head, arm and torso), using multiple filters in conjunction with deformable models to compute the score for a particular body part from image frames. After that, many algorithms can estimate human poses, models like OpenPose [12], AlphaPose [13] or even PoseNet [14] which give out the key point coordinates of the people in the image or video in real-time, searching for them on each body. However, an existing method HRNet (High-Resolution Network) is far more suitable for the human pose estimation problem for its reliable high-resolution representations [15]. Its architecture consists of parallel high-to-low resolution subnetworks with repeated information exchange across multi-resolution subnetworks (multi-scale fusion). This is the solution selected for the work of this paper and will be detailed further in this paper.

Finally, for the action recognition step, it is possible to focus on the image features, which resumes itself to an image classification problem for action recognition, or just on the predicted key points stored in a CSV file. Those who would like to focus on intrinsic features could use the famous convolutional Neural net VGG16 [16] or InceptionV3 [17]. On the other hand, for the key points approach, any performant algorithms could be suitable such as SVM (Support Vector Machines) classifier for instance [18]. More complex architecture can help to get higher performance such as the common use of a ResNet (Residual Neural Network) and FastAI [19], or a Recurrent Neural Network [20].

For work-related to intelligent conflict detection within airports, very little exists however there are other studies relating to crowd monitoring/surveillance. Thomopoulos et al. propose a deep learning architecture to provide a real-time risk assessment on passenger trajectories in the airport, assessing for malicious/suspicious behaviour [21]. On the issue of COVID-19, Fadzil et al. review a number of different crowd monitoring products for determining the number of people in crowded and confined spaces in airport terminals who are at risk for the spread of contagious diseases [22]. In terms of surveillance of crowds, Nishiyama covers how crowds are simulated, monitored, and secured. Nishiyama also covers the politics for security and concerns with crowd surveillance such as with racialized logic of suspicion [23].

### III. METHODOLOGY

Conflict in the proposed systems means physical conflicts between people (passengers, staff, and crew). These poses include pushes, punches, and kicks. The objective of this study is to develop a conflict detection algorithm using deep learning techniques to rapidly identify conflicts within crowds in an airport. The airport environment is highly varied containing areas for retail, food, passageways, security points, and lounges, and such a conflict detection system should be able to handle a different kind of scenarios. These settings are usually well lit however the system should be able to perform under various extreme conditions as well. Some of these areas will also be far busier than others such as the security checkpoint which would have high passenger flows compared to the likes of airport lounges, thus the system will be required to cope with a high number of potential subjects.

In sum, in this paper, the modelling phase is dedicated to developing an algorithm for the human pose analysis. It is composed of a human pose detector and a classifier to predict the different behaviours according to the postures.

#### A. System Architecture

The main pipeline (as shown in Figure 1) illustrates the process under two main phases: the segmentation phase which consists in plotting the key points using the HRNet model [24], and the classification phase involves action prediction using the estimated key points. This second phase has been designed by comparing two approaches: an SVM classifier and an MLP. In the end, the performant model is selected to classify fight poses.

![Figure 1. Main frame for the model. 1. Input data. 2. Human Detector. 3. Pose Segmentation. 4. Human Pose Estimation. 5. Human Action Detection.](image-url)
The model architecture (Figure 2) consists of obtaining a segmented dataset (a dataset with the key points plotted) using pictures of people fighting using a High-Resolution Network (HRNet) model. These pictures will be used to train a classifier by Transfer Learning when it is necessary. After that, the inference phase will be led using a real-time video sequence from a camera, to predict the violent behaviours (Pushing, Punching, Kicking, or Shooting) in the sequence using two different models. In the end, a comparison between both models will be done to choose the most performant one.

![Image of Model System Architecture](image)

**Figure 2.** Model System Architecture. Orange path for the training, Green path for the inference.

### B. Dataset

The dataset has been created using YouTube videos and various images we found on the internet. The videos used include fight movies, boxing matches, and street fights. The dataset contains actions for pushing, punching, kicking and shooting in varied environments such as in closed and open spaces. Varied styles for each pose were represented in the dataset in order to consider the poses diversity. Images are labelled as either a fight or normal action for binary classification. The dataset is composed of several widely used datasets and custom images, to assure the diversity of situations that our algorithm encounters. Images from a controlled environment, taken from the **ISR-UoL** dataset [25], will form half of our data. The rest is from our custom dataset, **G3D** [26] and **MPII Human Pose Dataset** [27], forming images with diverse environments with varying factors that impact our model: luminosity, background, and actors’ clothing. The final compilation is 452 normal and 218 fighting samples.

| Session | Action | Start Frame | End Frame | Actor | Action |
|---------|--------|-------------|-----------|-------|--------|
| 2       | 5      | 7           | 15        | 1     | 0      |
| 2       | 5      | 139         | 150       | 1     | 1      |
| 2       | 5      | 619         | 626       | 1     | 1      |
| 2       | 5      | 772         | 807       | 1     | 1      |
| 2       | 5      | 887         | 956       | 1     | 0      |
| 2       | 5      | 1436        | 1500      | 1     | 0      |

**TABLE I.** ISR-UoL ENHANCED LABELLING SAMPLE

It was required to label the ISR LCAS dataset (Table I). In some videos, the action of interest was repeated several times, separated with pauses, with people who did not share the same poses in the same frame. Thus, it was necessary to partition out interesting frames in the sequence. The protagonist carrying out the action is identified in each sequence which is how these sequences are labelled. Labelling the data more precisely allows us to only consider relevant images, avoiding confusion with ambiguous ones to have a robust model that can perform in various conditions. The **SDHA** dataset [28] serves as a validation dataset thanks to the good diversity in the behaviours: multiple people in the sequences, involved or not with the action.

### C. Segmentation Phase

To estimate the key points of human poses, a **High-Resolution Network (HRNet)** has been performed [24]. **HRNet** is a **High-Resolution Network** for multi-human pose estimation. It is pre-trained the **COCO** dataset which consists of 200,000 images and 250,000 person instances labelled with 17 key points (210 epochs: 50-60 hours). The method employed is a top-down approach which begins with detecting people on an image using a **Faster Region-Based Convolutional Neural Network (Faster RCNN)**, followed by plotting a bounding box around each person, and finally estimating the key points configurations with the bounding boxes. **HRNet** enables a segmented dataset to be obtained to train the pre-trained classifier, such as plotting the key points on bodies on a video launch. The detector will thus delimit the area of study for the future action classification of each person. **HRNet** has been chosen because it can provide accurate and precise heatmaps compared to some existing pose detectors [12]-[14], maintaining a high-resolution representation of the input data with an efficient computation complexity. A lighter version was chosen (**HRNet W-32**) due to its computation efficiency and adaptability to edge computing systems.

### D. Classification Phase

After the segmentation, predicted key points are used to train a classifier for conflict detection. Two classifiers are used, which are **SVM** and **MLP**. For pre-processing, images are cropped if there are several people present within the image. The 34 key points are not visually plotted on the images, instead, they are stored in a CSV file. They are then normalized considering not only the size of the bounding boxes but also the size of the images (cropped or not). Thus, each key point value is between 0 and 1. The relevance of this normalization is that it is invariant to scale. It only keeps the “shape” of the skeleton, without considering the position in the image or the size. During the inference, the model can be applied for the prediction of images or video streams.

### IV. Evaluation

#### A. Segmentation Phase

The results obtained for the segmentation part are very accurate with 73.7% accuracy on COCO dataset, with a learning rate of 1e-3, a mini-batch size of 128, 140 epochs, an **Adam** optimizer and **Mean Squared Error (MSE)** as loss function. **HRNet** can efficiently detect multiple people on a picture or on a video stream, thanks to the human detector at the top of its architecture. **HRNet** obtains high precision segmentations in low luminosity. Additionally, it is efficient regarding the different bodies’ angles, correctly associating the different body parts to each person, and considering the occlusions between people. Regarding the depth, the model can detect people which are quite far away from the objective (around 10 meters). The only limit encountered is that the model needs to have a view of the full body to be fully performant and to plot the feet key points properly.
B. Classification Phase: SVM

The precision value at the end of the final epoch is 94.37% (Table II). The score does not reach 100% due to a few people being classed as fighting when they are not. Six fighting cases were also misclassified as normal (6 False Negative) (Figure 3). False Negatives are more of a concern than False Positives, since detecting a false fight is not detrimental unlike classing a kick as a child could do (Figure 4) to fully verify the models’ performance. First, in conditions are not a problem for this model. Thus, it can be used misclassifications at human size. Low light luminosity which is more suitable camera should be placed at a high height to get a points are normalized before any classification. Thus, the classifications in varying camera angle views since the key values. Furthermore, the model can maintain highly accurate possible. But Frames Per Second (FPS) in order to get as smoother results as the rate frame selected for best performance was around 30

| Class: | Precision | Recall | F1-score |
|-------|-----------|--------|----------|
| 0     | 0.94      | 0.98   | 0.96     |
| 1     | 0.95      | 0.85   | 0.90     |

**TABLE II. CLASSIFICATION REPORT FOR SVM**

Figure 3. Confusion Matrix for SVM. 0: Normal, 1: Fight.

The results obtained using the SVM classifier show that the model is adequate for a fight classification. Four fighting actions at stake (punching, kicking, shooting, and pushing) are assimilated as a fight. Non-violent actions such as walking and shaking hands are correctly classified as normal behaviour on both inferences (images and videos). When bystanders are present in the flow, the model can make the difference between people fighting and those standing out from the fight, even when fights are confusing with many protagonists in view.

The model makes the prediction frame by frame, this is why the rate frame selected for best performance was around 30 Frames Per Second (FPS) in order to get as smoother results as possible. But SVM still provides good predictions for other FPS values. Furthermore, the model can maintain highly accurate classifications in varying camera angle views since the key points are normalized before any classification. Thus, the camera should be placed at a high height to get a clear view which is more suitable to get a full view and avoid misclassifications at human size. Low light luminosity conditions are not a problem for this model. Thus, it can be used in a diverse set of environments.

However, some ambiguous behaviours have been tested (Figure 4) to fully verify the models’ performance. First, kicking a ball as a child could do in an airport while waiting for a plane, or pushing a trolley with suitcases has correctly been classified as normal behaviour. However, ambiguity has been detected when people are giving a hug to each other. This error could be corrected by expanding the dataset and adding this action to the normal side of the dataset. Human behaviour is incredibly diverse and thus there will be more behaviours that have not been tested here. A further improvement to this work will be to test other potential ambiguous behaviours. It has also been observed that when a person is fighting, the predictions can sometimes swing between normal behaviour and a fight (alternating red and green on the frames continuously). When someone is fighting, they can take a normal pose within the fight, such as transitioning between a kick and a punch or pushing. This problem is because frames are considered one by one and not as a set of frames. To solve this problem, another model such as the Long-Short-Term Memory (LSTM) network [29] would have been more suitable for investigating the potential for optical flow analysis to track the trajectory.

Figure 4. Ambiguous scenarios results. Kicking a ball, hugging someone, and pushing a trolley.

C. Classification Phase: Neural Network

A Multilayer Perceptron (MLP) has been tested to classify the poses estimated on the image. MLPs are known to be good with regression, and more specifically with classification.

The following model hyper parameters were chosen as they gave the best results: learning rate of 1e-3, Sparse Categorical Cross Entropy as loss function, 20 epochs, batch size of 20 and Sigmoid as activate function. As the input data has only 34 feature vectors, a shallow network has been fixed to avoid the vanishing gradient issue. The layers chosen were a batch normalization layer between two dense layers and a dropout layer to counteract overfitting on the dataset.

After dividing the dataset with an 80-10-10 repartition (80% training data, 10% test data and 10% validation data), the model achieves 90% in every metric showing good model performance. The 0.95 in recall for the fight class is indicative of the model ability to theoretically catch most of the fight occurrences (Table III). Validation video sets were used to assess performance in real conditions (Figure 5 and Figure 6).

**TABLE III. CLASSIFICATION REPORT FOR MLP**

| Class: | Precision | Recall | F1-score |
|-------|-----------|--------|----------|
| 0     | 0.97      | 0.94   | 0.95     |
| 1     | 0.91      | 0.95   | 0.93     |

**TABLE III. CLASSIFICATION REPORT FOR MLP**

Figure 6. Validation video sets were used to assess performance in real conditions (Figure 5 and Figure 6).
revisit into one metric and with False Negatives being more of a concern than False Positives, this metric has more importance than the others. Where SVM has been applied directly using the sci-kit-learn library, the MLP has been trained using the parameters mentioned earlier.

The visualized difference between both models is that the Neural Network (NN) considers a fight without interruption compared to SVM which switches between normal and fighting behaviour during a fight, considering the fighting poses transition as normal. This is due to the frame-by-frame prediction. Unlike in the second video, the NN classifies normal poses as a fight when people are just standing. A mistake that SVM does not make. It is seen that the NN has overfitted the dataset and cannot take into consideration the full diversity of poses that can happen in various scenarios. Finally, the SVM model is most performant to be able to capture the environment in full which would be more realistic in an airport setting, thus this model has been chosen as a final model for the project. Though, the NN could have been improved without the time constraint.

E. Future Works

Results of the model show effective detection of conflicts however more work is needed for its implementation in an airport. The main problem regarding the SVM model was the movement fluidity. Since ambiguous behaviours can be managed from the dataset and the results from videos captured at a greater height, the smoothness is the only limit that cannot be managed. It is expected that a frame-by-frame prediction would be effective for our system, however, there is no doubt that considering a whole movement with at least several frames for a prediction would have given better results, even if the SVM classifier is already very performant for such a task. With the model created, it would have made more sense to include an intermediate class between a normal and a fighting behaviour when the model predicts a fighting behaviour at 50% accuracy. This can act as a warning to the user rather than being a full alert. Another method would be to use a rule-based classification system based on the pose classification of a person over time. That solution would require a tracking system that has memory, keeping people’s past positions available for use. It would also require a rule to discriminate between an ambiguous non-fighting pose and a true fighting position.

The proposed metrics to differentiate would be the velocity of the movements made by the person in a suspicious pose, assuming that fighting movement would be faster than other ambiguous poses that happen not to be fighting. This solution was explored, using the overlap of bounding boxes as a metric to track individuals: if a predicted box would overlap with a predicted one from the last frame, it is identified as the same person. If not, a new instance of the person is created. Predictions which are non-overlapping are considered out of the frame and thus eliminated. To be usable, the tracking algorithm needs to be improved (as the overlapping criteria are far from enough, completely failing in a crowded place). Nonetheless, that could be something to explore to improve the model so that it is capable of being implemented in an airport setting. Finally, to get a proper implementation in airport scenarios, our results showed that it was necessary to consider some points with high attention. First, even if the camera can be placed at the most appropriate height, it is undeniable that airports have high
passenger traffic therefore the model must be able to cope with detecting all potential subjects in a large crowd otherwise it could result in a fight misdirection. The results show that even if the model was performant, some people present at the back in the crowd were not detected (this is a problem of occlusion). It will still need to be paired up with high-performance hardware as an airport setting can experience thousands of passengers flowing through the complex in a day however if the suggestions are explored then conflict detection would be a viable enhancement to airport security surveillance.

V. CONCLUSION

This paper details the development of either a Support Vector Machine or a Neural Network to spot conflict within crowds. The HRNet was used as the backbone network to segment the subjects in a frame to be ready for pose classification by the pose classifier. It was found that the SVM-based classification head is the most suitable as it was the most performant for detecting conflicts. The model performs the weakest against ambiguous behaviour, and it is recommended to further develop the model against other such behaviours. It is also recommended to implement rules-based classification to improve movement fluidity in the model.

REFERENCES

[1] "Air Passenger Numbers to Recover in 2024", Iata.org, 2022. [Online]. Available: https://www.iata.org/en/pressroom/2022-releases/2022-03-01-01/. [Accessed: 24 May 2022].
[2] M. Andriluka, L. Pishchulin, P. Gehler, and B. Schiele, "2D Human Pose Understanding New Benchmark and State of the Art Analysis", ELCVIA Electronic Letters on Computer Vision and Image Analysis, vol. 13, no. 1, p. 18, 2014. Available: https://arxiv.org/pdf/1512.00567.pdf. [Accessed 27 May 2022].
[3] "A Guide to OpenPose in 2022 - viso.ai", viso.ai, 2022. [Online]. Available: https://viso.ai/deep-learning/opense/. [Accessed: 27 May 2022].
[4] "Pose Flow: Efficient online pose tracking." arXiv preprint arXiv:1802.00977 (2018).
[5] VNLSTM-PoseNet: A novel deep ConvNet for real-time 6-DOF camera relocalization in urban streets", Geo-spatial Information Science, vol. 24, no. 3, pp. 422-437, 2021. Available: 10.1080/109502020.2021.1960779.