Picture credit: ODSecurity

CONTRABAND DETECTION

Karen Kingham *examines the role that Deep Learning can play in stopping the smuggling of illicit goods into prison*

Recently, at the International Corrections and Prisons Association (ICPA) fourth Technology in Corrections Conference, ODSecurity together with the Netherlands Stenden University of Applied Sciences, presented their thought-provoking paper on an innovative approach to using Deep Learning and Artificial Intelligence in contraband detection in a prison environment.

One of the most important goals of any correctional facility, is to prevent contraband from entering the establishment. Any contraband in any prison the world over, as we all know, is going to cause difficulties for staff and prisoners alike. Be they, drugs, weapons, alcohol, dangerous substances or cell phones and sim cards. All of those items have been deemed contraband for a good reason. Smuggled contraband inevitably leads to problems within the institution, drug abuse, substance abuse, violence, threats, intimidation, and organised crime. Therefore, it is vital that these items are detected prior to entry to the establishment.

This need has led to body scanners increasingly appearing within our prisons to detect and visualise contraband, and those images are then interpreted by human experts.

These body scanners are used to scan, prisoners, visitors and staff alike in an attempt to ensure our prisons are safe from any outside threat and that prison staff can work on a level playing field, keep their charges safe and providing satisfactory level of duty of care.

The AI system detects anything out of the ordinary and flags those items as of interest

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Body scanners are made up of an x-ray emitter and an x-ray detector. To perform a scan, an individual stands between the emitter and the detector, and a low dose of x-ray radiation is passed through them. Radiation passes through the person being scanned, allowing the scanner to make an x-ray image of them. On this image you can see any items that are suspicious, from metal to plastics, ceramics to paper and fluids to herbs. As materials get less dense, detecting them becomes less obvious. The operator will naturally visually search for suspicious anomalies in and on the human body.

Of regular concern, is any health risk of high radiation levels associated with using body scanners. However, there is worldwide legislation covering body scanners, which work on the ALARA principal (As Low As Reasonably Achievable). ODSecurity is constantly working to reduce the radiation emissions, however that brings other challenges into play, because when you reduce emission levels the SNR (signal-to-noise ratio) noise levels increase, and the increased data produced often will contain additional information that cannot be displayed at the same time using conventional display systems, which increases the risk of a human operator failing to detect contraband in some situations. The signal-to-noise ratio in an ODSecurity body scanner is already lower than is typical for x-ray images in many fields.

For the purposes of this experiment, Dr. Klaas Dijkstra and Willem Dijkstra from the Netherlands Stenden University of Applied Sciences and Martin van der Kaap from ODSecurity posed the question: "How can the human operator be assisted with technological tools to maximise the chance of detecting contraband?"

Currently there is a Deep Learning revolution taking place. ImageNet, a worldwide database of images for visual object recognition software, has over 1.2-million images across 1,000 categories. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) evaluates algorithms for object detection and image classification on a large scale. In 2012 there was a large performance increase in Deep Learning and by 2015 it was outperforming humans.

Artificial Intelligence, or more specifically Deep Learning, has already achieved advanced and high-tech results in detecting a wide range of objects in many images. Benchmark datasets that contain millions of images of a range of common objects in different contexts, show Deep Learning achieving impressive results in both classification accuracy and on detecting the location of objects in those images.

Could Deep Learning be applied to technology used to detect contraband in x-ray images? If it could, imagine the exciting potential of increased detections available to our prisons.

However, for Deep Learning to be successful, algorithms for detecting objects need to be trained on many images. A representative set of images containing contraband needs to be annotated by manually specifying the location of each type of object. The image data and associate annotations are then fed into an Artificial Neural Network to train it to predict similar objects in unseen x-ray images. For common items like weapons and cell phones, this may be feasible, but for uncommon items collecting enough data poses a significant challenge.

Artificial Neural Networks are inspired by the human brain and are a data-driven and trainable system utilising a mix of processing power, smart algorithms and large datasets.

It is more convenient to train a system on only 'clean' images without contraband. The AI system would then need to detect anything out of the ordinary that was not encountered during training, and flag those items as contraband. In Deep Learning, this is known as 'Anomaly Detection', which is significantly more difficult to achieve because during training positive data – ie contraband – is missing. Anomaly detection using Deep Learning is currently garnering interest in many fields.

The method proposed for this experiment was where anomaly detection is trained to detect contraband and suspect objects in x-ray images of humans. But when an anomalous object is detected it can be used to further improve the object detection model. By feeding additional data into the already trained object detector, the system keeps, learning, growing and improving.

During the experiment, the team used 1,105 images and performed experiments to detect 11 different items, varying from opaque objects like knives to transparent ones like herbs. The neural network was trained to detect objects on 879 images. The results were evaluated on a separate testing set of 226 images.

FOR DEEP LEARNING TO BE SUCCESSFUL, ALGORITHMS NEED TO BE TRAINED ON MANY IMAGES

Additionally, an anomaly detection approach was used to detect contraband that was never seen by the system, using a set of 27 images containing opaque items. A restricted part of 130 images were used to train the system, in this case, the right arm.

For proof-of-concept, a humanoid phantom (model of a human body) was used, which allowed for the creation of a large data set of annotated x-ray images for testing. Several contraband items were purposely placed on the phantom and the pose of the phantom was slightly varied between images to represent the variety of human stances that are encountered in a real situation.

The neural network successfully detected 90 percent of the best performing item. The average for all types of items was 60 percent.

Both the location of the item on the phantom and the type of item influenced the detection rates, as did the specific deep learning method and way of presenting the image information to the neural network.

However, the anomaly detection method showed impressive descriptions of the unknown items in most of the 27 images that contained contraband. Although only a small part of the image was used, the method itself showed good promise for future research.

In conclusion, the team demonstrated that Deep Learning does indeed show potential to detect contraband in x-ray images of a humanoid phantom and that anomaly detection using deep learning is an interesting direction to apply it in a practical, automated, contraband detection system that can assist a human operator ●