# Image Detection using CNN: Contraband Classification

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## Problem Statement

#### What?

- Recognize the type of contraband in a luggage

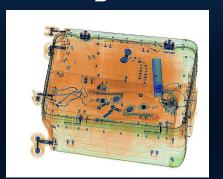
#### Why?

 Enhance both security (detect hard-to-see items) and efficiency (lead to shorter lines)

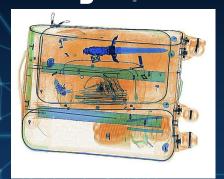


# X-ray Image Examples

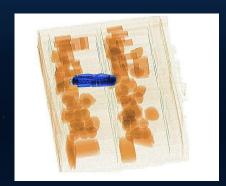
## Utility Knife



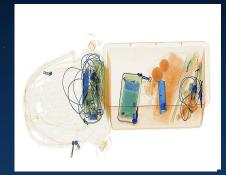
Straight Knife



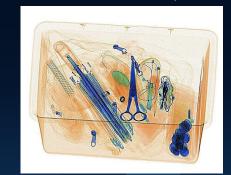
#### Multi-tool Knife



Folding Knife



#### Scissors





## Methods

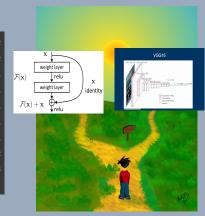
1. We failed...

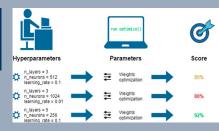
2. Then we explored different options

3. Hyperparameter Tuning and Data Augmentation

4. A lot of tests

Eooch 11/20 ==] - 247s 2s/step - loss: 1.4069 - accuracy: 0.2879 - val\_loss: 1.9056 - val\_accuracy: 0.2332 Epoch 12/20 ==] - 249s 2s/step - loss: 1.4093 - accuracy: 0.2728 - val\_loss: 2.0957 - val\_accuracy: 0.2332 Epoch 13/20 ==] - 241s 2s/step - loss: 1.4066 - accuracy: 0.2839 - val\_loss: 2.0118 - val\_accuracy: 0.2311 Epoch 14/20 ==] - 249s 2s/step - loss: 1.4057 - accuracy: 0.2877 - val loss: 2.0179 - val accuracy: 0.2311 Epoch 15/20 ==] - 248s 2s/step - loss: 1.4063 - accuracy: 0.2861 - val\_loss: 2.0415 - val\_accuracy: 0.2311 Epoch 16/20 ==] - 250s 2s/step - loss: 1.4068 - accuracy: 0.2882 - val\_loss: 1.9349 - val\_accuracy: 0.2311 Epoch 17/20 ==] - 252s 2s/step - loss: 1.4060 - accuracy: 0.2745 - val\_loss: 1.9207 - val\_accuracy: 0.2311 Epoch 18/20 124/124 [== ==] - 250s 2s/step - loss: 1.4046 - accuracy: 0.2831 - val loss: 1.9695 - val accuracy: 0.2332 Epoch 19/20 ==] - 236s 2s/step - loss: 1.4057 - accuracy: 0.2776 - val\_loss: 1.9698 - val\_accuracy: 0.2254 Epoch 20/20 ....] - ETA: 44s - loss: 1.4066 - accuracy: 0.2623







Resnet vs. VGG?



# Challenge

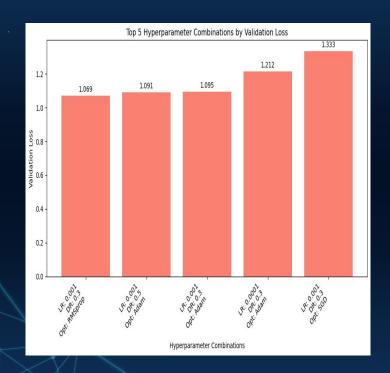
Imbalanced Dataset (amount of images in the Train, Validation, Test sets & the distribution of the contraband types throughout the images)

#### Solution:

- □ Step 1 **Consolidate Images**
- Step 2 Redistribute the Images
- Step 1 Oversampling the Minority Class with Data Augmentation: "Straight Knife"
- Step 2 Undersampling the Majority Class: "Utility Knife"



# Results





Validation Loss

Validation Accuracy

#### Results

Config 2

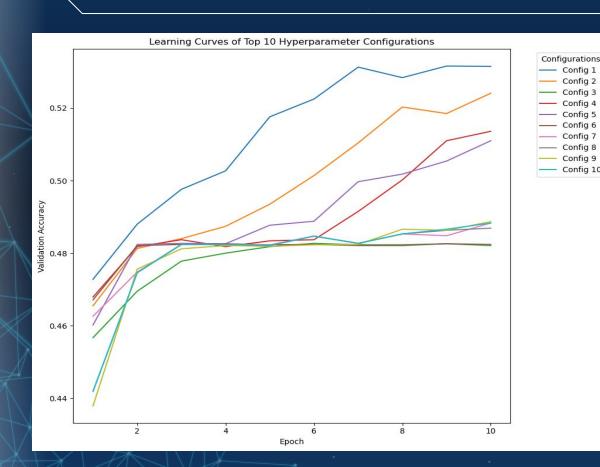
Confia 3 Confia 4

Confia 5 Config 6

Config 7

Config 8 Confia 9

Config 10



#### KEY:

Config 1: Learning Rate: 0.001, Dropout Rate: 0.3, Optimizer: Adam

Config 2: Learning Rate: 0.001, Dropout Rate: 0.3, Optimizer: RMSprop

Config 3: Learning Rate: 0.001, Dropout Rate: 0.3, Optimizer: SGD

Config 4: Learning Rate: 0.001, Dropout Rate: 0.5, Optimizer: Adam

Config 5: Learning Rate: 0.0001, Dropout Rate: 0.3, Optimizer: Adam

Config 6: Learning Rate: 0.001, Dropout Rate: 0.5, Optimizer: RMSprop

Config 7: Learning Rate: 0.001, Dropout Rate: 0.7, Optimizer: Adam

Config 8: Learning Rate: 0.0001, Dropout Rate: 0.5, Optimizer: Adam

Config 9: Learning Rate: 0.0001, Dropout Rate: 0.3, Optimizer: RMSprop

Config 10: Learning Rate: 0.0001, Dropout Rate: 0.7, Optimizer: Adam



# Conclusions

#### What we learned:

- The importance of a balanced dataset before running the model
- The crucial role hyperparameter tuning plays in model performance





Turns out, if the human eye struggles to make out what it's seeing in an x-ray image, a computer might just squint harder.





